Eleventh Annual Conference of the Pacific-Rim Real Estate Society

Melbourne, Australia, 23rd to 27th January 2005

TRADING RULES IN HOUSING MARKETS - WHAT CAN WE LEARN?

Greg 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: G.Costello@curtin.edu.au

Abstract: This paper examines the application of trading rules in testing informational efficiency in housing markets. Since the seminal work of Linneman (1986) there have been substantial advances in the volume and quality of data available to test information diffusion processes within housing markets. Given the sophistication of current data sources, it is surprising that there has not been more applied research in this field. The paper reviews and extends the work of Linneman (1986) and Londerville (1998) to an empirical analysis of Western Australian housing data. Whereas most previous studies have focused upon hedonic methods to predict future house prices, this study also incorporates repeat-sales data so that *predicted* and *actual* selling prices of individual properties are available for analysis. The results support the view that idiosyncratic information diffusion processes exist within housing markets. These processes are influenced by levels of aggregation within the data across spatial regions.

Introduction

Is it possible to consistently identify and trade under-priced properties profitably in Australian housing markets? This paper tests this proposition empirically by adapting a trading (buying) rule previously applied by Linneman (1986) and Londerville (1998) to North American housing markets. The trading rule is intuitively appealing in the current era of electronic information for housing in that *predicted* results can be evaluated against *actual* results by examination of the historical record of housing transactions that include repeat-sales of the same housing unit.

Information and commentary concerning house prices have appeared frequently in the popular press during the recent era of rapid house price growth in Australian housing markets. Major national and state newspapers regularly provide reports of housing market activity. It is apparent in many press reports that some commentators believe that specific market segments and/or suburbs might be under-priced relative to others, therefore ‘bargain’ buying opportunities exist. This view promotes a perception of inefficient housing markets in that suitably informed participants can trade profitably on the ‘right’ information.

This study extends the work of Linneman (1986) who developed a trading strategy to test housing market efficiency using hedonic regressions of recent transactions as a model to predict future house prices. In this way it is possible to identify homes that are ‘under-valued’ at the time of sale. If under-valued properties can be identified and traded profitably then an opportunity to earn abnormal profits exists and the housing market is inefficient. Linneman’s original (1986) study was limited by data problems in that owners’ estimates of house values were used in association with actual sale prices. Londerville (1998) used repeat-sales data to overcome this problem. This study extends a similar trading rule to examine whether results vary according to levels of spatial disaggregation of the data.

Theory and Related Literature

The central theme of this paper relates to Fama's (1970) efficient markets hypothesis (EMH) paradigm for testing how information influences asset prices. Fama argued that it was not enough to suggest that markets were inefficient purely because information influenced prices. To demonstrate that a market is inefficient there must be some way of exploiting the value of information so that investors can earn abnormal returns. Numerous trading rule strategies have been developed to test levels of market efficiency in many different asset markets although there have been very few studies applying rigorous trading rules to housing markets.

Efficiency in the housing market is desirable for the same reasons that efficiency is desirable in other product or securities markets. If prices provide accurate signals for purchase or disposition of housing assets then they facilitate the correct allocation of scarce financial resources. Several authors have suggested that if real estate markets are informationally efficient then the distribution of market prices should accurately reflect the full range of characteristics and risks associated with individual real estate assets (Gau (1987), Gatzlaff and Tirtiroglu (1995)). This definition of real estate market efficiency infers that in an informationally efficient real estate market, errors in the pricing of real estate assets are random. This proposition is tested specifically in the empirical tests that follow.

Meese and Wallace (1994) proposed an alternative view. They examined the present value relation (PVR) for housing. They argued that the efficient market condition in housing markets requires the real expected return for home ownership to equate to the real homeowner cost of capital. This argument suggests that another implication of the efficient markets hypothesis is that in an efficient housing market, observed prices are also correctly capitalised rents for those housing assets. This proposition is relevant to the empirical study that follows in that the methodology provides an imputed rental benefit that might be usefully applied in future tests of the PVR in housing markets.

