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Abstract: The nature and quality of housing price statistics have come under increased scrutiny as dwelling prices have risen significantly around the world. This has occurred nowhere more so than in Australia where the reliability of official measures of housing prices have been questioned. In this paper we use a large transactions data set on housing prices and characteristics for Australia's largest city, Sydney, over the period 2001-03, to examine the effects of different quality adjustment methods for both temporal and spatial price indexes. We find that failure to adequately account for changes in the composition of houses sold between time-periods creates an upward bias in the index, but this is not as large as may have been suspected a priori. Quality adjustment is of more significance in accounting for price changes across regions within Sydney. We find large spatial variation in prices for the 14 regions we examine. Furthermore, we test for convergence over the period and find evidence that prices in cheaper regions increased faster than in the more expensive regions.

Keywords: House prices; Price index; Multilateral comparisons; Hedonic regression.

JEL Classification Codes: C23, C43, E31.

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I. Introduction

Movements in the prices of housing are important indicators for most economies. Much of households' wealth is held in the form of housing so that movements in prices have important implications for national consumption and investment decisions. Access to housing is important for social equity and hence changes in price can have major political implications. Along with being an important economic indicator house price indexes can also be used to derive estimates of the total housing stock using the deflation method.

The issue of house price indexes has come to the fore recently in Australia, as well as other countries, because the value of houses has gone up so significantly. These developments have left the statisticians somewhat wrong-footed as measures of housing price appreciation leave a lot to be desired. The primary problem with many of the available measures of house prices is that they do not appear to adequately account for compositional change in the type of houses sold between comparisons. The most common approach taken internationally to recording dwelling inflation is to compare measures of average or median prices over time. This is the general approach taken by the Australian Bureau of Statistics (ABS) and numerous other agencies worldwide. However, the obvious problem with such a method is that the quality of houses sold is likely to change over time contaminating a measure of pure-price with changes in composition. This possibility of contamination has worried those involved in understanding, analysing, and managing the economy. In mid-2004 the then-Governor of the Reserve Bank of Australia, Ian Macfarlane, voiced concern with the Australian statistics for this reason.[1]

> 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).

[1] Also of concern to the Governor was the timeliness of the data. Because of the delay between agreement and settlement of contracts to buy, indexes for a given quarter can often reflect transactions which were agreed in a prior period. These problems have recently been addressed by the ABS (see ABS, 2005).

Because the issue of compositional change is not adequately addressed in the official price indexes much of the recorded price change over the boom period is debatable. While the existence of very rapid increases in house prices is unquestionable it it likely that some part of these changes were due to compositional differences between periods. In this paper we address the key question of how large is the compositional-change effect in price indexes and is it large enough to rewrite Australian economic history. We use a detailed data set for Sydney from 2001 to 2003, which contains over 40,000 transactions in 128 postcodes, to look at recorded price change under various hedonic quality adjustment techniques. Our data includes both physical characteristics of dwellings, such as property type, number of bedrooms, bathrooms, as well as geo-spatial or location characteristics; distance to beach, schools, railway station. One issue of general interest is the spatial and temporal price indexes that arise from different types of hedonic functions. For example, does excluding the geo-spatial characteristics lead to biased indexes?

In a recent contribution Hansen (2006), working under the auspices of the Reserve Bank of Australia (RBA), has investigated the question of compositional change bias. Using a decade long data set for Melbourne, Sydney and Brisbane, with prices and physical characteristics only he found that differences between indexes that controlled for quality change and those that did not were relatively minor. Interestingly, he found that the quality-controlled indexes increased faster than the average price measures indicating, as we will show more clearly below, that the average quality of housing had *decreased* over the period. This was particularly apparent in the more recent data, roughly from about 2000 to the present. In this paper we will explore the relationship between the quality controlled and average price measures and the extent to which Hansen's results hold up in our sample.

While the construction of the numbers is of interest so are the numbers themselves. We are particularly interested in the degree to which prices differ across the spatial dimension, i.e. between regions in Sydney, and in how indexes change as the type of variables, physical and geo-spatial, used to explain prices change. These issues have not been addressed in any research that the authors are familiar with. In this regard we outline a model which explores these differences and how they evolved over time. Previewing the empirical results, we find very large differences in prices for housing across regions even after controlling for a long list of housing-characteristics. These could be interpreted as inefficiencies in market prices or perhaps more realistically as reflecting the existence of region-specific characteristics/amenities which are excluded from the model but valued by buyers. Also, using the estimated price levels for each region we can determine the average *volume* of housing services available in each region. Finally, we explore the extent to which prices converged in Sydney's regions during the housing boom years of our study. That is, did the general rise in house prices lead people to a movement away from higher priced suburbs to cheaper areas leading to greater appreciation in the latter than the former?

In the next section we outline more rigorously the issues related to compositional change in price indexes and some of the common approaches – we settle on hedonic regression. In section 3 we discuss the data while section 4 applies our preferred hedonic method to the construction of temporal and spatial price indexes for Sydney over the years 2001-03. Section 5 analyses the extent to which convergence in prices occurred over the boom period while section 6 concludes.

II. Measuring House Prices

(i) Average Price Methods

There are a range of methods for constructing house price indexes. Perhaps the most common is the comparison of average prices across time over some set of sales. If p_{kth} is the price of a house $h = 1, \ldots, H_{kt}$ sold in region $k = 1, \ldots, K$ at time $t = 1, \ldots, T$ then one example of an index of average prices, $I^{AP}_{js,kt}$, between region-periods kt and js is;

$$I^{AP}_{js,kt} = \frac{\sum_{h=1}^{H_{kt}} w_{kth} p_{kth}}{\sum_{h=1}^{H_{js}} w_{jsh} p_{jsh}}. \tag{1}$$

Here w_{jsh} and w_{kth} are weights which sum to one and are chosen by the analyst. They could be chosen so that each house gets equal weight or selected in such a way that the median house in each region-period gets a weight of one. The potential problems with this approach are that the prices included in the numerator and the denominator could be for quite different houses so that the index reflects not only price but also quality and compositional differences.

