The 8th European Real Estate Society Conference
Alicante Spain, 27-29 June 2001

A Spatial Approach to Price Segmentation in Housing Markets

Gregory J Costello
Curtin University of Technology
Perth, Western Australia.

Contact author for all inquiries
GPO Box U1987 Perth, Western Australia, 6845
Phone: +61 8 9266 7778
Fax: +61 8 9266 3026
Email: costellog@cbs.curtin.edu.au

Keywords: Housing markets, housing market efficiency, housing sub-markets, price segmentation, Tukey's honestly significance difference test

Abstract: *This study develops a method for disaggregation of a housing market according to sale price. Variables are constructed for different price segments to focus upon issues of housing market efficiency. Results indicate that for the aggregate housing market, relative differences between price segments are consistent over time. Selling price criteria can provide useful specifications for relevant housing sub-markets independent of spatial proximity although this will vary with the hierarchy of price segments. There is strong evidence of a filtering influence. Cheapest price groups have the lowest and most volatile relative rates of price change and higher levels of price correction behavior.*

Introduction

The operational characteristics of a large urban housing market are often contingent in nature in that several households will be involved in a 'chain' of housing transactions. These transactions need not always be 'contingent' in a legal sense. Typically, in western economies during the past thirty years demographic influences have meant that the chain of transactions involves younger persons moving from lower to higher price segments as they grow older. This results in a hierarchy of price segments within the aggregate housing market, which provides a framework for the analysis of informational efficiency within housing markets.

Consider that households in these various sub-markets (price segments) will remain in a given dwelling for a period of time. In terms of the existing housing stock, this process involves the allocation of a given set of households to a given stock of housing. The existing stock of housing consists of dwellings with different capacities to satisfy individual housing utility functions. As a result, at any one time the existing housing stock is unlikely to represent the optimal allocation of housing units given the distribution of households by income and housing utility functions. Over time this necessitates the exchange of existing housing units between households so that changing household characteristics can be matched in terms of current housing requirements. In addition, the participants in transactions will have different information sets. The information set for the price segments in which they are intending to transact will be more fully developed than those price segments where the participant will have no direct involvement.

As an example, consider the situation whereby a retiree is selling an established family home in order to move into a newly constructed retirement home. In order to expedite the transaction there may be a chain involving three or more transactions. The retiree's existing family home will need to be sold to a younger family who may in turn need to sell a cheaper family home to a first homebuyer. The first homebuyer will have no direct contact with the retiree in negotiating the transaction for their home but will still be influenced by the information set influencing the retiree's transactions.

The processes by which households exchange housing units over time is important in analysing housing market efficiency in the widest sense. This process encompasses important issues of informational, allocative and operational efficiency within the housing market. In an efficient housing market the processes will exist so that this exchange occurs with the absence of market failure in all sub-markets (price segments). Information delays mean that lagged information of past prices is important for housing market participants in their pricing decisions. If transactions are to occur efficiently, the informational process will exist whereby relative price corrections between price segments can occur and be observed. In this situation market participants can use past prices as a useful information set in making decisions related to future housing requirements.

The degree to which housing markets incorporate information of past prices relating to own and different price segments are empirical issues explored in this study. This study examines whether differentials exist in the patterns of information diffusion that operate for different price segments within an aggregate housing market. Whereas some previous studies (Clapp and Giaccotto (1998), Costello (2000)) acknowledge the influence of price segmentation within aggregate citywide housing markets, these studies do not acknowledge the influence of important spatial sub-markets. More specifically, if the aggregate citywide housing market is segmented according to price then it is not clear whether observed differentials in price changes between price segments are due to specific price segment influences or specific spatial influences.

In this study repeat-sales transactions are used to identify a number of spatial regions in a major Australian housing market (Perth, Western Australia). Distinct spatial regions are identified according to postal code district and allocated into homogenous price groups using Tukey's *honestly significance difference test*, a post hoc multiple comparison test used with a one-way ANOVA procedure. These homogenous price groups include a number of similar priced housing sub-markets located in spatially distinct parts of the city. This framework is useful in testing the extent to which price changes are influenced by past price changes for sub-markets in own price groups and price groups either higher or lower than own price groups.

The following section extends the motivation for this study and reviews some appropriate theory and literature. The final sections present the data and methodology used in the empirical study review the results and provides some conclusions.

Motivation and related literature

The main aim of this study is to develop an empirical framework for disaggregation of housing market data according to price segment so as to focus upon issues of intra-market, inter-market, and full market efficiency. In a comprehensive review of early studies in this area, Gatzlaff and Tirtiroglu (1995) comment that at that time, compared to securities markets, the level of understanding of the informational efficiency of real estate markets was rudimentary. More recently Keogh and D'Arcy (1999) argue that the concept of real estate market efficiency remains poorly developed and inadequately theorized despite a growing body of empirical research. One reason for this observation is that many studies of housing market efficiency have used aggregate market data with little analysis of the influences of market segmentation. An obvious problem with this approach is that these tests are analogous to tests of market efficiency on a composite stock market index, the results are useful in examining aggregate market efficiency but may be misleading due to the aggregation of data. Goodman (1998) demonstrates that spatial aggregation of housing data is flawed in that local housing markets are functionally identical but nonlinear.

Empirical studies of housing market efficiency are relatively recent in the finance literature. In general, these studies can be classified according to the time period of completion. The central studies were completed by Case and Shiller (1989) (1990). Prior to their work, a number of early studies had applied methodology adapted from market efficiency studies for securities markets (see Gatzlaff and Tirtiroglu (1995) for a comprehensive summary of many of these early studies). In general, the early studies were models of real estate returns, based on data sets of dubious quality. These studies variously supported the fact that housing markets were weak-form or semi-strong form efficient after the inclusion of transaction costs.

Case and Shiller's (1989) (1990) studies were influential in that they significantly advanced the methodology for testing the efficiency of housing markets and they reported results significantly different from the earlier studies. They used large aggregate (city-wide) transaction data and reported that in general, the U.S. housing markets that they had tested were inefficient. Since the period of Case and Shiller's original work, the majority of studies examining information diffusion processes in real estate markets have used large transaction data sets with the emphasis on analysis of price changes instead of inferred returns.

In the more recent period, there has been an increasing emphasis on the analysis of information diffusion processes in and between specific geographic market segments (Clapp, Dolde and Tirtiroglu (1995), Dolde and Tirtiroglu (1997)). The methodology used in these studies is similar to the methodology used in the empirical study that follows. These studies examine spatial characteristics of house price dynamics that are consistent with rational learning. The results from these studies confirm significant patterns of temporal and spatial diffusion of information in housing markets.

Several recent studies demonstrate the influence of pricing size effects in housing markets. In a study examining index construction issues, Clapp and Giaccotto (1998) report evidence of differentials between price segments. They view differential price changes between market segments as being largely driven by demand differentials and argue that the housing market is a quality continuum from high to low rather than discrete market segments and that there is arbitrage up and down this continuum. Consistent with established theory they suggest that it is unlikely that one segment of the market continuum can grow at a much faster rate than any other over an extended period of time. More recently Costello (2000) demonstrates the presence of significant pricing size differentials in an aggregate housing market segmented according to price quartiles. These differentials suggest that the cheapest properties attract more short term speculative trading and the highest long term rates of price change are achieved by more expensive properties.

To further understand the motivations for this study consider the housing chain example in the introduction. In an idealized, perfectly efficient housing market all price segments would be perfectly correlated so as to facilitate the chain of transactions and the optimal allocation of housing services through time. In reality, housing markets are institutions characterised by numerous factors that will cause varying levels of informational inefficiency. Quan and Quigley (1989) describe housing markets as an environment where participants have incomplete information, heterogeneous search costs and varying expectations. In this environment, observed transaction prices may be considered as 'noisy signals', with the level of noise varying according to market segment and the completeness of market participants' information sets.

To illustrate how different information sets might influence the pattern of price discovery between market segments, consider the chain of transactions for three housing units, a first homebuyer, second homebuyer and retiree. It is not necessary to consider all participants in the chain to understand how information from different price segments will permeate through the housing market. From Quan and Quigley (1989) buyers will estimate the price for a property by inferring a *threshold price*, defined as the expectation of the true price conditional upon the information I^b available to the buyer. The threshold price for a buyer differs from the true price by an error term, e^b. For the first home buyer, b^1 in the housing chain, this is represented:

$$P_{b1} \; ? \; E[P / I^{b1}] \; ? \; e^{b1} \; ? \; P^{b1} \; ? \; e^{b1} \qquad (1)$$

The first homebuyer has no existing dwelling to sell, so the relevant information set I^{b1} will only contain price information relevant to dwellings for sale in the price segment of interest to the first homebuyer. Buyer 2 is moving to a more expensive price segment and in doing so needs to successfully become seller 1 to the first home buyer. A similar buying model as shown in equation (1) will apply to buyer 2. However, the information set will be more developed due to the fact that buyer 2 is more experienced in housing transactions having already purchased the existing dwelling and in this case buyer 2 is also seller 1. The threshold price for seller 1 is defined as:

$$P_{s1} \ ? \ E[P / I^{s1}] \ ? \ e^{s1} \ ? \ P^{s1} \ ? \ e^{s1} \qquad (2)$$

In the housing chain, the seller’s given information set I^{s1} will also contain I^{b2}, the information relevant to the purchase in a higher price segment. For the seller, the threshold price represents the minimum acceptable selling price that will facilitate the purchase of the home in the higher price segment. It follows that the information set from seller 1 will contain price information from higher price segments that will in turn impact upon information sets and prices for lower price segments. Within this framework, a transaction cannot occur below a seller’s or above a buyer’s threshold price. Transactions must occur in the region between these two prices, a transaction price, P_T, is defined as:

$$P_T \ ? \ P \ ? \ We^{s1} \ ? \ (1 \ ? \ W)e^{b1} \qquad (3)$$

This represents the observable transaction price as the sum of the true price plus the weighted error terms that result from the incomplete information sets for buyer and seller. Note from I^{s1} in equation (2) that in the housing chain the error term for the seller, e^{s1} will also contain some element of error from the subsequent buying transaction e^{b2}. As a result of this process, pricing errors from different price segments will compound into the transaction process for other price segments.