Gatzlaff and Tirtiroglu (1995) provided a comprehensive review of studies examining real estate market efficiency. They argued that real estate market efficiency should not be viewed as an absolute concept, rather more one of degree.

Given housing market imperfections, it is likely that housing markets are not as efficient as securities markets and that some regional housing markets are more or less efficient than others. It is also likely that housing markets capitalise different types of information at different rates and in differing degrees. Some information may be fully capitalised, whereas prices may fail to reflect some other sets of information.

The empirical study to follow utilises spatial disaggregation as a tool for analysis. Housing markets can be disaggregated according to various criteria, where similarity is most commonly defined by spatial region. The implicit assumption being that the spatial market segment represents a relatively homogenous asset market and the variance decomposition of housing prices has a principal fixed effect according to the spatial (neighbourhood) criteria defining segmentation. Where a housing market is disaggregated according to spatial criteria, then the distance between neighbourhoods becomes a determinant of price dispersion and spatial distribution of prices becomes relevant.

There have been some important empirical studies testing information diffusion processes in and between specific geographic market segments (Clapp, Dolde and Tirtiroglu (1995), Dolde and Tirtiroglu (1997)). These studies provide evidence of rational learning behaviour in housing markets. Their results indicate that housing market participants learn most from past prices in their own spatial regions. Tirtiroglu and Clapp (1994) showed empirically that spatial barriers can alter information diffusion processes in housing markets. More recently spatial distribution models have been used to examine varying autocorrelation properties of house prices (Gillen, Thibodeau and Wachter (2001)).

Trading rules have been utilised in several studies examining efficiency in housing markets (Gau (1985 and 1987) Case and Shiller (1989), Linneman (1986)). Gau's initial studies utilised small specific sets of data whereas Case and Shiller used large sets of data for major US cities. They used several models to test whether observed serial dependence in house price series could be exploited. First they used a model of housing returns with an index supplemented with rental information and reported that the serial dependence in the time series could be used in some cities to generate profits higher than those that could be achieved with a naive buy and hold strategy.

They reported considerable variation in the results for tests between different cities indicating that these tests are probably more appropriate for use with disaggregated data.

Case and Shiller (1989) also used a trading rule procedure with price changes estimated from a repeat-sales index. The procedure involved regressing changes in *individual* house prices between time *t* and a subsequent period on information available at time *t – 1*. Under the efficient market hypothesis anything in the information set at time *t* should have no explanatory power for individual house price changes subsequent to that date. Case and Shiller argued that it is quite natural to set up a test for the efficient market hypothesis in this way as an investor wanting to exploit serial dependence in a time series needs to be able to forecast future house prices accurately.

Linneman (1986) provided an important contribution by introducing a cross-sectional approach that addressed some of the specific issues associated with real estate market structure and *individual* house price formation processes. The buying rule used hedonic regressions of recent transactions as a model to predict future house prices. The key thrust of this trading strategy is that there are two types of error associated with the use of hedonic analysis of a housing market. The first is defined as ‘analyst’ or measurement error, associated with errors-in-variables or incorrect specification of the hedonic model. The second is ‘transactor’ error, where market participants either sell too cheaply, or pay too much. The expected transactor error component would be zero in a perfectly informed market. Linneman argued that it is empirically impossible to distinguish between analyst and transactor errors. His trading rule procedure is based upon the important assumption that as the explanatory power of hedonic pricing equations increases then analyst error will decrease. This work was further developed by Londerville (1998) who introduced methodology to analyse risk-adjusted buying rules.