(ii) The Repeat Sales Method

There are two main techniques that have been used to get around the problem of compositional change in housing price indexes. The first is to use a repeat sales methodology which dates back to Bailey, Muth and Nourse (1963). Here the index is constructed so that the comparators are the same houses so that the numerator and denominator reflect the same dwellings with the same weights. For example, a very simple repeat sales index, $I^{RS}_{js,kt}$ may be written as follows:

$$I^{RS}_{js,kt} = \frac{\sum_{h=1}^{H_{kt}} \theta_{jsh,kth} w_{kth} p_{kth}}{\sum_{h=1}^{H_{js}} \theta_{jsh,kth} w_{jsh} p_{jsh}}. \tag{2}$$

Here we have defined $\theta_{kth,jsh} = 1$ if house h is sold in both js and kt and zero otherwise. While the repeat sales index is an improvement on average price indexes there are still some problems. First, it is only possible to construct a repeat sales index across time, where exactly the same houses are bought and sold, and not across space. This clearly implies that the repeat sales method is of no use if the researcher wants spatial price indexes to come out of the analysis. Second, along the temporal dimension it is likely that there will be renovations to existing houses so that while the street address may be the same the characteristics may change. Also, over the longer term the quality of the house may depreciate due to wear and tear. These factors imply that even the repeat sales index may be subject to quality change. Third, the index ignores all non-matched observations, which are likely to constitute a very large proportion of the overall data set. This means that potentially useful information is not incorporated into the comparison of prices. For short data sets of a few years, like ours, repeat sales indexes are impractical as they leave too little data on which to base estimation. Finally, there may be weighting issues related to the fact that some types of houses sell more frequently than others.

More recently, the repeat sales method has been extended to deal with some of these problems. More sophisticated econometric techniques can be used to partially address the depreciation and renovations problem and weighting can be used to deal with some house-types selling more often than others (see Shiller, 1991, 1993; Englund, Quigley and Redfearn, 1998; Dreiman and Pennington-Cross, 2004). However, the key problem is that there is just not enough information available to fully address the compositional change issue. This brings us to the hedonic regression method.

(iii) Hedonic Regression Methods

The hedonic regression method takes a somewhat related approach to the repeat sales; here a relationship is hypothesised and estimated between house prices and characteristics with the characteristics being held fixed in any comparison. The hedonic method dates back at least to Court (1939), and was revived by Griliches (1961). The conceptual basis of the approach was laid down by Lancaster's (1966) characteristics approach to consumer theory and Rosen (1974) who set out the meaning of the hedonic function. Hedonic regression is now widely used globally in the construction of official price indexes as well as in research, particularly for high-tech goods (see for example, Pakes, 2003; Berndt, Griliches and Rappaport, 1995; Triplett, 2004).

There are a number of hedonic techniques available for the construction of price indexes (see Triplett, 2004; ILO, 2004). The key choices are the form of the hedonic function, which relates prices and characteristics, and the way in which the hedonic function is used to construct price indexes. Our focus in this paper is in quantifying the influence that quality adjustment has on the housing price index, in comparison with no quality adjustment. We use a relatively straightforward and intuitively appealing approach to constructing temporal and spatial price indexes. We use what Hill and Melser (2006) refer to as the region-time dummy method.[2] Here we pool across all the regions and periods in the sample and estimate the characteristics prices as well as a region-period specific fixed effect. This gives the following model:

$$\ln(p_{kth}) = \sum_{c=1}^{C} \beta_c z_{kthc} + \sum_{\tau=1}^{T} \sum_{\kappa=1}^{K} \delta_{\tau\kappa} d_{kth\tau\kappa} + \varepsilon_{kth}, \qquad h = 1, \ldots, H_{kt},\ k = 1, \ldots, K,\ t = 1, \ldots, T, \tag{3}$$

where z_{kthc} $c = 1, \ldots, C$ are a set of quality characteristics, which we will be more specific about in the next section, and the $d_{kth\tau\kappa}$ are dummy variables such that $d_{kth\tau\kappa} = 1$ if the observation is from region-period kt (i.e. if $\tau = t$ and $\kappa = k$) and zero otherwise. The implicit assumption of the approach is that the characteristics prices are the same across regions. While this can be questioned it seems a reasonable assumption given the relatively short length of our data set, three years, and the fact that we are analysing a single city.

[2]This method was first proposed by Aizcorbe and Aten (2004), who refer to it as the Time-interaction-Country Product Dummy Method.

The advantage of this region-time dummy model is that the price indexes between regions and periods are easy to construct. Under this econometric model it can be seen that for all characteristics configurations that the relative price between two region-periods for a house with the same attributes is equal to the exponent of the difference between the dummy coefficients.

$$\frac{\hat{p}_{kt}(z)}{\hat{p}_{js}(z)} = \exp(\hat{\delta}_{kt} - \hat{\delta}_{js}) \tag{4}$$

In fact, it can be shown that the index above will give a biased estimate of the desired population parameters due to the fact that we are taking a nonlinear transformation of random variables (see Gardaren and Shah, 2002). A better approach, following Kennedy's (1981) suggestion, is to use the adjusted index, $I^{HR}_{js,kt}$, which will be approximately unbiased.

$$I^{HR}_{js,kt} = \exp\left[\hat{\delta}_{kt} - \hat{\delta}_{js} - \frac{\mathrm{Var}(\hat{\delta}_{kt}) + \mathrm{Var}(\hat{\delta}_{js})}{2}\right] \tag{5}$$

(iv) Decomposing Average Price Change

The hedonic method provides a neat way of decomposing price change into pure price differences and quality differences. Consider comparing two prices in separate regions. Using the hedonic function we can write the difference as the product of a price index, the first component, and a characteristics quantity index, the second factor in (6) below.

$$\frac{\hat{p}_{kt}(z_{kth})}{\hat{p}_{js}(z_{jsh})} = \left[\frac{\hat{p}_{kt}(z_{kth})}{\hat{p}_{js}(z_{kth})}\frac{\hat{p}_{kt}(z_{jsh})}{\hat{p}_{js}(z_{jsh})}\right]^{\frac{1}{2}} \left[\frac{\hat{p}_{js}(z_{kth})}{\hat{p}_{js}(z_{jsh})}\frac{\hat{p}_{kt}(z_{kth})}{\hat{p}_{kt}(z_{jsh})}\right]^{\frac{1}{2}} \tag{6}$$

The left-hand-side of (6) represents the raw differences in price level, much as is included in the average price index measures. The extent of the error, if the desired goal is to measure pure price change, is equal to the second component on the right-hand-side of (6) which is the characteristics-quantity index and the extent to which this differs across regions or periods.