In order for the housing market to consistently facilitate transactions through all price segments over time some ‘correction behavior’[1] must exist within the market to bring prices in different price segments within the range where transactions will occur. This argument has some parallels with the market efficiency literature in securities markets. The ‘long term patterns’ literature (Shiller (1984) Summers (1986)) suggests that there are kinds of inefficiency in markets that can only be detected by taking a long term view. Small pricing errors may accumulate over time and require long term corrections that would be observed with negative serial correlation coefficients at longer lag periods.

The issue of price discovery and adjustment between price segments has been addressed in urban economic theory but remains poorly researched in terms of empirical studies. DiPasquale and Wheaton (1996) summarise the established body of urban economic theory related to housing

[1] The term *correction behavior* is used extensively in this study and is discussed in more detail in the context of the empirical study. The term refers to the scenario whereby different price groups are converging in terms of relative price differences, thereby facilitating transactions between higher and lower price segments. This is an important issue in interpreting empirical results. In the empirical study that follows a *shock* as distinct from a correction behavior is discussed in terms of results for serial correlation tests.

markets. They describe an aggregate housing market as a product differentiated market where *relative* prices of individual properties remain very stable over time and change little as the overall market undergoes either cyclic fluctuations or long term growth. Overall market movements will tend to raise and lower all prices by proportionate amounts.

The stability of relative property prices results from the high degree of household and firm mobility within metropolitan markets. This mobility acts as a form of price 'arbitrage' whereby locations or price segments within a market can rarely stay under-priced or over-priced with respect to other locations because of the mobility of potential buyers or users. The demand for any individual dwelling or location is price elastic with respect to competitor sites. Small adjustments to prices should be sufficient to attract many buyers. Competition, demand elasticity and arbitrage all imply prices at one location cannot move independently of prices at other locations. Locations and price segments within a market are closely connected and rarely have independent price movements or cyclic behavior.

Consistent with these characteristics of housing markets is the view that an aggregate housing market comprises a number of interrelated sub-markets. There is a considerable literature in this area. Megbolugbe et al (1996) argue that housing sub-markets are dynamically shaped by shifts in demand and supply and that sub-markets are distinguishable by the fact that the homes within them are viewed as more or less perfect substitutes by the households demanding them. The distinct character of sub-markets makes some more sensitive than others to shifts in housing demand or supply and distinct sub-markets are linked together by an intricate web of connections driven by cross-elasticity in demand. Hence a change in any one sub-market has the potential to affect many others though most powerfully in own sub-markets. The empirical study that follows examines the issue of whether housing sub-markets might be effectively defined by price segment as an 'economic neighborhood' independent of spatial proximity.

The analysis of price discovery and information diffusion processes between price segments has links to the theory of 'filtering' or neighborhood succession. This issue is specifically addressed in the empirical study that follows. Filtering or neighborhood succession is one of the established areas of housing market theory that in some respects contrasts with the view of the housing market as a product differentiated market where demand and supply differentials ensure the stability of relative prices over time.

Over the years ‘filtering’ has taken on multiple meanings but generally refers to the process of changing housing occupancy from higher income to lower income groups. In time, this process creates a downward shift in the relative price or rent of an individual unit and is therefore linked to general price changes. It has been suggested that homes failing to appreciate at the rate of general price inflation are filtering down. Grigsby et al (1987) argue that filtering affects entire neighborhoods not just scattered structures. Megbolugbe et al (1996) suggest those empirical studies examining filtering processes are not clear on the causes and effects of this process.

Data and methodology

Data

The empirical study that follows uses housing transaction data and census information for the city of Perth, Western Australia. Perth has a population of approximately 1.3 million and is the capital city of a state with a strong regional economy. The data for the 1996 census were obtained from the Australian Bureau of Statistics (ABS) and transaction data for the period 1988-2000 were obtained from the Western Australian Valuer General’s Office (VGO).

To facilitate analysis and to estimate homogenous price groups, the transaction data were segmented according to Australian postcode districts. This level of disaggregation is such that a sufficient transaction sample can be used to estimate individual price indexes for each postcode district. The ease in which transaction data can be supplemented with demographic detail from ABS census information makes this method of segmentation well suited for a study of this type. The criterion for selection of postcode districts was according to the volume of repeat-sales transactions. The fifty most numerous postcode districts in terms of repeat-sales were selected. The VGO transaction data were screened so that only ‘arms-length’ transactions were included and individual properties with major structural alterations between sales were excluded from the analysis. Vacant land sales were not included in the study.

Some important descriptive statistics for the data are contained in Table (1), which is presented, so that statistics for the individual postcode regions can be viewed by rank in ascending order according to the average selling price for the postcode district for the sample period. Descriptive statistics are shown for the VGO data and the ABS data. It is evident from the standard deviations (shown in parentheses) of the mean selling price variable that there are wide ranges of selling prices in some postcode districts. This is a consequence of the large sample taken from the aggregate urban housing market. Some districts are characterised by homogenous condominium building styles in densely populated inner city areas whereas other districts are characterised by more variation in building styles including dwellings on larger land holdings. A general trend that can be observed is that those districts with the lowest relative standard deviations for mean sale price also tend to have lower relative standard deviations for the age of the building.

The variable *R** shown in Table (1) is the effective real annual rate of price change for *individual* repeat-sales. Further detail for the construction of this variable is given in the Appendix. Mean values for the *R** variables are given for each postcode district for all holding periods and long holding periods (one year or more). The results for all holding periods have very high relative standard deviations for some districts, a consequence of short term trading. Costello (2000) uses this variable to demonstrate significant differentials in price changes between price quartiles within the aggregate housing market.

A general examination of transaction types associated with high short term price changes confirms that many of these transactions occur in districts where significant redevelopment is occurring. This indicates that many of these transactions might be speculative ‘off the plan’ sales for condominium style developments where an initial sale occurs prior to building completion and a subsequent sale occurs on completion. A number of these short holding period sales are also associated with redevelopment sites where there have been significant changes in land values in a short period of time associated with the amalgamation of sites suitable either for urban subdivision or condominium development. Irrespective of the causes for the high short term price changes these results provide evidence that incentives exist in some districts for market participants to exploit opportunities for short run profits. This confirms that some degree of informational inefficiency exists in these districts. It can be seen that when only long holding periods are used the relative standard deviations for *R** are much smaller. An important general trend that can be observed is that when only long holding periods are used, the highest mean *R** rates are observed for the most expensive postcode districts.

The ABS statistics shown in Table (1) are taken from the 1996 Australian Census. Australian housing markets are characterised by some unique institutional characteristics, one of the most important being the high levels of owner occupation. Australia does not have a strong social housing sector. In this study, the proportion of public housing as tenure type was calculated but the results are not reported. This is due to the fact that in all districts shown in Table (1) more than 95% of households were housed in privately owned dwellings and in most districts this level was higher than 99%. The high and stable home ownership rate in Australia has led to owner-occupation being accepted as the tenure of choice. It has been estimated that owner-occupied housing represents 66 percent of net household wealth in Australia (King and Baekgaard (1996)).

The ABS census data provides detail for household age, size, weekly income, unemployment rate, tenure type and vacancy rate information. There does not appear to be any significant differences between the median age and median household size for the cheaper or more expensive housing districts. As expected, the cheaper rank districts have higher unemployment rates and lower median weekly household incomes. The tenure type information reports the proportions of dwellings that were either wholly owned, being purchased, or rented. As expected, these statistics indicate that the highest proportion of wholly owned dwellings occurs within the upper-middle and most expensive districts. The proportions of dwellings being purchased appears higher in the lower and middle groups although this trend is not clearly defined in that there are also some expensive districts with high proportions and low and middle groups with low proportions. There appears to be a general trend of the cheapest districts having the highest proportion of rented dwellings although this also appears to vary in some districts. The vacancy rate information indicates that the highest rates appear to apply to both the cheapest and most expensive districts.

To identify homogenous price groups the mean selling prices for the sample period were used in Tukey's *honestly significance difference test*, a post hoc multiple comparison test used with a one-way ANOVA procedure. This test uses the studentized range statistic to make all pairwise comparisons between groups. When testing a large number of pairs of means, this test is useful for identifying homogenous groups.