Data and Methodology

The Linneman (1986) trading rule used hedonic regressions of recent transactions as a model to predict future house prices. Following the hedonic pricing literature, the value of an individual property V_i can be represented:

$$V_i = f(Z_i; a) + U_i \quad (1)$$

Where Z_i is a vector of relevant structural and neighborhood traits, a is a parameter vector representing shadow prices of these traits and U_i is a random error term. Linneman's trading strategy identified two types of error from equation (1), 'analyst' or measurement error (noise), and 'transactor' error, where market participants either sell too cheaply, or pay too much. The key element of the trading rule is in identification of transactor errors, which provide arbitrage opportunities for informed investors. Individual property information can be used in periodic cross-sectional analysis to identify sellers who undervalue their housing units, $(U_i < 0)$. If these properties can be purchased at or below the asking price and subsequently resold at or above market value $(U_i > 0)$ then arbitrage profits are possible. By using a large repeat-sales sample it is possible to analyse the historical record of house sales by applying this trading rule.

Linneman's full trading strategy model also accounted for the impact of capital gains tax and transaction costs. He concluded that properties with negative estimation errors did on average earn higher appreciation returns. However when the level of transaction costs associated with US housing were at market levels, on average excess returns could not be achieved.

There are several difficulties associated with applying Linneman's full trading strategy in Australian housing markets. First, capital gains tax assumptions cannot be applied as a constant to all house sales as owner-occupied housing is exempt. Second, over a longer sample period there are variations in levels of transaction costs that make the selection of these variables arbitrary.

Londerville (1998) also recognised these problems when testing a longer time-series of repeat-sales and simplified the trading strategy. Consider the logarithmic functional form shown as equation (1). The size of the error, U_i required for positive profits, will also depend on the level of transaction costs and taxes on the sale of the property relative to the price of the property. As an example, in logarithmic form a level of $U_i = -0.10$ as a level of estimation error for 'undervalued' properties implies a price of 90% of the estimated value given the hedonic equation. In this case the purchaser is buying a property at a 10% discount on the estimate of market value.

To test the trading rule, a comprehensive data set of selected repeat-sales for the Perth metropolitan area was provided by the W.A. Valuer General's Office (VGO). Accurate hedonic data series require suitable data for individual house characteristics. The data set was selected on the basis of availability of information for specific structural characteristics of individual housing units. Initially, cross-sectional hedonic regressions were estimated using twelve months of data for periodic estimations. The model was applied to the aggregate Perth housing market with the estimating equation being of the following form:

$$LnP_{it} = \beta_0 + \beta_1 Ln(AREA_{it}) + \beta_2 Ln(AGE_{it}) + \beta_3 Ln(CARS_{it}) + \mu_{it} \qquad (2)$$

In this model LnP_{it} represents the natural logarithm of selling price for property *i* at time *t* and the variables $Ln(AREA_{it}), Ln(AGE_{it}), Ln(CARS_{it})$ are the natural logarithms for the building area, building age and number of car bays for property *i* at time *t* and μ_{it} represents the regression disturbance term. The functional form shown in equation (2) is a functional form that can be applied effectively to the aggregate Perth data for all sample periods. The results for the cross-section regressions used to predict selling prices are summarised in Table 1.