We will make use of this decomposition to highlight any bias found in average price methods. In particular we will use an index version of the decomposition.

$$\frac{\prod_{h=1}^{H_{kt}}[\hat{p}_{kt}(z_{kth})]^{\frac{1}{H_{kt}}}}{\prod_{h=1}^{H_{js}}[\hat{p}_{js}(z_{jsh})]^{\frac{1}{H_{js}}}} = \left[\prod_{h=1}^{H_{kt}}\left(\frac{\hat{p}_{kt}(z_{kth})}{\hat{p}_{js}(z_{kth})}\right)^{\frac{1}{H_{kt}}}\prod_{h=1}^{H_{js}}\left(\frac{\hat{p}_{kt}(z_{jsh})}{\hat{p}_{js}(z_{jsh})}\right)^{\frac{1}{H_{js}}}\right]^{\frac{1}{2}} \left[\frac{\prod_{h=1}^{H_{kt}}(\hat{p}_{js}(z_{kth})\hat{p}_{kt}(z_{kth}))^{\frac{1}{H_{kt}}}}{\prod_{h=1}^{H_{js}}(\hat{p}_{js}(z_{jsh})\hat{p}_{kt}(z_{jsh}))^{\frac{1}{H_{js}}}}\right]^{\frac{1}{2}} \tag{7}$$

While this decomposition looks complicated the price index component simplifies for the case of a region-time dummy hedonic function which we have applied. After adjusting for the bias in the transformation and with a little algebra we have the following version of the decomposition:

$$\frac{\hat{p}_{kt}(\bar{z}_{kt})}{\hat{p}_{js}(\bar{z}_{js})} = \exp\left[\hat{\delta}_{kt} - \hat{\delta}_{js}\right]\left[\frac{\hat{p}_{js}(\bar{z}_{kt})\hat{p}_{kt}(\bar{z}_{kt})}{\hat{p}_{js}(\bar{z}_{js})\hat{p}_{kt}(\bar{z}_{js})}\right]^{\frac{1}{2}}, \tag{8}$$

$$\bar{z}_{ktc} = \frac{1}{H_{kt}}\sum_{h=1}^{H_{kt}} z_{kthc}, \qquad \bar{z}_{jsc} = \frac{1}{H_{js}}\sum_{h=1}^{H_{js}} z_{jshc}, \qquad c = 1, \ldots, C. \tag{9}$$

The left hand side represents the hedonic function evaluated at the average characteristics vectors, $\bar{z}_{kt}$ and $\bar{z}_{kt}$, which are the vector versions of (9). This equals a price index multiplied by an average characteristics index. In our empirical application that follows we will replace the pure difference in the exponent of dummy variables with the adjusted price index shown in (5). The second component on the right hand side of (8) has the interesting interpretation of the average difference in characteristics between two region-periods. We will focus on this value between regions as it indicates the average quantity of housing services consumed in each region.

With our approach now outlined we proceed in the next two sections to outline the data and then apply our methods to it.

III. The Data

Our data records all the sales of houses across 128 Sydney postcodes from the beginning of 2001 to the end of 2003. The data were purchased from a private housing data provider, Australian Property Monitors, who obtain some of their information from the New South Wales Valuer General and supplement this by going out and collecting additional data themselves. The hedonic approach is data-intensive and requires detailed characteristics information in order to implement. While the full data set contained around 200,000 observations much of these had too little characteristics information to be useable, for example they lacked bedroom and bathroom counts. The subset of data which did have sufficient characteristics information for use in hedonic regression was just over 40,000 observations, which is still a very large data set. While the exclusion of a large portion of the data is undesirable there is little else that can be done with these observations as, in the absence of details on their characteristics, there is no way the data can be used in inference regarding price change.

For this subset of observations we have full information on the key characteristics, *property type* (i.e. house, unit, terrace, townhouse, cottage, semi, villa, duplex), number of *bedrooms*, and number of *bathrooms*. To these core attributes we were able to add a number of characteristics by 'mining' a free-form description of the property written by the data collector. We supplemented these predominantly *physical* characteristics by *geo-spatial* features of the property, reflecting the distance of each dwelling to local amenities such as beaches, shopping centres, schools, hospitals and the like. The full list of characteristics used can be found in the succeeding table of regression results in the Appendix.

IV. The Results and Their Interpretation: Temporal and Spatial House Price Indexes for Sydney

(i) Overview

Using the methods and data discussed above we construct spatial and temporal price indexes for 14 regions in Sydney at a quarterly frequency from 2001 to 2003.[3] In the hedonic regression we include a suite of quality characteristics along with dummy variables for each postcode in each region and quarterly dummy variables for each region. Along the spatial dimension the inclusion of postcode dummies means that we can calculate the average price level in each postcode over the three years. There is not enough data, however, to include dummy variables for each postcode in each quarter so we use time-dummy variables at the region-level which implicitly assumes that price trends within postcodes in each region are the same.

[3]The regions used, with postcode ranges in brackets, are: Inner Sydney (2000 to 2020), Eastern Suburbs (2021 to 2036), Inner West (2037 to 2059), Lower North Shore (2060 to 2069), Upper North Shore (2070 to 2087), Mosman/Cremorne (2088 to 2091), Manly/Warringah (2092 to 2109), North Western (2110 to 2126), Western Suburbs (2127 to 2145), Parramatta Hills (2146 to 2159), Fairfield/Liverpool (2160 to 2189), Canterbury/Bankstown (2190 to 2200), St George (2201 to 2223), Cronulla/Sutherland (2224 to 2249), Campbelltown (2552 to 2570), Penrith/Windsor (2740 to 2771). These regions were based upon those used by Residex, a private housing data provider, and also accorded with our on idea of Sydney housing sub-markets.

The results of the regression are shown in the Appendix. We considered three models. First, we estimated a full model, Model 1, where we included all available physical and geo-spatial characteristics along with region-time dummy variables. The regression statistics and parameter estimates for the variables are shown in the first column of the table. The R^2 of the regression is 0.7882, the F-Statistic for the test of the null model is highly significant at 450.82, indicating that the model does a good job of explained the observed data. The coefficients on the quality-characteristics generally have the expected sign and are of reasonable magnitude. Given the logarithm of price is the dependent variable the coefficients can be interpreted as giving the approximate percentage effect on price. For example, in Model 1, having two bathrooms rather than one raises the price by approximately 6.54%.