A summary of the homogenous price groups estimated from the Tukey test output is contained in Table (2). Note that there are 23 *overlapping* homogenous price groups. For example, groups 1 and 2 are individual homogenous price groups that contain three of the same postcode regions. The Tukey procedure enables non-overlapping price groups to be identified, group 1 does not overlap with group 3. In Table (2) a full set of non-overlapping price groups is shaded to indicate different independent price segments through the full price hierarchy of postcode districts. An informal analysis of the spatial allocation of postcode districts within the homogenous price groups indicates that many of the price groups contain postcode districts from a wide range of differing spatial regions. A distinct advantage of using this method of market segmentation is that specific price segments can be identified consistent with spatial criteria. For example, price groups 1-6 can be considered as the groups representing the lowest price quartile of postcode districts.

For each homogenous price group, real logarithmic price indices were constructed using the weighted repeat-sales (WRS) method (Case and Shiller (1989)). Each index was deflated by the Australian consumer price index. Case and Shiller (1989) show that where repeat-sales data are used then measurement error can cause serial correlation models to be prone to problems of spurious correlation for several periods. This problem together with index accuracy issues is addressed in more detail in the next section.

Abnormal Price Changes

Housing market activity for different market segments will be influenced by general trends influencing all market segments. For this reason spurious correlation is an important consideration in examining differences between price segments. In this study, the data were detrended using a form of 'benchmarking' through a transformation to differential procedure. A similar procedure has been used in analysing spatial patterns of information diffusion between housing markets (Clapp Dolde and Tirtiroglu (1995), Dolde and Tirtiroglu (1997)).

Let $\hat{c}_{it}$ represent the natural logarithm coefficient for a real WRS index constructed for a price group sample as shown in Table (2). The first difference is the continuously compounded quarterly rate of real percentage change in house prices. These quarterly changes are subject to seasonality, removed by shifting to annual rates of change (fourth differences):

$$?P_{it} ? ?\hat{c}_{it} ? \hat{c}_{it?4}?? ?\hat{c}_{it} ? \hat{c}_{it?1}?? ?\hat{c}_{it} ? \hat{c}_{it?2}?? ?\hat{c}_{it} ? \hat{c}_{it?3}?? ?\hat{c}_{it} ? \hat{c}_{it?4}? \qquad (4)$$

The 'abnormal price change' variable for any homogenous price group, $?PA_{it}$, is defined as the price change difference from the unweighted average real price change for all *non-overlapping* homogenous price groups in the sample:

$$?PA_{it} ? ?P_{it} ? ?P_{Gt} \qquad (5)$$

The construction of $?P_{Gt}$ is important in that it will vary for different price groups. Note from Table (2) that for homogenous price group 1, $?P_{Gt}$ is an unweighted average constructed from the sum of $?P_{it}$ for groups 1,3,9,12,14,17,20,22 and 23. None of these price groups overlap by sharing common postcode regions. In a similar manner, for group 2 $?P_{Gt}$ is constructed from groups 2,6,11,14,17,20,22 and 23. It is important to note that for any single time period, this transformation will result in half the price groups in a set of non-overlapping price groups recording positive abnormal price changes and the other half of the price groups recording negative abnormal price changes. This has some important implications for the construction and interpretation of serial correlation tests and is discussed in more detail in the section titled *Serial correlation tests – interpretation*.

Measurement error

The abnormal price change variables constructed for homogenous price groups are statistical estimates subject to measurement error. This causes several errors in variables problems that require further discussion.

Case & Shiller (1989) demonstrate that serial correlation tests using repeat-sales data are prone to spurious correlation due to the same measurement error contaminating both dependent and independent variables. This problem can be corrected by splitting the repeat-sales sample into two random samples (A and B). Serial correlation tests can be completed by regressing variables constructed from index A on index B and vice versa. In accordance with this procedure, individual random sub-samples (A and B) were constructed for each homogenous price group shown in Table (2) and a WRS index was estimated for each sample[2]. Let $?A_{it}$ and $?B_{it}$ represent the abnormal price changes for random sub-samples A and B respectively, then from equation (5), $?A_{it} ? ?P_{Ait} ? ?P_{AGt}$ and $?B_{it} ? ?P_{Bit} ? ?P_{BGt}$ where the *A* and *B* subscripts denote random sub-samples A and B respectively.

From equation (5), Clapp Dolde and Tirtiroglu (1995) argue that $?P_{Gt}$ may also introduce spurious correlation since it is the average of the $?P_{it}$. To demonstrate, assume a serial correlation model of the form $?PA_{it} ? ? ? ??PA_{it?k} ? ?_{it}$ where the subscript *k* represents the lag structure. Spurious correlation is likely to occur because the same measurement error in the construction of $?P_{Gt}$ is present in both sides of the model through the construction of the dependent and independent variables. Clapp Dolde and Tirtiroglu (1995) demonstrate that the likely effect of this influence is to bias coefficients towards zero and that the potential for spurious correlation tends to decline as the number of groups used in the construction of $?P_{Gt}$ increases. From Table (2) it can be seen that in this study, the Tukey procedure provides only a fixed number of non-overlapping groups, thereby increasing the potential for spurious correlation of this type.

---

[2] The accuracy of indices were tested with the same procedure used by Case and Shiller (1989) whereby a ratio is calculated from the standard deviation of an index variable to the average standard error for that variable. Higher ratios indicate more accurately measured index characteristics. Case and Shiller (1989) describe ratios in excess of 2.0 for annual differences as "fairly accurate". For the homogenous price groups in Table (2), the majority of groups have index accuracy ratios in excess of 3.0. The accuracy of indexes tends to decline with the most expensive price groups 21-23. The random split sample procedure whereby indexes A and B are estimated does not adversely influence index accuracy because in all groups there is still a large sample of transactions to facilitate the split sample procedure.

The use of Case and Shiller's (1989) split sub-sample procedure eliminates some of the influence from this type of spurious correlation. Assuming that with random sub-samples, the $?PA_{it}$ are denoted $?A_{it}$ and $?B_{it}$, then the serial correlation model becomes $?A_{it}\ ?\ ?\ ?\ ??B_{it?k}\ ?\ ?_{it}$ or the alternative model $?B_{it}\ ?\ ?\ ?\ ??A_{it?k}\ ?\ ?_{it}$. The dependent and independent variables in these models are constructed from different samples. The $?P_{Gt}$ are constructed from either sub-samples *A* or *B*. Although the indexes constructed from these samples should be closely correlated they use different observations and are therefore subject to different measurement error, thus eliminating the influence of this form of spurious correlation.

The combination of splitting the sample into random sub-samples with the transformation to differential procedure increases the noise that is present in the serial correlation tests that follow. This will tend to bias results towards zero thereby decreasing the likelihood of finding statistically significant results. Despite this influence, an advantage of the random sub-sample procedure is that 'stacking' the abnormal price change variables doubles the number of observations available for serial correlation tests. This is discussed in more detail in the next section.

Any occurrence of terms subject to observation error common to both sides of equation (5) may bias the coefficient estimates in serial correlation tests. Note from equation (4), that both $?PA_{it}$ and $?PA_{it?4}$ will contain $\hat{c}_{it?4}$ with opposite sign and will therefore be negatively correlated. As a result the variable $?PA_{it?4}$ is not used as an explanatory variable in the serial correlation tests that follow.

Note also from equation (4) that because $?P_{it}$ is a fourth interval difference it will overlap with its three predecessors sharing three quarterly changes with $?P_{it?3}$, two with $?P_{it?2}$ and one with $?P_{it?1}$. As a result, the $?P_{it}$ are not independently distributed. Consistent with other studies of this type, the serial correlation test models that follow are estimated by a method of moments (Hansen and Hodrick (1980), Case and Shiller (1989), Clapp Dolde and Tirtiroglu (1995)).

Serial correlation tests - construction

The hypotheses that homeowner-investors make inferences from lagged price changes in their own and different price groups can be tested by regressing abnormal price changes on lagged abnormal price changes in own price groups and different homogenous price groups (either higher or lower) from the own price group. To reduce the possibility of spurious correlation, the dependent variable is estimated from index A and the independent variables from index B. The procedure is then repeated but with the variables in the opposite order. This procedure is followed for each price group i = 1…23. The method of moments estimation procedure (Hansen and Hodrick (1980)) is used to estimate equations of the following form for different 'stacked' sets of observations:

$$?A_{it} ? ?_{g} ? \underset{k}{?} ?_{k} ? B_{it?k} ? \underset{k}{?} ?_{k} ? B_{git?k} ? ?_{it} \quad (6a)$$

$$?B_{it} ? ?_{g} ? \underset{k}{?} ?_{k} ? A_{it?k} ? \underset{k}{?} ?_{k} ? A_{git?k} ? ?_{it} \quad (6b)$$

With reference to equation (6a) the dependent variable $?A_{it}$ represents the abnormal price change for random sample *A*, $?_{g}$ is a constant term, the subscript *g* denoting the set of price groups used in the particular model and $?_{it}$ is an error term[3]. Serial correlation is modeled explicitly with the independent variables. The term $\underset{k}{?} ?_{k} ? B_{it?k}$ represents lagged *own* price group abnormal price changes estimated from random sample *B* with the lag index $k = 1,2,\ldots K$, the maximum lag length. The term $\underset{k}{?} ?_{k} ? B_{git?k}$ represents lagged abnormal price changes estimated from *adjoining* non-overlapping price groups. The subscript *git* is used because the selection of adjoining price groups is unique for each individual price group. This term also accommodates the possibility that adjoining price groups either above or below an individual price group can be tested in different models. For example, from Table (2) for price group 3, the adjoining non-overlapping price groups are groups 1 and 9. In this case a model to test the influence of higher price groups on abnormal price changes for group 3 would include abnormal price changes from group 9 (denoted as Group + 1) as the independent variable in $\underset{k}{?} ?_{k} ? B_{git?k}$. In a different model testing the influence of lower price groups, the Group - 1 variable would be the abnormal price changes estimated from group 1.