Table 1: Summary of Hedonic Regressions

Year	N *S.E.E.*	Adj R^2	Constant *(t)*	LN_area *(t)*	LN_age *(t)*	LN_cars *(t)*
1988	1,667 *0.23*	0.68	7.03 *(78.7)*	0.95 *(49.5)*	0.00 *(-0.6)*	0.22 *(5.6)*
1988-89	3,397 *0.23*	0.67	7.20 *(111.8)*	0.93 *(66.9)*	-0.001 *(-0.3)*	0.31 *(10.9)*
1989	3,065 *0.19*	0.74	7.42 *(126.2)*	0.90 *(71.1)*	-0.01 *(-2.8)*	0.34 *(14.0)*
1989-90	3,115 *0.21*	0.69	7.69 *(125.4)*	0.85 *(63.8)*	-0.025 *(-6.9)*	0.22 *(9.0)*
1990	3,640 *0.22*	0.67	7.72 *(130.8)*	0.84 *(65.5)*	-0.03 *(-9.3)*	0.15 *(6.8)*
1990-91	4,061 *0.23*	0.65	7.48 *(121.8)*	0.88 *(66.6)*	-0.027 *(-7.8)*	0.19 *(8.6)*
1991	3,895 *0.24*	0.63	7.48 *(114.2)*	0.88 *(62.8)*	-0.03) *(-6.4)*	0.23 *(9.4)*
1991-92	4,022 *0.24*	0.64	7.42 *(115.1)*	0.90 *(64.9)*	-0.029 *(-7.3)*	0.19 *(8.0)*
1992	4,623 *0.25*	0.64	7.32 *(120.3)*	0.93 *(70.8)*	-0.03 *(-7.9)*	0.16) *(7.7)*
1992-93	5,049 *0.26*	0.65	7.33 *(127.3)*	0.93 *(75.1)*	-0.023 *(-6.7)*	0.19 *(9.7)*
1993	5,712 *0.26*	0.68	7.20 *(129.9)*	0.96 *(81.4)*	-0.02 *(-6.4)*	0.22) *(12.5)*
1993-94	6,385 *0.27*	0.67	7.15 *(127.3)*	0.99 *(82.7)*	-0.022 *(-6.5)*	0.21 *(11.9)*
1994	5,687 *0.28*	0.65	7.24 *(116.2)*	0.98 *(74.0)*	-0.02 *(-6.5)*	0.18) *(9.0)*
1994-95	4,183 *0.29*	0.65	7.10 *(93.7)*	1.01 *(63.0)*	-0.017 *(-3.8)*	0.17 *(7.6)*
1995	3,638 *0.30*	0.66	7.04 *(83.4)*	1.02 *(57.9)*	-0.02 *(-4.4)*	0.17 *(6.7)*
1995-96	3,284 *0.31*	0.64	7.20 *(77.6)*	1.00 *(51.5)*	-0.039 *(-7.0)*	0.17 *(6.2)*
1996	2,789 *0.34*	0.61	7.37 *(68.8)*	0.97 *(43.3)*	-0.06 *(-8.4)*	0.20 *(6.3)*
1996-97	2,359 *0.35*	0.59	7.42 *(61.4)*	0.96 *(38.1)*	-0.058 *(-7.6)*	0.16 *(4.6)*
1997	2,299 *0.34*	0.61	7.28 *(61.2)*	0.99 *(39.8)*	-0.05 *(-6.4)*	0.18 *(5.3)*
1997-98	2,199 *0.33*	0.65	7.02 *(58.8)*	1.05 *(42.0)*	-0.039 *(-5.3)*	0.21 *(6.8)*

Regression results: A new regression was run every 6 months using a twelve-month sample period. Since the data used is repeat-sales there is a lack of subsequent (second) sales in the later periods of the sample. To overcome this problem the sample was truncated as at the end of 1998. This cross-section specification enables a suitable sample period to be used with a sufficient volume of transactions to assure statistical validity.

In order to further test the trading strategy, the hedonic data was also segmented according to *suburb*. Four suburbs, Scarborough, Maylands, Como and South Perth were selected as the four highest ranking suburbs for volume of transactions in the sample period tested. By selecting spatial data sets, the influence of regional differentials that were present in the aggregate data for equation (2) is removed, thereby removing a major source of 'analyst error' in the residual terms.

To improve the explanatory power of the cross-sectional regressions and reduce the level of 'analyst error' for each suburb, additional variables were added to equation (2) so that varying complex hedonic models are estimated for each period. Here the emphasis is on maximising the explanatory power of the regressions. The method used was to estimate *stepwise* regressions in order to select the best combination of statistically significant explanatory variables. In summary, the average adjusted *R* squared result for these complex hedonic models was in the vicinity of 80% - 90% whereas for the simple hedonic models in Table (1) it was in the vicinity of 60% - 70%.