We are also interested in the extent to which the price indexes changed when we excluded different types of characteristics. This is an important issue because many of the hedonic regression models run in the literature are implemented without the detailed information which we have available, particularly the geo-spatial information. For this reason the robustness of the coefficient estimates and most importantly the estimated price parities to the omission of variables is of some interest. First, we excluded the geo-spatial characteristics, which gives Model 2. We also experimented with excluding all characteristics we deemed *non-core*, that is everything except bedrooms, bathrooms and property type which gives Model 3. Finally, we also estimated a model, what we have called Model 4, where we excluded all quality characteristics except the postcode and time dummy variables to determine what such an unadjusted set of price indexes would look like. The results of this last regression are not shown, as when no implicit characteristics prices are estimated there is nothing to show. However, the R^2 coefficient of the regression in this case was 0.3783. This is surprisingly low and indicates that there is a great deal of heterogeneity of housing within regions. Finally, we undertook an F-Test of whether the exclusion of parameters in Models 2, 3 and 4 led to a statistically significant erosion of explanatory power. In each case the hypothesis of no difference was soundly rejected indicating that we should place our confidence in Model 1. Our aim is to determine whether the results from the other models accord with those in Model 1 or not. Let us now turn to a discussion of the resulting indexes.

(ii) Multilateral Indexes

Each of the hedonic regression models above implies a particular set of spatial and temporal price parities between Sydney's housing regions. We report the results for Model 1, the full regression model with all characteristics, in Table 1.

Table 1: Multilateral Housing Price Indexes for Sydney – Model 1

Quarter/ Region	A	B	C	D	E	F	G	H	I	J	K	L	M	N
2001 Q1	1.00	0.98	0.89	0.97	0.68	1.20	0.71	0.66	0.73	0.57	0.41	0.53	0.63	0.58
Q2	1.05	1.02	0.97	1.02	0.70	1.19	0.73	0.71	0.79	0.58	0.42	0.55	0.68	0.57
Q3	1.15	1.08	1.03	1.06	0.74	1.31	0.76	0.75	0.84	0.59	0.46	0.60	0.71	0.63
Q4	1.14	1.09	1.06	1.09	0.74	1.30	0.83	0.79	0.84	0.63	0.49	0.62	0.75	0.65
2002 Q1	1.14	1.17	1.08	1.09	0.81	1.36	0.85	0.81	0.89	0.64	0.52	0.70	0.76	0.66
Q2	1.24	1.25	1.17	1.17	0.85	1.43	0.90	0.87	0.96	0.67	0.55	0.74	0.84	0.72
Q3	1.26	1.27	1.19	1.23	0.87	1.44	0.95	0.93	1.01	0.69	0.60	0.76	0.89	0.80
Q4	1.29	1.29	1.23	1.25	0.89	1.42	0.99	0.95	1.03	0.76	0.62	0.78	0.90	0.80
2003 Q1	1.32	1.31	1.19	1.27	0.90	1.48	1.06	0.98	1.02	0.77	0.64	0.78	0.90	0.80
Q2	1.32	1.34	1.27	1.29	0.91	1.51	1.03	0.99	1.09	0.76	0.67	0.83	0.95	0.86
Q3	1.40	1.43	1.34	1.37	0.95	1.57	1.06	1.05	1.12	0.81	0.71	0.87	1.00	0.93
Q4	1.38	1.42	1.32	1.38	0.96	1.59	1.09	1.07	1.16	0.90	0.74	0.89	1.01	0.91
Total Change (%)	38.2	44.8	47.7	43.0	40.7	32.2	52.8	61.6	58.4	57.3	80.5	69.9	60.4	56.7

Note: A=Inner Sydney, B=Eastern Suburbs, C=Inner West, D=Lower North Shore, E=Upper North Shore, F=Mosman-Cremorne, G=Manly-Warringah, H=North Western, I=Western Suburbs, J=Parramatta Hills, K=Fairfield-Liverpool, L=Canterbury-Bankstown, M=St George, N=Cronulla-Sutherland.

The results are normalized such that Inner Sydney, region A, is equal to 1.00 in the first quarter of 2001. The interpretation of the numbers are that, for example, region N (Cronulla-Sutherland) in the first quarter of 2001 had prices which were only 58% as high as those in region A (Inner Sydney) in the same period, after controlling for physical and geo-spatial price-determining characteristics. Turning first to the spatial dimension, there is clearly a great deal of disparity across the regions in the cost of housing with significant premiums being paid for dwellings in the region F (Mosman-Cremorne) and to a lesser extent B (Eastern Suburbs). For example, in the first quarter of 2001 we calculate that exactly the same house in region F (Mosman-Cremorne) would have cost over 100% more than in region K (Fairfield-Liverpool). Such premiums have two potential interpretations. First, they can be thought of as 'good' or 'bad' deals, people in Fairfield-Liverpool are getting more for their money than those in more expensive suburbs. While this is possible it does seem entirely likely that such large price differentials would exist and persist, as they do not disappear over time. A second explanation is that the premiums embody unmeasured characteristics – reflecting everything that is left out of the hedonic function. That is, if we had access to all price determining characteristics then we would not expect to find such premiums. Without the full information set we find that some of the important omitted characteristics are correlated with regions. While this is no doubt true it is still of interest to examine the extent to which the prices for the same set of physical and geo-spatial characteristics differ across regions. We do this in greater detail below.

Another interesting feature of the multilateral results is the diversity in price trends exhibited by the 14 regions over 2001-03. For example, prices increased by 80.5% over the period in region K (Fairfield-Liverpool) and 69.9% in region L (Canterbury-Bankstown) but just 32.0% in F (Mosman-Cremourne). The faster appreciation of the more inexpensive regions is suggestive of convergence in house prices, a phenomenon which we investigate further below. We first turn to the construction of a housing price index for the whole of Sydney.

(iii) Temporal Price Indexes for Sydney

Much interest focuses on price changes Sydney-wide. We use our set of multilateral indexes to estimate city-wide indexes of price change. The respective regions are weighted together using the average value of house sales over the entire sample period in each region. Using value weights is more consistent with the price index tradition but we also investigated democratically weighting the regions together, by the number of housing sales, and both methods gave indexes which were virtually indistinguishable. Temporal price indexes for Sydney are shown in Table 2.