This general form of serial correlation model allows for tests with stacked data sets including all 23 homogenous price groups for the aggregate sample or for selected sub-samples of price segments. The split sample procedure increases the number of observations available for use in the serial correlation tests. For example, in the results that follow in Table (3), model 1 uses 22 homogenous price groups. With the lag structure used, each sample A and B provides 37 observations. According to equations (6a and 6b), for group 1 the observations for sample A are stacked above sample B then above the A and B samples for group 2 and so on. This procedure results in 22 groups x 2 samples for each group x 37 observations = 1,628 total observations for use in the serial correlation model.

Serial correlation tests - interpretation

It is expected that the constant term $?_g$ in these tests will provide useful information concerning the relative level of price changes for different price segments and therefore an insight to the influence of filtering processes in this housing market. Table (1) provides evidence that mean long run rates of real price change for individual dwellings are lowest for the cheapest price groups and highest for the more expensive groups. If this trend were widespread through many spatial regions it would be evidenced by statistically significant negative $?_g$ terms for serial correlation tests using the lowest price groups and positive $?_g$ terms for the most expensive groups.

An important a priori expectation for these tests is that homogenous price groups are an effective determinant of housing sub markets. If this is correct, from equations (6a and 6b), the $?$ coefficients will be positive, persistent and statistically significant. This result would constitute evidence to support the notion of an ‘economic neighborhood’ independent of spatial proximity. It is possible that this result will vary according to the price hierarchy of groups. Logic suggests that market participants in some price groups will have more in common in terms of an economic neighborhood than others. An example would apply to those price groups where there are significant proportions of homeowners purchasing their homes through mortgage financing. Changes in interest rates are more likely to have a common influence on price changes in these groups than they would have in those groups where there is a low influence from mortgage financing.

If the $?$ coefficients in the results that follow are consistently positive for short and long lag periods, this will constitute strong evidence that the housing market is stable over time with little variation in relative price differences for similar priced districts. The presence of negative $?$ coefficients will indicate some correction behavior within own price groups. If this pattern were repeated for short lag periods it would provide evidence of volatility and pricing error in own groups. In the longer run, negative $?$ coefficients could indicate persistent pricing errors.

From equations (6a and 6b), the $?$ coefficients will provide important information for the pattern of price correction or adjustment between price groups. One key area of interest concerns the direction and magnitude of information diffusion from price groups higher or lower than own groups. Returning to the example in the introduction and the observation that the predominant pattern of

[3] Because of the overlap of annual differences with quarterly lags, the error term is not independently distributed, necessitating estimation by the method of moments (Hansen and Hodrick (1980).

movement in housing chains is for younger persons living in cheaper price groups to 'trade up' to more expensive housing as they grow older. Does this mean that information for price changes in higher price groups is more influential in influencing price changes than the information from lower groups? The ? coefficients can provide useful information in this area.

If the aggregate housing market is stable over time with small relative price differences between price segments, then the expectation is that the ? coefficients for tests with neighbouring price groups will be positive and statistically significant for shorter lag periods. This result would confirm that in the short run, the direction of price changes is similar for the different price groups. Long run stability between price segments suggests that this pattern should also be observed for longer lag periods.

The a priori expectation for the ? coefficients is that somewhere within the lag structure there will be negative serial correlation, constituting evidence of correction behavior between price segments. From equations (1)-(3), theory suggests that over time small pricing errors will compound and market participants will need to amend their pricing expectations so that transactions between different price groups can occur.

The abnormal price change transformation procedure shown in equation (5) transforms price groups into either positive or negative abnormal price changes, irrespective of the magnitude of the price change. Quite simply for any one period, half of the groups in a set of non-overlapping groups will register positive and the other half, negative abnormal price changes. The criteria for being either positive or negative is the location of a group's price change for that period in terms of the mean for all groups. This will result in the situation whereby groups with only small differences in actual price changes are negatively correlated in terms of relative price changes. This has some important implications in interpreting negative ? coefficients in the results that follow.

To illustrate, consider the example of the set of non-overlapping price groups shown in Table (2). Consider that in one period, groups 1 and 9 report positive abnormal price changes and group 3 reports a negative abnormal price change. Disregarding the magnitude of the abnormal price changes, this result will mean that for one period, relative price changes between groups 1 and 3 are negatively correlated and prices are converging, a correction behavior. However for price groups 3 and 9, relative prices are diverging and are also negatively correlated[4]. It follows from this example that correction behavior cannot occur between all three adjoining price groups during the same period but the groups can still be negatively correlated. In this situation, the negative serial correlation coefficient ? does not give any information as to the *direction* of the price changes associated with the negative serial correlation and interpretation of the pattern of ? coefficients becomes important.

In this situation, where significant negative serial correlation was observed in the ? coefficients for both higher and lower groups in the same short run lag period then it would constitute a major market 'shock' rather than a correction behavior. In the tests that follow, the use of large stacked sets of observations means that for statistically significant negative serial correlation to occur, the pattern will be occurring consistently within a number of price groups. If as expected, adjoining price groups follow similar short run patterns of abnormal price changes over time then the ? coefficients for shorter lags should be positive and statistically significant. Given this scenario, relative price differences will be small and a market 'shock' is unlikely.

Logic suggests that the more likely pattern for correction behavior is that there will be alternate patterns of positive and negative ? coefficients for tests with higher and lower groups. Remembering that for one price group a convergence of relative prices with a higher group will correspond with a divergence from a lower group, this process might prompt subsequent correction behavior with the lower group. In discussing the results that follow, ? serial correlation coefficients are closely scrutinised. If there is a significant negative ? serial correlation this is checked against the corresponding and subsequent ? serial correlation coefficients for the model using either the higher or lower group. In this way the important pattern concerning whether price groups are correcting from higher or lower price groups can be established.

Empirical results and discussion

The results for models explaining abnormal price changes for homogenous price groups are shown in Tables (3) and (4). These models have been estimated with the general form of serial correlation model shown in equations (6a and 6b). The results shown in Table (3) include lagged variables for own homogenous price groups and *nearest* non-overlapping adjoining price groups, denoted as Group + 1 and Group – 1. Results are reported for tests on the full sample and selected price groups

[4] Of course there are other means by which abnormal price changes might be positively or negatively serially correlated. For example two groups might both report positive (or negative) abnormal price changes but differences in the magnitude of the change indicate that one group is declining in magnitude over time whereas the other is increasing in magnitude.

corresponding with quartile divisions of the price hierarchy of the 23 individual homogenous price groups.

Models 1 and 6 are models that use the maximum available sample of price groups from the aggregate sample. It is important to note that neither of these models uses the same set of abnormal price changes. By reference to Table (2) it can be seen that price group 23 does not have an adjoining upper price group to be included as an independent variable in model 1, hence only 22 homogenous price groups are used in the stacked data set of observations. Similarly, neither price group 1 or 2 has an adjoining non-overlapping lower price group to be used as an independent variable in model 2, therefore only 21 price groups can be used.

Despite this difference, models 1 and 6 display similar results for the influence of lagged own price group changes. The ? own group coefficients for short lag periods confirm that information from own group changes is influential and persistent in the pattern of future own price group changes. In both models, the ? coefficients are positive for all lag periods up to six quarters and all coefficients excepting the third lag display coefficients with statistical significance at levels higher than 1%. An interesting feature of these results is that for both models, the highest levels of positive information diffusion occur in lagged quarters one and five. These results suggest that within the aggregate housing market, homogenous price groups are effective in defining sub-markets. The positive serial correlation suggests that similar priced districts experience similar patterns of price change independent of spatial proximity. The persistent pattern of positive serial correlation especially for lagged periods longer than one year provides evidence that the differences in price changes for own groups tend to be quite consistent with the pattern from previous years. Of course the influence of aggregation within the data must be considered and it will be shown below that when smaller specific sub-samples are tested these results vary.

Continuing the discussion of models 1 and 6, note the weaker ? coefficients applying to the lagged third quarter. This warrants further discussion in respect of the results applying to adjoining ? group coefficients. The general pattern for ? coefficients for both higher and lower price groups is similar to the pattern for own groups with the exception of lagged quarter 3. Note that the lagged first and fifth quarter ? coefficients are positive and highly significant, consistent with own group patterns. This confirms that relative price differences between adjoining price groups vary little over time and in general, the direction of price changes for adjoining groups is similar.

From the discussion of the likely causes of negative serial correlation in the previous section it is unlikely that a major ‘shock’ would occur given these conditions of strong positive serial correlation between adjoining groups. However, the presence of low levels of negative serial correlation at the lagged third quarter suggests that some correction behavior is occurring within the aggregate market. In model 1 for higher groups, the negative serial correlation at the lagged third quarter is low but statistically significant at a level higher than 5%. In model 6 for lower groups, the negative serial correlation is lower and insignificant. This result could be interpreted as providing evidence that the pattern of correction behavior within the housing market is influenced more by information from higher price groups but such a judgement might be misguided. The presence of low levels of negative serial correlation in both models at the same lagged third quarter suggests aggregation influences might be masking more important patterns of correction behavior. It is more likely that within specific segments of the hierarchy of price groups there are contrasting patterns of negative serial correlation which when combined within the aggregate data tend to ‘diversify away’ the influence of each other.