Each regression equation was used to predict values of properties that sold during the subsequent six months based upon their individual hedonic characteristics. The difference between the *actual* selling price of each property and the *predicted* price using the previous period hedonic equation is e_i the *estimation* error:

$$e_i = \hat{y}_{it} - P_{it+1} \qquad (3)$$

where: $\hat{y}_{it}$ is the predicted price of property *i* using time *t*, the six month cross-section of hedonic data and P_{it+1} is the actual selling price of property *i* in the subsequent six month sample period. It is important to note that this term is *not* a regression residual but the estimation error from predicting future sale prices from historical data from the previous period.

For further analysis the individual sales are grouped into four portfolios according to the size of e_i.

($e_i \le -0.10,\ -0.10 < e_i \le 0,\ 0 < e_i < +0.10$ and $e_i \ge +0.10$)

The trading strategy assumes that a property with a negative estimation error of -0.10 has a value of approximately 90% of true market value according to sale prices of similar properties in the recent past. If this difference is due to pricing error by the seller then an arbitrage profit opportunity (excess return), exists if the property can be sold at or above 100% of its true market value at the subsequent sale. Excess returns, *ER* were calculated:

$$ER = R - Rf \qquad (4)$$

where: *R* is a nominal annualised internal rate of return (IRR) for each pair of sales of an individual property[1] and *Rf* is a proxy measure for the risk free rate of return during the relevant holding period. Consistent with methodology of the finance literature, *Rf* is the yield at the initial purchase date for a government bond with maturity of comparable length to the holding period was subtracted from *R* to obtain the excess return. To complete the empirical analysis the results are tested for statistical significance. Consistent with Londerville (1998) the results are analysed with the Sharpe ratio (reward-to-variability ratio) to adjust the returns for risk and test whether there are statistically significant differences between the returns for any of the portfolios. The statistical test for difference between two Sharpe ratios for two portfolios *i* and *j* is the hypothesis test where $H_{0S1}: Sh_i - Sh_j = 0$ and the test statistic assumes a *Z* distribution. The higher the value of the ratio, the better the portfolio has performed, since the return per unit of risk is higher.

---

[1] $$R = \left(\frac{1 + \left(\left(\frac{sale\_t1}{sale\_t} \right)^{\frac{1}{h}} - 1 \right) \times 12}{12} \right)^{12} - 1$$

Where; *sale_t* represents the initial selling price, *sale_t1* represents the subsequent selling price and *h* represents the holding period expressed in discrete calendar months.

Empirical Results

The results in this section are presented sequentially so that first the trading rule as applied to the aggregate Perth housing market are discussed followed by the spatially segmented market samples.

From equations (3) and (4), Table 2 summarises the excess returns and the mean estimation error e at the time of purchase for each of the four portfolios for the aggregate Perth data. Note that there are more positive estimation errors than negative errors in these tables. This is because e is an estimation error and not a regression residual. An important feature of the excess returns is the positive skewness in the distribution. For this reason both the mean and median are reported as measures of central tendency.

In Part A, the full sample is analysed. One fact that is immediately evident is the very high standard deviation of excess returns. Whereas the mean of -2.2% indicates that on average excess returns are close to zero, the standard deviation of 88.9% confirms very significant variation in individual property returns. It can be seen that the greatest variation is within the $e < -0.10$ 'undervalued' portfolio where the mean excess return is -0.1% and the standard deviation is 142.7%. All other portfolios confirm lower level negative excess returns and lower relative standard deviations. This suggests the possibility of significantly different levels of risk between portfolios.