The key message of our estimates of housing inflation in Sydney are that the different hedonic models, where we control for differing sets of characteristics, exhibit much the same temporal price change. Model 1, our primary hedonic regression which controls for physical

Table 2: Temporal Price Indexes for Sydney

Quarter/ Model	Model 1	Model 2	Model 3	Model 4	ABS
2001 Q1	1.00	1.00	1.00	1.00	1.00
Q2	1.05	1.05	1.05	1.07	1.03
Q3	1.11	1.11	1.11	1.09	1.09
Q4	1.14	1.14	1.14	1.13	1.15
2002 Q1	1.19	1.19	1.19	1.22	1.20
Q2	1.28	1.28	1.29	1.31	1.25
Q3	1.33	1.33	1.34	1.35	1.32
Q4	1.36	1.36	1.37	1.38	1.40
2003 Q1	1.37	1.38	1.39	1.40	1.45
Q2	1.42	1.42	1.44	1.46	1.51
Q3	1.50	1.50	1.52	1.52	1.54
Q4	1.51	1.51	1.53	1.56	1.62

and geo-spatial characteristics, showed an overall price rise of 51% over the 12 quarters. At the other end of the spectrum, Model 4, which takes no account of compositional change other than postcode dummy variables, increased by 56%. As Model 4 represents average price change while Model 1 reflects full hedonic adjustment, the difference between the two indexes, with reference to decomposition (8), reflects the change in average characteristics. The difference between the two indexes of just 5% indicates only a small increase in average quality over the 3 years and hence a small upward bias in average price index methods. Our results do not accord with those of Hansen (2006) who found that the hedonic index increased faster than the average/median price index. The increase in average characteristics-quantity mean that the opposite happens in our case.

One interesting feature of the results is that the exclusion of geo-spatial characteristics, Model 2, has very little impact on estimated temporal price change. That is, Method 1 and 2 are virtually indistinguishable indicating that the inclusion of geo-spatial characteristics does not add a great deal to the estimation of temporal price change. This result is not too surprising as geo-spatial characteristics are less likely to change than physical characteristics over time. Moreover, the inclusion of postcode dummy variables appears to 'mop up' much of the geo-spatial characteristics when they are excluded.

For comparative purposes we have also included the Australian Bureau of Statistics (ABS) index for the period from their house price index series (ABS, 2003) in Table 2. The results from the ABS differ from ours but are most similar to those for Model 4 where we have allowed compositional change. There are likely to be a multitude of reasons for these differences. The ABS series covers a narrower range of dwellings than our indexes focusing only on 'project homes' and 'established houses' – essentially residential dwellings on their own block of land (see the 'Explanatory Notes' of ABS (2003)). This excludes a great deal of inner city apartment housing and high rise dwellings. Furthermore, the ABS index is constructed using a complicated stratification and median price method which is not the same as our Model 4 – a Geometric mean of prices controlling for postcodes. The differences between our indexes and those of the ABS are suggestive, however, and may indicate that established houses, as defined by the ABS, increased at a faster rate than apartment-style dwellings.

(iv) Spatial Price Indexes for Sydney's Regions

Also of interest are spatial indexes of house prices, indicating on average, which is Sydney's most expensive region. The regional price parities are shown in Table 3 and were constructed by taking the geometric mean over three years of data (i.e. in the case of Model 1 we take the geometric mean of the set of multilateral price indexes found in Table 1 for each region).

Table 3: Spatial Price Indexes for Sydney

Model/ Region	A	B	C	D	E	F	G	H	I	J	K	L	M	N
Model 1:	1.00	1.00	0.94	0.97	0.68	1.15	0.74	0.72	0.78	0.57	0.46	0.58	0.68	0.60
Model 2:	1.00	1.13	0.86	0.98	0.67	1.31	0.96	0.63	0.66	0.44	0.35	0.49	0.63	0.65
Model 3:	1.00	1.13	0.85	0.99	0.74	1.30	0.95	0.65	0.67	0.45	0.36	0.49	0.63	0.67
Model 4:	1.00	1.36	1.15	1.45	1.45	1.56	1.40	1.03	0.96	0.78	0.60	0.74	0.93	1.11

Note: A=Inner Sydney, B=Eastern Suburbs, C=Inner West, D=Lower North Shore, E=Upper North Shore, F=Mosman-Cremorne, G=Manly-Warringah, H=North Western, I=Western Suburbs, J=Parramatta Hills, K=Fairfield-Liverpool, L=Canterbury-Bankstown, M=St George, N=Cronulla-Sutherland.

The first point to note is that for all the methods there are significant differences in prices across the 14 regions. The different types of quality adjustment also give significantly different results, indicating that the quantity of characteristics differs across regions.

The most expensive region by some margin over the period 2001-2003 was Mosman-Cremorne (F) while the least expensive was Fairfield-Liverpool (K). For our preferred quality adjusted indexes, Method 1, where both physical and geo-spatial characteristics are included, the spread between highest and lowest priced suburbs was 2.5. That is, the most expensive region was 150% more pricey than the cheapest region. The spread is similar for the other methods though the relativities between regions change somewhat.

In stark contrast to the temporal results it can be seen that the spatial indexes are very sensitive to the type of quality adjustment undertaken. Importantly, the nature of the hedonic function, and particularly the characteristics available to the researcher, has a more significant effect in the spatial dimension than the temporal. The reason for this is that the region dummys are likely to be closely correlated with many of the characteristics, particularly the geo-spatial features, so that excluding some of these characteristics biases the estimate of regional prices. A good example of this can be seen for region B, which represents Sydney's Eastern Suburbs. In the full model, B is estimated to have prices just equivalent to Inner Sydney (A) but this jumps out to a 15% premium when the geo-spatial characteristics are excluded. Much of the price-premium paid for living close to the beach has been included in the region dummy variables under the second specification leading to false inferences regarding relative prices.