When the aggregate market is segmented it can be seen that the patterns observed in specific price segments are quite different. In Table (3), models 2-5 and 7-10 test specific price group quartiles derived from the hierarchy of the 23 price groups. Quartile 1 includes groups 1-6, quartile 2 groups 7-12, quartile 3 groups 12-17 and quartile 4 groups 18-23.

An important feature of the results for the segmented samples is the information revealed by the ? constants. For the cheaper price samples these models display statistically significant negative ? constants, confirming that the cheapest groups of districts display a general pattern of negative abnormal price changes relative to the rest of the aggregate sample. For the more expensive price groups the reverse applies, abnormal price changes are significantly higher. Note that this result is consistent for the short run lag models and the longer-run models shown in models 12-15 and 17-20. This general feature of the results constitutes strong evidence that there is a filtering influence active within the market. The cheapest price districts are also the districts with the lowest relative price changes.

Models 2 and 7 apply to the cheapest quartile of districts but are from quite different samples. From Table (2), the two lowest price groups are not included in model 7 because there is not a lower non-overlapping price group to be tested. These results are quite different from the results for the full sample. First, both of these models display statistically significant negative ? constants. Second, the lack of any statistically significant positive serial correlation for lag periods of less than one year for the ? coefficients indicates that similar price groups are not useful determinants of appropriate sub-markets for the cheapest districts. Third, the patterns of negative serial correlation for the ? coefficients are more pronounced than the patterns observed for the full sample.

The lack of statistically significant ? coefficients at shorter lag periods indicates that there may be important local influences associated with individual spatial districts influencing price changes in the short run. Despite this influence, the stronger positive diffusion of information at the fifth quarterly lag confirms that in the longer run, price changes occurring one year previously are still important in explaining own price group changes in the cheapest districts.

The pattern of negative serial correlation for the ? coefficients is different from the results for the aggregate sample. In model 2, negative serial correlation for higher price groups is observed at the second third and sixth quarterly lags although only the third lag is at a high level of statistical significance. In model 7, significant negative serial correlation for lower price groups is observed later at the fifth and sixth quarterly lags. This pattern indicates that in the cheaper price districts, the pattern of information diffusion and correction behavior between different price segments is influenced by information from higher price segments before lower price segments. This correction behavior is also more pronounced in the cheaper price groups confirming greater relative price volatility between adjoining price segments.

Models 3 and 8 are for the second quartile of price districts. Both of these models have higher adjusted R square results than for the other price quartile models. Both also have significant negative constants consistent with results for the lowest price quartile. In contrast to the cheapest price districts, the ? coefficients for own price group changes are positive and highly significant in the early lag periods, confirming that homogenous price group samples provide an effective determinant of sub-markets for this set of price groups. The negative ? coefficients for the own group lagged third quarter indicate some relative price correction occurring within own groups. The results for ? coefficients confirm a number of statistically significant negative serial correlations consistent with correction behavior between adjoining price segments. Note that in contrast to the cheapest price quartile it appears that the pattern of correction behavior here commences with lower priced groups at the lagged second quarter. In model 8, the ? coefficients for the second and sixth quarterly lags are negatively correlated with the sixth lag being very influential. In model 3, the higher price groups are positively correlated with own groups at the early lag periods and then negatively correlated at lagged quarters 3 and 5.

Models 4-5 and 9-10 apply to the most expensive quartiles of price groups. In general, these models confirm some of the patterns applicable to the cheaper price groups in quartile 2. There is a general pattern of positive ? coefficients for own price groups although at lower levels of statistical significance. There is some pattern of negative serial correlation for the ? coefficients but the lack of any statistical significance confirms a lower level of correction behavior between adjoining price segments. The most notable feature of the results for these models is the higher levels of positive serial correlation for the ? coefficients for lagged information from adjoining higher price groups at short lags (models 4 and 5). Note that in models 5 and 10 there is negative serial correlation for the ? coefficients at the same lagged third quarter. This result should be considered in context of the different samples used that are quite different as evidenced by the number of observations applying to each. Model 5 for the higher groups must exclude several groups, as there are no non-overlapping groups that can be included in this model for the highest groups.

Models 11-20 are long run serial correlation models using a non-overlapping lag structure consistent with Case and Shiller (1990). Models 11 and 16 use the full aggregate sample. The ? coefficients confirm positive diffusion of information for own price group changes at lagged periods of one and two years. The ? coefficients confirm a similar pattern for adjoining price groups indicating that the relative differences between adjoining price groups are quite consistent in the longer term.

When the data is segmented into quartile groups the long term patterns for some groups are quite different. For most groups, the long term models have very low adjusted R squared results, confirming low levels of explanatory power for long term models. The most notable feature is the difference applying to the ? constants. The cheaper price samples display statistically significant negative ? constants and for the more expensive price groups the reverse applies. This result provides substantial evidence of a longer term filtering influence. In the cheaper price groups (models 12 and 17), the presence of statistically significant negative serial correlation in the ? coefficients suggests more long term volatility in these groups and a lower level of informational efficiency in the longer-run.

In Table (4), results are presented for models where the ? coefficients provide information for groups further apart in the price hierarchy. Instead of adjoining non-overlapping groups the groups designated as Group +2 are two non-overlapping groups removed from the own group. For example, from Table (2), group 3 is the closest higher non-overlapping group from group 1, group 9 is two non-overlapping groups removed (Group +2) and group 12 is three non-overlapping groups removed (Group +3). These results are not segmented into price quartiles, as tests that are structured in this way are largely a test on a specific part of the price hierarchy. By reference to Table (2) and consideration of the example given above it can be seen that model 21 is mostly a test on the lower price groups. The specification of Group +2 criteria means that a number of the most expensive groups are removed from the sample.

These results are useful in supporting the pattern of information diffusion from ? coefficients in the previous models. These coefficients are generally positive and persistent, confirming that similar priced districts have similar patterns of relative price changes. The results for ? coefficients provide some interesting information. The most interesting feature of these results is revealed in comparing models 1 in Table (3) with models 21 and 22 in Table (4). These models for the full sample use higher price groups as independent variables, but with the higher groups becoming progressively higher in the hierarchy of price groups. Note that in model 1, the first lagged ? coefficient is positive and highly significant. In model 21 the second quarterly lag is positive and highly significant and in model 22 it is the third quarterly lag that is positive and highly significant. Note also that in the corresponding models (models 6, 23 and 24), where ? coefficients are given for the lower price groups, there is not a similar pattern. This provides evidence that the most influential direction of information diffusion in the price hierarchy is from higher priced properties down to lower priced properties. This information diffusion may also display a ‘ripple’ influence. It appears that the pattern of price changes will influence the closest price groups first and progress through to the more distant groups in the price hierarchy at later lag periods.

In Table (4), models 25-28 use the same long run non-overlapping lag structure as is used in models 11-20. Models 25-26 are structured so that they use mostly the cheaper price groups and models 27-28 use mostly the more expensive price groups. These results confirm the pattern of ? constants from previous models. The results for the lagged own, higher and lower group coefficients are also generally consistent with the results for the previous long run models using the full sample (models 11 and 16)

Conclusions

This study develops an empirical framework for disaggregation of housing market data according to price segment so as to focus upon issues of intra-market, inter-market, and full market efficiency. Repeat-sales data for the period of 1988-2000 for the city of Perth, Australia are used. The Tukey honestly significance difference test procedure is used to identify homogenous price groups for spatially distinct districts. An *abnormal price change* variable is constructed for different price segments for use in serial correlation models and several hypotheses are tested. These tests are applied to the aggregate sample and specific sub-samples based upon the hierarchy of price groups.

First, the tests examine whether homogenous price groups are effective criteria for the specification of appropriate housing sub-markets. Second the patterns of information diffusion between different price segments are examined. Third, the evidence of *filtering* and associated low relative price changes in cheaper price districts is examined.

There is some evidence that selling price criteria can provide a useful specification for relevant housing sub-markets independent of spatial proximity, although this varies with the hierarchy of price segments. For all parts of the price hierarchy price criteria appear to be appropriate determinants of sub-markets in the long run. In general, relative price changes for price groups are positively correlated for lag periods of one year and longer, confirming consistent and persistent patterns of price change in similar price groups. In the short run, the influence can vary significantly. In the cheapest and most expensive districts past price changes are not effective in influencing short run patterns of future price change. This indicates that spatial influences are influential in some of these districts. In the mid-price groups, price criteria are more influential with significant positive serial correlation for relative price changes for short run lag periods.

In terms of the patterns of information diffusion that operate between different price groups, the results yield some useful evidence. For the aggregate housing market, relative differences between price segments are consistent over time, although there is significant variation within specific sub-samples. The cheapest price groups have the lowest and most volatile relative rates of price change and higher levels of price correction behavior, both within own groups and between adjoining groups. There is also some evidence that within the aggregate market, the predominant direction of information diffusion is from higher to lower price groups. This is consistent with what might be expected where the general pattern of housing transactions is for participants to be 'trading up'.

There is strong evidence of a filtering influence within the aggregate housing market. The serial correlation models provide compelling results to indicate that the lowest levels of relative price changes are in the cheapest price districts and the highest levels are in the most expensive districts. This pattern is consistent for both short run and long run lag models.