The main cause of this variation in excess returns becomes evident when Parts B and C of Table 2 are analysed. Here the sample is further divided into short holding periods of one year or less and longer holding periods of more than one year. For short holding periods the mean excess return is 34.5% and when the $e < -0.10$ 'undervalued' portfolio is used, it is 54.8%. These returns are accompanied by standard deviations of 349.3% and 529.8% respectively. The other portfolios are also accompanied by positive excess returns and high standard deviations. The median excess return figures are much lower for all groups but still significantly positive. This confirms higher excess returns and positive skewness in the excess returns for short holding periods.

Table 2: Return and Estimation-Error Statistics for Varying Portfolios

Part A: Full Sample							
	Excess Return (%)			Estimation Error			
Range of Est. Error	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**	**N**
Total sample	-2.2%	-5.1%	88.9%	0.03	0.02	0.28	37,086
e < - 0.10	-0.1%	-5.1%	142.7%	-0.26	-0.23	0.14	11,830
-0.10 < *e* <0	-3.0%	-5.6%	79.8%	-0.05	-0.05	0.03	5,650
0 < *e* < + 0.10	-4.1%	-5.4%	20.7%	0.05	0.05	0.03	5,736
e > + 0.10	-3.0%	-4.8%	31.6%	0.31	0.26	0.18	13,870
Part B: Short Holding Periods – One Year or Less							
	Excess Return (%)			Estimation Error			
Range of Est. Error	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**	**N**
Total sample	34.5%	5.1%	349.3%	0.03	0.01	0.33	2,364
e < - 0.10	54.8%	5.7%	529.8%	-0.30	-0.27	0.17	847
-0.10 < *e* <0	38.6%	4.2%	337.1%	-0.05	-0.05	0.03	311
0 < *e* < + 0.10	16.4%	3.5%	86.0%	0.05	0.05	0.03	288
e > + 0.10	20.1%	5.3%	118.3%	0.36	0.30	0.21	918
Part C: Long Holding Periods – More Than One Year							
	Excess Return (%)			Estimation Error			
Range of Est. Error	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**	**N**
Total sample	-4.7%	-5.3%	6.5%	0.03	0.02	0.27	34,722
e < - 0.10	-4.3%	-5.4%	7.2%	-0.26	-0.22	0.13	10,983
-0.10 < *e* <0	-5.4%	-5.8%	5.7%	-0.05	-0.05	0.03	5,339
0 < *e* < + 0.10	-5.2%	-5.6%	6.1%	0.05	0.05	0.03	5,448
e > + 0.10	-4.6%	-5.0%	6.3%	0.31	0.26	0.18	12,952

Properties are divided into portfolios based on the size of the estimation error (actual transaction price less price predicted by most recent regression prior to sale). Excess return for each property is measured as annualised property appreciation less the yield at the time of the initial purchase on a government bond of similar duration to the holding period between property transactions.

In Part C it is evident that when only long holding periods are considered the mean excess returns are negative for all portfolios, there is less positive skewness and the standard deviations are very much lower. The calculation of excess returns is derived from house price changes excluding any implicit housing dividend accruing to the homeowner or investor. If it is assumed that this dividend is in the region of 4% - 5% per annum then the excess returns for all groups in the sample are very close to zero. This would be the expectation for an efficient housing market. The benefits of debt financing and tax relief are also not considered in this trading strategy and it is likely that these factors would also increase returns to some investors.

These results indicate quite clearly that there are incentives to investors in short-term trading for some housing units. In Table 2 Part B, the $e < -0.10$ 'undervalued' portfolio shows clearly the highest level of returns indicating that knowledge of an individual housing unit's estimation error is useful information that can be used by an investor. However the accompanying very high standard deviation confirms a corresponding higher level of risk. All other portfolios for short holding periods in Part B confirm positive excess returns indicating that the regression model used contains 'analyst error' in that positive estimation errors (over-priced properties) are still being traded short term for positive excess returns.

An important consideration here is that there is likely to be considerable capital expenditure involved with these short-term transactions. The data have been screened so that only buildings with the same main building area are used in the sample, confirming that there have been no additions to the structure. It is not possible to check for internal renovations. The likely scenario is that many of these short-term transactions are housing units that are purchased, substantially renovated and quickly re-sold. The level of capital expenditure involved together with transaction costs would further reduce the levels of excess returns recorded here.