Our focus has mainly been upon looking for trends across the Sydney housing market at the district or regional level. However, there is obvious interest in the more disaggregated postcode-level trends. Unfortunately, there are simply not enough transactions to estimate detailed temporal price trends at this level but we do estimate cross-sectional variation over the 3-year sample. In Table 4 we present a ranking of the top 25 postcodes in Sydney of the 128 postcodes used in our analysis.[4]

[4]Note that we have not used every postcode in Sydney and indeed some of the more expensive, such as 2028 (Double Bay) are not included in our sample. The 128 postcodes in our sample are: 2000, 2009, 2010, 2011, 2016, 2018, 2021, 2022, 2023, 2024, 2026, 2027, 2029, 2030, 2031, 2032, 2033, 2034, 2035, 2036, 2037, 2040, 2041, 2042, 2046, 2047, 2049, 2060, 2064, 2065, 2066, 2067, 2068, 2069, 2070, 2073, 2074, 2075, 2076, 2077, 2086, 2087, 2088, 2089, 2090, 2093, 2095, 2096, 2097, 2099, 2100, 2101, 2107, 2111, 2112, 2113, 2114, 2117, 2118, 2120, 2121, 2122, 2125, 2126, 2131, 2133, 2134, 2135, 2137, 2141, 2142, 2144, 2145, 2146,

Table 4: The Postcode League Table

Postcode	Suburbs	Region	Price Level (Rank) (Average 2001-2003)			
			Model 1	Model 2	Model 3	Model 4
2027	Darling Point, Edgecliff, Point Piper	B	1.20 (1)	1.30 (1)	1.26 (1)	1.61 (3)
2000	Dawes Point, Haymarket,					
	Millers Point, Sydney, The Rocks	A	1.00 (2)	1.00 (4)	1.00 (4)	1.00 (30)
2088	Mosman, Spit Junction	F	0.92 (3)	1.06 (2)	1.02 (2)	1.72 (2)
2030	Dover Heights, Rose Bay North,					
	Vaucluse, Watsons Bay	B	0.91 (4)	1.04 (3)	1.01 (3)	1.94 (1)
2023	Bellevue Hill	B	0.90 (5)	0.99 (5)	0.95 (5)	
2029	Rose Bay	B	0.87 (6)	0.95 (6)	0.92 (6)	1.41 (7)
2011	Elizabeth Bay, Potts Point,					
	Rushcutters Bay, Woolloomooloo	A	0.85 (7)	0.91 (9)	0.85 (10)	0.80 (58)
2090	Cremorne	F	0.83 (8)	0.90 (10)	0.86 (8)	1.24 (9)
2021	Centennial Park, Moore Park,					
	Paddington	B	0.83 (9)	0.84 (13)	0.79 (13)	1.24 (10)
2089	Neutral Bay	F	0.83 (10)	0.91 (8)	0.87 (7)	1.16 (17)
2060	Lavendar Bay, McMahons Point,					
	North Sydney, Waverton	D	0.77 (11)	0.86 (11)	0.83 (11)	1.10 (21)
2009	Pyrmont	A	0.75 (12)	0.73 (19)	0.70 (17)	0.84 (54)
2047	Drummoyne	C	0.75 (13)	0.71 (20)	0.69 (20)	1.05 (24)
2022	Bondi Junction, Queens Park	B	0.74 (14)	0.78 (16)	0.74 (16)	1.12 (19)
2068	Castlecrag, Middle Cove, Willoughby	D	0.73 (15)	0.69 (23)	0.67 (23)	1.28 (8)
2041	Balmain, Birchgrove	C	0.73 (16)	0.74 (18)	0.70 (19)	1.18 (16)
2010	Darlinghurst, Surrey Hills	A	0.71 (17)	0.68 (24)	0.64 (26)	0.80 (60)
2064	Artarmon	D	0.71 (18)	0.67 (26)	0.64 (29)	0.97 (38)
2065	Crows Nest, Greenwich, Naremburn,	D				
	St Leonards, Wollstonecraft	D	0.71 (19)	0.71 (22)	0.68 (21)	1.02 (28)
2135	Strathfield	I	0.70 (20)	0.56 (40)	0.56 (39)	1.05 (26)
2066	Lane Cove, Linley Point,					
	Longueville, Northwood, Riverview	D	0.68 (21)	0.66 (29)	0.65 (25)	1.21 (12)
2037	Forest Lodge, Glebe	C	0.68 (22)	0.61 (36)	0.57 (38)	0.92 (43)
2024	Bronte, Waverley	B	0.67 (23)	0.85 (12)	0.80 (12)	1.10 (20)
2069	Castle Cove, Roseville	D	0.67 (24)	0.66 (27)	0.68 (22)	1.53 (4)
2031	Clovelly, Randwick, St Pauls	B	0.67 (25)	0.74 (17)	0.70 (18)	0.97 (35)
2095	Manly	G	0.63 (31)	0.92 (7)	0.86 (9)	0.99 (32)

The most expensive postcode in our sample, by a very large margin, is 2027 – the home of movie stars, business moguls and some of the country's prize real estate. The postcode takes in Darling Point, Edgecliff and Point Piper and it will come as no surprise that it comes in first. Second on the list is the central Sydney postcode 2000 (Dawes Point, Haymarket, Millers Point, Sydney, and The Rocks) while 2088 (Mosman and Spit Junction) come in third. Most of the pricey postcodes come from the Eastern Suburbs (B), and Mosman-Cremourne (F) with a few also from Inner Sydney (A) and the Inner West (C) also making an appearance.

Turning back now to the regional results, note that using the decomposition shown in (8) above we can estimate the average difference in housing quality across Sydney's regions. The results are shown in Table 5.

Table 5: Regional Differences in Average Housing Quality

Model/ Region	A	B	C	D	E	F	G	H	I	J	K	L	M	N
Model 1:	1.00	1.39	1.26	1.52	2.12	1.39	1.80	1.42	1.26	1.40	1.34	1.30	1.38	1.83
Model 2:	1.00	1.22	1.37	1.50	2.16	1.22	1.40	1.62	1.48	1.82	1.74	1.57	1.48	1.70
Model 3:	1.00	1.22	1.39	1.48	1.95	1.22	1.40	1.57	1.46	1.77	1.73	1.57	1.48	1.65

Note: A=Inner Sydney, B=Eastern Suburbs, C=Inner West, D=Lower North Shore, E=Upper North Shore, F=Mosman-Cremorne, G=Manly-Warringah, H=North Western, I=Western Suburbs, J=Parramatta Hills, K=Fairfield-Liverpool, L=Canterbury-Bankstown, M=St George, N=Cronulla-Sutherland.