This work demonstrates that price segmentation of housing markets can yield useful information in several areas. This approach might be usefully applied in terms of analysis of appropriate housing policy. There are many areas of housing policy where the results must be scrutinized in terms of the influence on specific price groups. These groups will be associated with the demographic components of an aggregate housing market. It would also be useful to examine the applicability of this empirical framework in terms of comparative studies. While this study has focussed upon an individual aggregate housing market in Australia, it is feasible that this empirical framework could be extended to encompass several major housing markets within a national economy.

Table (1)		Valuer General's Office repeat-sales data 1988-2000					Australian Bureau of Statistics census data 1996							
Australian Postcode District	Price Rank	Mean sale price ($'000)	Mean year built	Mean holding period (years)	Mean R^* all holding periods (%) 1.	Mean R^* long holding periods (%) 2.	Median household age (years)	Median household income ($ week)	Median household size (persons)	Unemploy-ment rate (%)	Owned (%)	Being purchased (%)	Rented (%)	Vacancy (%)
6167	1	74.9 (60)*	1974 (12)*	4.2 (2.5)*	3.4 (34)*	1.4 (7)*	31	500-699	2.7	14	30	40	25	11
6061	2	86.6 (19)	1973 (12)	4.4 (2.4)	3.9 (17)	2.9 (7)	31	300-499	2.6	15	25	33	36	7
6112	3	87.1 (39)	1979 (14)	4.2 (2.3)	3.3 (69)	0.1 (7)	29	500-699	2.9	10	28	45	22	6
6051	4	88.4 (66)	1974 (18)	4.1 (2.5)	3.2 (20)	1.5 (7)	34	300-499	1.7	16	22	17	53	14
6064	5	94.2 (30)	1983 (7)	4.4 (2.4)	2.9 (17)	1.6 (8)	28	500-699	3.0	11	24	45	25	5
6110	6	94.2 (31)	1979 (11)	4.6 (2.4)	0.5 (9)	0.0 (6)	30	500-699	2.8	9	30	43	22	6
6168	7	94.5 (47)	1979 (12)	4.3 (2.4)	1.6 (13)	0.9 (6)	33	300-499	2.6	12	36	31	29	12
6107	8	99.1 (36)	1971 (15)	4.4 (2.4)	2.9 (14)	1.7 (7)	32	500-699	2.6	10	36	32	27	7
6147	9	99.3 (26)	1977 (8)	4.6 (2.3)	6.1 (99)	0.6 (5)	31	500-699	2.8	10	36	36	24	6
6056	10	99.5 (40)	1973 (20)	4.5 (2.4)	2.1 (12)	1.4 (6)	31	500-699	2.8	9	34	37	23	8
6054	11	103.3 (35)	1966 (22)	4.2 (2.4)	6.7 (74)	3.2 (7)	33	500-699	2.6	10	35	33	26	8
6111	12	105.5 (46)	1976 (9)	4.4 (2.4)	1.3 (13)	0.5 (6)	34	700-999	2.9	7	44	38	14	6
6164	13	107.2 (26)	1986 (3)	4.6 (2.3)	2.6 (43)	0.6 (5)	27	700-999	3.0	7	23	52	21	6
6053	14	107.3 (38)	1962 (22)	4.2 (2.4)	5.6 (17)	3.7 (8)	36	500-699	2.3	10	39	29	26	7
6060	15	108.7 (44)	1977 (14)	4.2 (2.4)	3.7 (41)	1.7 (6)	35	500-699	1.9	11	35	18	41	9
6169	16	110.6 (41)	1982 (11)	4.0 (2.3)	1.6 (9)	1.3 (6)	30	500-699	2.9	10	33	41	22	12
6210	17	112.9 (57)	1982 (12)	4.1 (2.4)	2.9 (49)	1.1 (7)	36	300-499	2.6	14	40	29	24	25
6108	18	113.2 (31)	1980 (9)	4.5 (2.3)	0.4 (8)	0.3 (5)	30	700-999	3.0	7	36	44	16	4
6030	19	116.9 (48)	1989 (7)	3.4 (2.0)	4.7 (19)	3.1 (8)	27	500-699	3.0	11	17	61	17	9
6065	20	119.5 (72)	1979 (7)	4.4 (2.4)	2.0 (12)	1.2 (5)	34	500-699	2.9	8	39	40	15	5
6101	21	119.6 (36)	1960 (25)	4.3 (2.3)	4.5 (19)	3.2 (7)	32	500-699	2.1	11	28	21	44	8
6100	22	119.7 (52)	1970 (23)	4.4 (2.4)	5.5 (62)	2.2 (6)	32	500-699	2.0	10	26	17	49	10
6062	23	120.6 (39)	1975 (10)	4.8 (2.5)	2.6 (12)	1.9 (6)	35	500-699	2.7	7	50	24	20	6
6066	24	120.8 (32)	1989 (4)	4.3 (2.3)	1.8 (7)	1.4 (5)	28	700-999	3.2	7	23	58	16	4
6163	25	121.7 (48)	1975 (13)	4.4 (2.4)	3.3 (31)	2.3 (7)	33	500-699	2.7	9	41	27	26	6
6024	26	124.3 (26)	1976 (4)	4.6 (2.4)	2.4 (9)	1.7 (6)	33	700-999	2.9	6	43	38	15	4
6059	27	134.1 (59)	1976 (12)	4.4 (2.4)	3.9 (30)	2.4 (7)	38	500-699	2.4	7	51	19	24	7
6025	28	135.6 (66)	1980 (7)	4.4 (2.4)	2.2 (6)	1.8 (5)	32	700-999	2.9	7	35	45	16	5
6027	29	138.4 (50)	1985 (5)	4.3 (2.4)	3.0 (29)	1.8 (6)	30	700-999	3.1	8	29	49	18	5
6016	30	140.2 (66)	1955 (23)	4.3 (2.5)	7.1 (61)	4.2 (7)	32	500-699	2.2	10	34	24	36	10
6019	31	143.4 (72)	1976 (14)	4.3 (2.4)	4.5 (10)	3.6 (7)	33	500-699	2.1	9	36	24	35	11
6014	32	147.5 (106)	1967 (18)	4.3 (2.4)	8.1 (41)	3.3 (7)	35	500-699	2.3	7	41	22	31	9
6155	33	154.2 (52)	1982 (7)	4.3 (2.4)	2.2 (8)	1.8 (5)	31	700-999	3.1	5	40	42	14	5
6148	34	155.7 (101)	1976 (9)	4.5 (2.3)	2.7 (8)	2.4 (6)	36	700-999	2.7	6	46	28	20	6
6026	35	159.0 (42)	1985 (6)	4.2 (2.4)	4.0 (42)	2.2 (6)	32	700-999	3.3	4	37	48	11	4
6157	36	159.3 (123)	1974 (18)	4.3 (2.3)	4.7 (11)	3.8 (7)	38	500-699	2.1	7	44	23	27	8
6076	37	161.3 (60)	1973 (13)	4.3 (2.4)	3.3 (18)	2.1 (5)	37	700-999	2.9	6	51	30	14	6
6018	38	162.8 (72)	1970 (16)	4.2 (2.4)	6.9 (32)	4.6 (6)	36	500-699	2.4	7	44	25	26	7
6012	39	162.9 (187)	1965 (18)	4.2 (2.5)	4.2 (14)	2.9 (7)	36	500-699	2.2	10	37	16	39	10
6152	40	170.3 (82)	1976 (14)	4.4 (2.4)	3.9 (14)	2.9 (6)	34	500-699	2.1	7	33	17	42	10
6023	41	171.9 (70)	1979 (6)	4.6 (2.4)	3.2 (8)	2.6 (5)	34	700-999	3.1	5	44	39	13	4
6050	42	174.5 (113)	1959 (21)	4.3 (2.4)	6.1 (21)	4.3 (7)	36	500-699	2.2	9	34	19	35	8
6149	43	177.0 (44)	1983 (6)	4.6 (2.4)	1.8 (8)	1.4 (4)	34	700-999	3.1	4	47	35	12	4
6156	44	192.8 (156)	1969 (15)	4.1 (2.4)	5.5 (11)	4.3 (7)	37	500-699	2.4	8	46	22	27	7
6020	45	206.4 (88)	1978 (11)	4.2 (2.4)	4.9 (13)	4.0 (7)	37	700-999	2.8	6	48	31	17	7
6151	46	213.6 (143)	1965 (21)	4.1 (2.5)	8.4 (35)	5.0 (7)	34	700-999	2.1	7	32	17	42	14
6008	47	218.5 (98)	1953 (27)	4.2 (2.5)	7.8 (16)	5.7 (7)	35	700-999	2.1	6	32	18	44	10
6153	48	263.1 (234)	1974 (15)	4.0 (2.4)	6.1 (12)	5.1 (7)	39	700-999	2.4	6	49	20	26	10
6010	49	273.9 (180)	1969 (22)	4.0 (2.3)	7.4 (18)	5.8 (7)	37	700-999	2.3	5	46	18	26	10
6009	50	370.8 (261)	1958 (20)	4.4 (2.5)	6.7 (13)	5.3 (7)	35	700-999	2.5	6	45	15	29	8

This table provides descriptive statistics of the data used in the empirical study. The left hand side of the table ranks Australian postcode districts in ascending order according to mean selling price for the sample period, 1988-2000. For each postcode district there is further detail for property characteristics obtained from the Valuer General's Office of Western Australia and a summary of 1996 census information obtained from the Australian Bureau of Statistics.