Londerville (1998) also used the Sharpe ratio (reward-to-variability ratio) to adjust the returns for risk and test whether there are statistically significant differences between the returns for any of the portfolios. The higher the value of the ratio, the better the portfolio has performed, since the return per unit of risk is higher. The results for these tests are reported in Table 3.

Table 3: Sharpe Ratio Analysis for Different Portfolios

Part A: Sharpe Ratio Values

Range of Estimation Error at Time of Purchase	Sharpe Ratio		
	All Holding Periods 1989-1998	Short Holding Periods 1993-1998 [1].	Long Holding Periods 1989-1998
Total sample	-0.09	0.45	-0.84
e < - 0.10	0.06	0.30	-0.77
-0.10 < *e* <0	-0.08	0.17	-0.95
0 < *e* < + 0.10	-0.49	0.30	-0.81
e > + 0.10	-0.40	0.52	-0.86

Notes: The Sharpe ratio is calculated as the mean excess return earned by properties in the portfolio divided by the standard deviation of the excess returns for properties in the portfolio.
1. The short holding period sample was restricted for several groups in the early sample periods, with a lack of observations for 1989-1993. The short holding period sample uses the 1993-98 sample period to overcome this problem.

Part B: Statistical Significance of Differences in Sharpe Ratios

Range of Estimation Error at Time of Purchase	Z_{Sh} Compared with Portfolio of All Properties for Same Time Period		
	All Holding Periods	Short Holding Periods	Long Holding Periods
e < - 0.10	0.14	0.15	0.07
-0.10 < *e* <0	0.01	0.28	0.11
0 < *e* < + 0.10	0.40	0.16	0.03
e > + 0.10	0.31	0.07	0.02

Notes: Z_{Sh} is a test statistic to measure whether the Sharpe ratio for each portfolio is significantly different from the Sharpe ratio for the portfolio of all properties. None of the test statistics is statistically significant, leading to the conclusion that the risk-adjusted performance is the same for all portfolios, including those of ‘undervalued’ properties.

Unlike the results for excess returns in Table 2 there are not clear patterns emerging with the Sharpe ratios. Higher value ratios indicate a lower volatility in excess returns. It is evident in Part A that the Sharpe ratios for all holding periods are very low for the total sample and the ‘undervalued’ *e* < - 0.10 and -0.10 < *e* <0 portfolios. The ratios are higher for the other groups.

The ratios are also higher when only short holding period and long holding period transactions are measured. The results for short holding periods should be treated with some caution, as the sample was restricted for several groups in the early sample periods, with a lack of observations for 1989-1993. The short holding period sample uses the 1993-98 period to overcome this problem.

The ratios for long holding periods use the same time series as for all holding periods and are significantly higher confirming that the volatility in excess returns decreases when short holding periods are excluded from the sample.

In Part B of Table 3 the statistical significance of the difference between ratio values is analysed to assess whether the performance of any portfolio is significantly different than the performance for the total sample. The z_{Sh} statistic tests the null hypothesis that the difference in the Sharpe ratio for two portfolios is zero. The z_{Sh} statistic is compared with the standard normal distribution. None of the individual Sharpe ratios is significantly different from the Sharpe index for the total property portfolio at even a 10% level. In this case the null hypothesis that the risk-adjusted return performance of all portfolios was the same could not be rejected.

A number of previously mentioned studies confirm that information diffusion processes within housing markets are significantly influenced by spatial proximity. This suggests that market participants are more likely to base pricing decisions on the basis of ‘local’ information sets determined by spatial criteria than by factors influencing the aggregate housing market in general. Can these local information sets be used to develop trading strategies to exploit informational inefficiencies? Might these results for a trading rule be more effective if regional data sets were used?