The results are quite startling and indicate large differences in the average quality of housing in the different regions. Focusing first on Model 1, Lower North Shore (E) has the highest average quality of housing while Inner Sydney (A) has the lowest average quantity of characteristics. This is to be expected on two counts. First, in the centre of the city space is at a premium so homes tend to be smaller having fewer bathrooms and bedrooms so the amount of physical characteristics is less. Second, access to geo-spatial characteristics – such as beaches, schools, parks – is also likely to be diminished in the centre of the city.

2147, 2148, 2150, 2151, 2153, 2154, 2155, 2160, 2161, 2162, 2163, 2164, 2165, 2166, 2168, 2170, 2171, 2176, 2177, 2190, 2192, 2193, 2194, 2195, 2196, 2199, 2200, 2203, 2204, 2206, 2207, 2208, 2209, 2210, 2211, 2212, 2213, 2216, 2217, 2218, 2219, 2220, 2221, 2222, 2223, 2224, 2226, 2227, 2228, 2229, 2230, 2232, 2233, 2234.

More generally speaking, we may expect to see a negative correlation between the price level of a region and the average characteristics quantity. If the price level for a region is interpreted as the intrinsic value or land price then households may react to a higher land price by purchasing less of it which means the capacity to have more physical characteristics (dwelling type, bedrooms, bathrooms, etc.) is diminished. We find a correlation of -0.29. Though this is not significant at conventional levels it is suggestive of a systematic relationship.

V. Have Prices Converged?

One question of interest is the extent to which prices have converged across Sydney's regions. Over the period 2001 to 2003 we have seen extraordinarily rapid price growth Sydney-wide. In this situation one possibility is that there would be some substitution away from higher priced regions, such as those on the harbour and in the east, toward lower-cost regions in the west. The likely results of such increased relative demand for lower priced housing would see the prices of the cheaper regions increase faster than those that are more expensive. That is, we speculate that the price levels may have converged across Sydney during the housing boom. Of course this may not have happened. Much of the strength in housing prices reflected the strong economy and it is possible that those who are doing best out of income growth are those who are wealthy and have a penchant for more expensive housing. In this scenario the prices could have diverged across Sydney. What has happened?

There is a large literature on testing convergence mainly on international comparisons of prices and income levels (for example see, Sala-i-Martin, 1996). Following this literature we distinguish between two types of convergence; σ-convergence and β-convergence. The first type of convergence measures the variance of the cross-section of price parities and then examines whether this has declined over time. That is, we calculate and compare

$$\sigma_t^2 = \frac{1}{K}\sum_{k=1}^{K}\left[\ln\left(I_{kt}\right) - \ln\left(\bar{I}_t\right)\right]^2, \qquad \ln\left(\bar{I}_t\right) = \frac{1}{K}\sum_{k=1}^{K}\ln\left(I_{kt}\right), \qquad t = 1,\ldots,T. \tag{10}$$

The other type of convergence, β-convergence, tests the extent to which the price level explain changes in prices. Consider the regression below where I_{kt} is the estimated parity for region-period kt.

$$\ln\left(\frac{I_{kt}}{I_{kt-1}}\right) = \alpha_0 + \sum_{\tau=2}^{T} \alpha_\tau a_{kt\tau} + \beta \ln(I_{kt-1}) + e_{kt}, \qquad t = 2, \ldots, T,\ k = 1, \ldots, K \tag{11}$$

If convergence is occurring then in (11), β should have a negative sign – the higher the price level the lower the price change. The two convergence concepts are intuitively appealing and closely related and clearly measure much the same phenomenon. However, note that while β-convergence implies σ-convergence the converse does not necessarily hold. If prices cross – so that the cheaper regions become the more expensive – then we would have β-convergence without necessarily having σ-convergence (Sala-i-Martin, 1996).

We implement both these approaches to measuring convergence for Sydney using the results from our preferred specification, Model 1. We find surprisingly strong evidence for convergence in house prices over 2001-03. Table 6 shows our results for both β-convergence and σ-convergence.

Table 6: Measuring Convergence

$\beta-$Convergence			$\sigma-$Convergence	
R-Squared	0.3390			
Observations	154			
Parameters	12			
Variables	Coefficient	Std. Error	Quarter	Variance
Intercept	0.0307	0.0089	2001 Q1	0.0813
Price Level	-0.0292	0.0081	Q2	0.0848
2001 Q2	0.0233	0.0114	Q3	0.0835
Q3	-0.0059	0.0108	Q4	0.0732
Q4	0.0057	0.0124	2002 Q1	0.0684
2002 Q1	0.0310	0.0101	Q2	0.0699
Q2	0.0113	0.0108	Q3	0.0609
Q3	-0.0082	0.0105	Q4	0.0560
Q4	-0.0170	0.0113	2003 Q1	0.0573
2003 Q1	-0.0026	0.0124	Q2	0.0546
Q2	0.0253	0.0096	Q3	0.0529
Q3	-0.0123	0.0121	Q4	0.0459

We find a negative, and highly statistically significant, coefficient on β of -0.0292. One point to note about the β-convergence regression is that it does not take account of the randomness of the independent variables, i.e. the estimated price parities. In the case where a regressor is measured with error the coefficient on this variable will tend to be biased toward zero (see for example, Greene, 2000, p. 375-7). This means that our *beta*-convergence result is even stronger than it first appears. The hypothesis of convergence is given further support by the consistent and marked decline in the cross-sectional variation in price levels over time. In the first quarter of 2001 the variance is estimated at 0.0813 and this drops, almost continuously, to 0.0459 in the final quarter of 2003.

The strong evidence for convergence is good for equality in that it evens up house prices Sydney-wide. However, it may also indicate that cheaper regions were the more vulnerable at the end of the boom. While we do not have data after 2003 when price growth reversed anecdotal evidence does suggest that it is these cheaper regions that have fallen by more than the expensive regions since 2003 undoing much of the earlier convergence.

VI. Conclusion

In this paper we have outlined and constructed hedonic housing price indexes for Sydney at the level of 14 regions and a quarterly frequency. In order to make the most of our data we estimated a region-time dummy hedonic model which gave parities as the coefficients on dummy variables while also estimating implicit prices on the characteristics included in the regression. We found that the temporal price indexes arising from this method were insensitive to the exclusion of various characteristics to the extent that the bias between quality adjusted and non-quality adjusted indexes was around 5% on a total price change of 51%. This should give some comfort to those who compile and use official statistics where quality adjustment has been minimal – the bias from such indexes appears to be small, at least in our data. This will serve to assuage those who are concerned about the quality of the existing official indexes.