* Denotes the standard deviation for mean values.

1. The variable R^* is the real annual effective rate of price change for individual repeat-sales. Further detail for the construction of this variable is available in the appendix.
2. Long holding periods are longer than one year.

Table (2)		Homogenous Price Groups (Mean repeat-sale price $'000)																						
Postcode	**N**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
6167	848	74.9																						
6061	1,487	86.6	86.6																					
6112	1,738	87.1	87.1																					
6051	1,611	88.4	88.4																					
6064	1,410		94.2	94.2																				
6110	1,626		94.2	94.2																				
6168	1,521		94.5	94.5																				
6107	1,225		99.1	99.1	99.1																			
6147	983		99.3	99.3	99.3	99.3																		
6056	1,325		99.5	99.5	99.5	99.5																		
6054	1,123			103.3	103.3	103.3	103.3																	
6111	1,340			105.5	105.5	105.5	105.5	105.5																
6164	864			107.2	107.2	107.2	107.2	107.2	107.2															
6053	978			107.3	107.3	107.3	107.3	107.3	107.3															
6060	1,867				108.7	108.7	108.7	108.7	108.7	108.7														
6169	1,552				110.6	110.6	110.6	110.6	110.6	110.6														
6210	3,071					112.9	112.9	112.9	112.9	112.9	112.9													
6108	1,404						113.2	113.2	113.2	113.2	113.2													
6030	664							116.9	116.9	116.9	116.9													
6065	677								119.5	119.5	119.5													
6101	963								119.6	119.6	119.6													
6100	1,071								119.7	119.7	119.7													
6062	1,433								120.6	120.6	120.6	120.6												
6066	902								120.8	120.8	120.8	120.8												
6163	2,372									121.7	121.7	121.7												
6024	905										124.3	124.3	124.3											
6059	1,140											134.1	134.1	134.1										
6025	2,210												135.6	135.6										
6027	3,152													138.4										
6016	791													140.2										
6019	2,183													143.4	143.4									
6014	1,561													147.5	147.5	147.5								
6155	1,304														154.2	154.2	154.2							
6148	974														155.7	155.7	155.7							
6026	1,294															159.0	159.0	159.0						
6157	996															159.3	159.3	159.3						
6076	982																161.3	161.3	161.3					
6018	1,687																162.8	162.8	162.8					
6012	864																162.9	162.9	162.9					
6152	1,645																	170.3	170.3	170.3				
6023	923																	171.9	171.9	171.9				
6050	1,095																		174.5	174.5				
6149	1,012																			177.0				
6156	881																				192.8			
6020	1,081																				206.4	206.4		
6151	1,563																					213.6		
6008	874																					218.5		
6153	1,151																						263.1	
6010	852																						273.9	
6009	929																							370.8

This table provides output from Tukey's *honestly significance difference test*, a post hoc multiple comparison test used with a one-way ANOVA procedure. It shows 23 homogenous and overlapping price groups. The variable used in the test is the mean selling price of repeat-sales for the sample period 1988-2000. The grouping variable is the Australian postcode district.

Table (3)	Full Sample		First Quartile		Second Quartile		Third Quartile		Fourth Quartile	
	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*	
Adj *R* squared	0.117		0.037		0.114		0.036		0.044	
Observations	1628		444		444		444		370	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
? Constant	0.00	-2.4	-0.02	-5.0	0.00	-2.4	0.00	0.4	0.00	1.4
? Own group *k* ? 1	0.14	5.1	0.06	1.2	0.25	4.5	0.08	1.6	0.08	1.4
? Own group *k* ? 2	0.10	3.8	0.04	0.8	0.12	2.2	0.12	2.3	0.02	0.3
? Own group *k* ? 3	0.01	0.6	0.02	0.5	-0.07	-1.7	0.07	1.6	-0.02	-0.4
? Own group *k* ? 5	0.13	5.2	0.15	3.0	0.08	1.7	0.07	1.4	0.10	2.2
? Own group *k* ? 6	0.10	4.1	-0.09	-1.8	0.17	3.6	0.05	1.0	0.12	2.7
? Group + 1 *k* ? 1	0.14	5.8	0.10	1.5	0.08	1.8	0.14	3.2	0.09	2.2
? Group + 1 *k* ? 2	0.03	1.3	-0.08	-1.3	0.10	2.2	0.04	0.9	-0.02	-0.5
? Group + 1 *k* ? 3	-0.05	-2.6	-0.15	-2.9	-0.09	-2.2	-0.04	-1.1	-0.06	-1.7
? Group + 1 *k* ? 5	0.11	5.2	0.09	1.4	-0.10	-2.6	0.03	0.7	0.15	4.2
? Group + 1 *k* ? 6	0.01	0.3	-0.08	-1.4	0.02	0.5	0.00	-0.1	-0.02	-0.5
	Model 6		*Model 7*		*Model 8*		*Model 9*		*Model 10*	
Adj *R* squared	0.096		0.077		0.113		0.014		0.028	
Observations	1554		296		444		444		444	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
? Constant	0.00	0.3	-0.02	-4.5	-0.01	-4.1	0.00	0.0	0.01	2.6
? Own group *k* ? 1	0.14	4.8	0.07	1.0	0.22	3.9	0.07	1.2	0.05	0.9
? Own group *k* ? 2	0.07	2.3	0.08	1.3	0.10	1.8	0.12	2.3	-0.04	-0.8
? Own group *k* ? 3	0.05	1.8	0.10	1.7	-0.07	-1.7	0.07	1.5	0.03	0.6
? Own group *k* ? 5	0.12	4.7	0.12	1.8	0.06	1.2	0.07	1.5	0.09	1.7
? Own group *k* ? 6	0.09	3.7	0.00	0.0	0.22	4.5	0.07	1.5	0.02	0.5
? Group - 1 *k* ? 1	0.16	5.5	0.07	1.6	0.05	1.0	0.04	0.6	0.22	2.8
? Group - 1 *k* ? 2	0.00	0.0	-0.03	-0.7	-0.18	-3.5	-0.10	-1.7	-0.03	-0.4
? Group - 1 *k* ? 3	-0.02	-0.8	0.01	0.3	-0.04	-0.9	0.00	0.0	-0.09	-1.4
? Group - 1 *k* ? 5	0.06	2.3	-0.08	-2.0	0.03	0.7	0.00	0.1	0.10	1.4
? Group - 1 *k* ? 6	0.01	0.3	-0.16	-4.0	-0.19	-4.3	-0.06	-1.2	0.09	1.3
	Model 11		*Model 12*		*Model 13*		*Model 14*		*Model 15*	
Adj *R* squared	0.054		0.013		-0.004		-0.008		0.009	
Observations	1496		408		408		408		340	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
? Constant	0.00	-4.3	-0.02	-8.2	-0.01	-7.7	0.00	-0.5	0.01	3.4
? Own group *k* ? 5	0.14	5.5	0.01	0.1	-0.05	-1.0	0.02	0.4	0.05	1.0
? Own group *k* ? 9	0.10	4.3	-0.05	-1.1	-0.01	-0.2	0.01	0.1	0.03	0.7
? Group + 1 *k* ? 5	0.12	5.6	-0.02	-0.3	-0.03	-0.7	-0.02	-0.4	0.06	1.7
? Group + 1 *k* ? 9	0.04	2.3	-0.12	-2.1	0.02	0.5	0.02	0.4	-0.04	-1.3
	Model 16		*Model 17*		*Model 18*		*Model 19*		*Model 20*	
Adj *R* squared	0.058		0.047		0.001		-0.002		-0.001	
Observations	1428		272		408		408		408	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
? Constant	0.00	-1.0	-0.02	-8.1	-0.01	-6.5	0.00	-0.1	0.01	3.5
? Own group *k* ? 5	0.16	6.3	0.04	0.6	-0.01	-0.2	0.03	0.6	0.08	1.4
? Own group *k* ? 9	0.09	3.7	-0.11	-1.9	0.01	0.2	0.00	0.0	0.04	0.7
? Group - 1 *k* ? 5	0.07	2.6	-0.13	-3.0	-0.07	-1.4	0.00	0.0	0.00	0.0
? Group - 1 *k* ? 9	0.12	5.1	-0.10	-2.4	0.01	0.3	0.08	1.6	0.05	0.8

This table reports regression coefficients and *t-statistics* for models explaining abnormal price changes for homogenous price groups. Models are shown for the full sample and selected sub-samples. Own group coefficients denoted ? are lagged values of own group abnormal price changes where *k* represents the quarterly lag period. Models 1-5 and 11-15 also show ? coefficients for Group + 1 where lagged values from the nearest higher non-overlapping price group are used as an independent variable. Models 6-10 and 16-20 follow a similar procedure but use lower groups, as the independent variable. Models are shown for the full sample and price group quartiles. From Table (2), quartile 1 includes groups 1-6, quartile 2 groups 7-12, quartile 3 groups 12-17, quartile 4 groups 18-23. Models 11-20 are long run lag models using a non-overlapping lag structure.

Table (4)	*Model 21*			*Model 22*	
Adj *R* squared	0.113		Adj *R* squared	0.081	
Observations	1554		Observations	1406	
	Coeff	*t*-stat		Coeff	*t*-stat
? Constant	0.00	-3.2	? Constant	-0.01	-4.5
? Own group *k* ? 1	0.14	5.2	? Own group *k* ? 1	0.15	5.3
? Own group *k* ? 2	0.14	5.0	? Own group *k* ? 2	0.11	4.0
? Own group *k* ? 3	0.01	0.6	? Own group *k* ? 3	0.02	0.8
? Own group *k* ? 5	0.12	5.0	? Own group *k* ? 5	0.14	5.2
? Own group *k* ? 6	0.13	5.3	? Own group *k* ? 6	0.05	2.1
? Group + 2 *k* ? 1	0.00	-0.2	? Group + 3 *k* ? 1	0.05	3.0
? Group + 2 *k* ? 2	0.11	5.3	? Group + 3 *k* ? 2	0.02	1.0
? Group + 2 *k* ? 3	-0.03	-1.6	? Group + 3 *k* ? 3	0.05	3.2
? Group + 2 *k* ? 5	0.05	2.8	? Group + 3 *k* ? 5	-0.01	-0.6
? Group + 2 *k* ? 6	0.04	2.2	? Group + 3 *k* ? 6	0.01	0.6
	Model 23			*Model 24*	
Adj *R* squared	0.047		Adj *R* squared	0.023	
Observations	1110		Observations	888	
	Coeff	*t*-stat		Coeff	*t*-stat
? Constant	0.00	2.5	? Constant	0.01	3.5
? Own group *k* ? 1	0.12	3.6	? Own group *k* ? 1	0.07	1.9
? Own group *k* ? 2	0.03	0.8	? Own group *k* ? 2	0.00	0.1
? Own group *k* ? 3	0.04	1.5	? Own group *k* ? 3	0.06	1.8
? Own group *k* ? 5	0.10	3.5	? Own group *k* ? 5	0.11	3.5
? Own group *k* ? 6	0.07	2.7	? Own group *k* ? 6	0.04	1.4
? Group - 2 *k* ? 1	0.11	2.6	? Group - 3 *k* ? 1	0.05	1.0
? Group - 2 *k* ? 2	-0.03	-0.6	? Group - 3 *k* ? 2	0.05	1.0
? Group - 2 *k* ? 3	0.04	1.1	? Group - 3 *k* ? 3	-0.01	-0.1
? Group - 2 *k* ? 5	0.07	2.0	? Group - 3 *k* ? 5	0.10	2.3
? Group - 2 *k* ? 6	0.02	0.4	? Group - 3 *k* ? 6	0.02	0.4
	Model 25			*Model 26*	
Adj *R* squared	0.051		Adj *R* squared	0.022	
Observations	1428		Observations	1292	
	Coeff	*t*-stat		Coeff	*t*-stat
? Constant	-0.01	-6.2	? Constant	-0.01	-7.5
? Own group *k* ? 5	0.14	5.6	? Own group *k* ? 5	0.11	3.8
? Own group *k* ? 9	0.09	4.2	? Own group *k* ? 9	0.05	1.8
? Group + 2 *k* ? 5	0.11	5.9	? Group + 3 *k* ? 5	0.02	0.8
? Group + 2 *k* ? 9	0.05	2.9	? Group + 3 *k* ? 9	0.06	3.7
	Model 27			*Model 28*	
Adj *R* squared	0.034		Adj *R* squared	0.033	
Observations	1020		Observations	816	
	Coeff	*t*-stat		Coeff	*t*-stat
? Constant	0.00	2.6	? Constant	0.01	5.0
? Own group *k* ? 5	0.11	3.4	? Own group *k* ? 5	0.09	2.6
? Own group *k* ? 9	0.07	2.4	? Own group *k* ? 9	0.05	1.8
? Group - 2 *k* ? 5	0.15	4.0	? Group - 3 *k* ? 5	0.20	4.5
? Group - 2 *k* ? 9	0.07	2.0	? Group - 3 *k* ? 9	0.13	3.2

This table reports regression coefficients and *t-statistics* for models explaining abnormal price changes for homogenous price groups. Own group coefficients denoted ? are lagged values of own group abnormal price changes where *k* represents the quarterly lag period. The ? coefficients provide information for groups further apart in the price hierarchy. The groups designated as Group +2 are two non-overlapping groups removed from the own group and Group +3 three non-overlapping groups removed. A similar procedure applies to the lower price groups. These results are for the full sample only.

Appendix 1: Construction of the variable *R**

The variable R^* shown in Table (1), is the effective real annual rate of price change for *individual* repeat-sales. Let PR_i represent the price relative for an individual repeat-sale: $PR_i = \frac{P_{it+h}}{P_{it}}$ where P_{it} is the initial sale of property *i* at time *t*, and P_{it+h} is the subsequent sale at time *t* plus the holding period *h* for property *i*. The price relative can also be used to calculate $R_{i|h}$ the nominal (or effective) rate of price change for individual repeat-sale *i*, given holding period *h*. In this study, the holding period *h* for an individual repeat-sale is measured as a discrete number of quarterly periods between the initial sale and subsequent sale dates:

$$R_{i|h} = \left[\left(\frac{P_{it+h}}{P_{it}} \right)^{\frac{1}{h}} - 1 \right] \tag{1}$$

For the results in Table (1), $R_{i|h}$ is calculated as an annual effective rate.[i] Full notation for the variable R^* shown in Table (1) is represented by $R^*_{i|h}$

$$R^*_{i|h} = R_{i|h} - \Delta CPI \mid h \tag{2}$$

where $R_{i|h}$ is the annual effective rate of price change for individual repeat-sales unadjusted for inflation as shown in equation (1). The deflator $\Delta CPI \mid h$ is the contemporaneous consumer price index (CPI) change for the holding period.[ii]

---

i. $R_{i|h}$ as an effective annual rate is calculated [{1 + ((((*Pit* + *h* / *Pit*) ^ (1 / *h*) - 1) × 4) / 4)} ^ 4] – 1

ii. $\Delta CPI \mid h$ is calculated [{1 + (((((exp(*ln_cpi_t* + *h*) / exp(*ln_cpi_t*)) ^ (1 / *h*)) - 1) × 4) / 4)} ^ 4] – 1 where *ln_cpi_t* is the natural logarithm of the CPI index number corresponding with the initial selling price period *ln_cpi_t* + *h* is the logarithm of the CPI index number corresponding with the subsequent selling price period.

References

Case, K. E., and Shiller, R.J. (1989). “The Efficiency of the Market for Single-Family Homes”, *The American Economic Review* 79, 125-137.

Case, K.E., and Shiller, R.J. (1990). “Forecasting Prices and Excess Returns in the Housing Market”, *Journal of the American Real Estate and Urban Economics Association,* 18, 253-273.

Clapp, J.M., and Giaccotto, C. (1998). “Price Indexes Based on the Hedonic Repeat-Sales Method,” *Journal of Real Estate Finance and Economics*, 16 (1):5-26.

Clapp, J.M., Dolde, W., and Tirtiroglu, D. (1995). “Imperfect Information and Investor Inferences from Housing Price Dynamics”, *Real Estate Economics*, Fall 1995, Vol 23 No 3, 239-269.

Costello, G., (2000) “Pricing Size Effects in Housing Markets”, *Journal of Property Research*, Vol 17 (3), pp 1-17.

DiPasquale, D. and Wheaton, W.C. (1996). *Urban Economics and Real Estate Markets.* Prentice Hall Inc, New Jersey, 1996.

Dolde, W., and Tirtiroglu, D. (1997). “Temporal and Spatial Information Diffusion in Real Estate Price Changes and Variances”, *Real Estate Economics*, Winter 1997, Vol 25 No 4, 539-565.

Gatzlaff, D.H., and Tirtiroglu, D. (1995). “Real Estate Market Efficiency: Issues and Evidence” *Journal of Real Estate Literature*, Vol 3, No 2, pp 157 189.

Goodman, J. (1998). “Aggregation of Local Housing Markets”, *The Journal of Real Estate Finance and Economics*, Vol 16 (8) pp 43-54.

Grigsby, W., Baratz, M., Galster, G. and Maclennan, D. (1987). *The Dynamics of Neighbourhood Change and Decline*, Oxford: Pergamon.

Grigsby, W.G. (1963) *Housing Markets and Public Policy*, Philadelphia: University of Pennsylvania Press.

Hansen, L.P., and Hodrick, J.R. (1980). “Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis”, *Journal of Political Economy*, October 1980, 88, 829-53.

Keogh, G. and D’Arcy, E. (1999) Property Market Efficiency: An Institutional Economics Perspective, *Urban Studies*, 36, pp.2401-2414.

King, A. and Baekgaard, H. (1996)). *The dynamics of housing wealth*. Paper presented to the *8th National Conference of the Australian Population Association*, Adelaide 3-6 December.

Megbolugbe, I.F., Hoek-Smit, M.C. and Linneman, P.D. (1996). “Understanding Neighbourhood Dynamics: A Review of the Contributions of William G. Grigsby”, *Urban Studies*, Vol 33 (10), pp 1779-1795.

Quan, D.C., and Quigley, J.M. (1989). “Inferring an Investment Return Series for Real Estate from Observations on Sales”, *Journal of American Real Estate and Urban Economics Association,* 17, 218-234.

Shiller, R.J. (1984). “Stock Prices and Social Dynamics”. *Brookings Papers on Economic Activity,* 457 498.

Summers, L.H. (1986). “Does the Stock Market Rationally Reflect Fundamental Values?” *Journal of Finance,* 41, 591 -601.