In terms of the spatial dimension, a much neglected area, we find that the results from the hedonic function are very much dependent on the type of variables included. The exclusion of geo-spatial and some of the physical characteristics led to erroneous estimates of price change. This is another lesson that estimation of price differences in the spatial dimension can be a lot more complicated than across time (Melser and Hill, 2005). This is an important issue. Only with panel (i.e. spatial and temporal) price indexes can one address questions such as the extent of convergence in price indexes. We did this for our preferred set of multilateral price indexes and found that over the boom years of our data set, 2001-03, there had indeed been a narrowing in the dispersion of housing prices across regions.

While our analysis has focused exclusively upon Sydney from 2001-03 it is likely that much the same trends were evident in other parts of Australia which experienced a similarly strong appreciation over the period. Moreover, it is likely that the Sydney market can be viewed as a case study of housing price booms. In this context the finding of convergence and only minor compositional change are interesting and may indicate the nature of many of the housing booms seen worldwide recently. Further work is required in this area using data over a longer span of time and also covering the down swing along with the boom phase.

APPENDIX

Table 7: Regression Results

	Model 1		Model 2		Model 3	
R-Squared	0.7882		0.7616		0.7402	
Adj. R-Squared	0.7865		0.7597		0.7383	
Observations	41,154		41,154		41,154	
Parameters	339		318		298	
F-Stat	450.82		411.47		393.22	
MSE	0.0634		0.0714		0.0776	
Variables	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Core Physical Characteristics:						
Intercept	13.8987	0.0612	13.7285	0.0606	13.8624	0.0631
Unit	-0.5052	0.0052	-0.4773	0.0054	-0.5054	0.0051
Terrace	-0.1263	0.0069	-0.1326	0.0072	-0.1663	0.0075
Semi	-0.1385	0.0055	-0.1522	0.0058	-0.1693	0.0059
Cottage	-0.0402	0.0059	-0.0408	0.0063	-0.057	0.0065
Townhouse	-0.3156	0.0076	-0.3128	0.0080	-0.3084	0.0074
Duplex	-0.1403	0.0161	-0.1399	0.0171	-0.1541	0.0176
Villa	-0.2636	0.0120	-0.2628	0.0128	-0.2477	0.0116
Bedrooms 1	-0.5068	0.0072	-0.5147	0.0075	-0.5448	0.0078
2	-0.1727	0.0036	-0.1788	0.0038	-0.1974	0.004
4	0.1251	0.0042	0.1322	0.0045	0.157	0.0047
5	0.2079	0.0084	0.2193	0.0089	0.2627	0.0094
≥ 6	0.2639	0.0195	0.2761	0.0207	0.3168	0.0225
Bathrooms 2	0.0654	0.0037	0.0711	0.0040	0.0924	0.0041
3	0.1650	0.0083	0.1853	0.0089	0.2353	0.0093
≥ 4	0.3283	0.0187	0.3768	0.0198	0.4843	0.0207
Other Physical Characteristics:						
Area	9.19E-05	9.24E-06	9.81E-05	9.89E-06	...	...
Area Squared	2.59E-08	6.38E-09	2.87E-08	6.80E-09	...	...
Extra Room	0.0323	0.0029	0.0358	0.0031	...	...
Air Conditioner	0.0723	0.0059	0.0775	0.0062	...	...
Alarm System	0.0482	0.0100	0.0440	0.0106	...	...
Brick Construction	0.0100	0.0066	0.0132	0.0073	...	...
Ensuite Bathroom	0.0662	0.0052	0.0709	0.0055	...	...
Fireplace	0.0299	0.0048	0.0261	0.0050	...	...
Garden	0.0262	0.0054	0.0248	0.0058	...	...
Ground Floor	-0.0712	0.0186	-0.0756	0.0193	...	...
Gym	0.1029	0.0204	0.1143	0.0227	...	...
Heating	0.0495	0.0173	0.0422	0.0184	...	...
Secure Parking	0.0530	0.0027	0.0519	0.0028	...	...
Pool	0.0766	0.0046	0.0889	0.0049	...	...
Sandstone	0.0799	0.0844	0.0789	0.0809	...	...
Sauna	0.1068	0.0471	0.1311	0.0553	...	...

Table 8: Regression Results (Continued)

Variables	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Strata	-0.0814	0.0105	-0.0799	0.011	...	...
Tennis Court	0.2393	0.0241	0.2582	0.0247	...	...
Top Floor	0.0860	0.0189	0.1201	0.0203	...	...
Unrenovated	-0.0096	0.0089	0.0046	0.0096	...	...
Walk-in-Wardrobe	0.0371	0.0109	0.0414	0.0115	...	...
Geo-Spatial Characteristics:						
Beachfront	0.3151	0.1927	...	...	...	...
City Views	0.0509	0.0159	...	...	...	...
Harbour Views	0.1849	0.0068	...	...	...	...
Waterfront	0.4665	0.0245	...	...	...	...
Log(Distance to Airport)	-0.0013	0.0203	...	...	...	...
$(\text{Log(Distance to Airport)})^2$	0.0137	0.0070	...	...	...	...
Log(Distance to Beach)	-0.1051	0.0056	...	...	...	...
$(\text{Log(Distance to Beach)})^2$	-0.0103	0.0020	...	...	...	...
Log(Distance to Park)	0.0417	0.0056	...	...	...	...
$(\text{Log(Distance to Park)})^2$	0.0084	0.0012	...	...	...	...
Log(Distance to Large Shopping Centre)	0.0340	0.0035	...	...	...	...
$(\text{Log(Distance to Large Shopping Centre)})^2$	0.0442	0.0028	...	...	...	...
Log(Distance to Local Shopping Centre)	0.0404	0.0031	...	...	...	...
$(\text{Log(Distance to Local Shopping Centre)})^2$	-0.0001	0.0020	...	...	...	...
Log(Distance to School)	0.0517	0.0060	...	...	...	...
$(\text{Log(Distance to School)})^2$	0.0133	0.0020	...	...	...	...
Log(Distance to Hospital)	-0.0088	0.0030	...	...	...	...
$(\text{Log(Distance to Hospital)})^2$	-0.0045	0.0020	...	...	...	...
Log(Distance to Railway)	-0.0314	0.0034	...	...	...	...
$(\text{Log(Distance to Railway)})^2$	-0.0107	0.0022	...	...	...	...

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