In order to further test this application of the trading strategy, the hedonic data were segmented according to *suburb*. Four suburbs, Scarborough, Maylands, Como and South Perth were selected on the basis that these suburbs were the four highest ranking suburbs for volume of transactions in the sample period tested. By selecting spatial data sets, the influence of regional differentials that were present in the aggregate data is removed, thereby removing a major source of ‘analyst error’ in the residual terms.

Table 4 summarises the excess returns for each of the four suburbs and the four portfolios. The full sample of all holding periods is analysed in Part A consistent with the analysis of the aggregate data in Table 2.

Table 4: Spatial Regions - Return Statistics for Varying Portfolios

Part A: All Holding Periods

Error Range	All Suburbs Mean	All Suburbs Med	All Suburbs *S*	All Suburbs N	Scarborough Mean	Scarborough Med	Scarborough *S*	Scarborough N	Maylands Mean	Maylands Med	Maylands *S*	Maylands N	Como Mean	Como Med	Como *S*	Como N	South Perth Mean	South Perth Med	South Perth *S*	South Perth N
Total sample	-1.4	-4.6	*35.8*	6,882	-1.7	-3.9	*24.7*	2,150	-2.3	-5.3	*47.5*	2,029	-2.4	-5.0	*24.7*	1,455	1.7	-3.9	*40.5*	1,248
e < - 0.10	3.8	-3.4	*65.5*	1,595	2.9	-2.9	*50.0*	448	3.8	-4.1	*89.5*	535	2.8	-3.7	*39.4*	269	5.9	-2.5	*54.7*	343
-0.10 < *e* <0	-2.2	-4.6	*25.6*	1,375	-2.2	-3.8	*11.5*	488	-3.4	-5.2	*18.2*	388	-3.1	-5.1	*10.9*	293	1.7	-4.3	*57.3*	206
0 < *e* < + 0.10	-3.1	-4.6	*18.1*	1,560	-2.8	-3.7	*8.3*	578	-5.2	-6.3	*8.8*	394	-2.2	-4.9	*31.5*	379	-1.2	-3.7	*17.2*	209
e > + 0.10	-3.4	-5.2	*14.8*	2,352	-3.4	-4.9	*10.8*	636	-4.6	-5.7	*12.4*	712	-4.9	-5.7	*9.6*	514	0.1	-4.4	*23.7*	490

Part B: Short Holding Periods Only

Error Range	All Suburbs Mean	All Suburbs Med	All Suburbs *S*	All Suburbs N	Scarborough Mean	Scarborough Med	Scarborough *S*	Scarborough N	Maylands Mean	Maylands Med	Maylands *S*	Maylands N	Como Mean	Como Med	Como *S*	Como N	South Perth Mean	South Perth Med	South Perth *S*	South Perth N
Total sample	31.0	6.9	*121.4*	537	22.9	6.9	*89.4*	140	26.8	4.7	*152.9*	185	25.1	7.2	*84.0*	107	55.3	19.9	*126.4*	105
e < - 0.10	63.0	11.8	*205.3*	147	59.6	12.6	*183.7*	30	64.0	7.5	*267.6*	57	57.3	18.2	*124.4*	22	67.4	25.5	*150.7*	38
-0.10 < *e* <0	24.0	6.1	*88.9*	100	17.3	6.4	*35.2*	28	13.3	1.7	*54.5*	35	15.1	8.7	*29.1*	25	89.3	12.4	*227.6*	12
0 < *e* < + 0.10	18.1	5.9	*65.5*	97	11.8	8.3	*18.9*	34	5.6	5.7	*20.3*	30	38.8	8.3	*124.8*	22	29.7	4.0	*66.3*	11
e > + 0.10	16.8	4.4	*42.0*	193	11.1	3.8	*27.0*	48	10.7	2.7	*32.2*	63	5.1	1.8	*29.0*	38	41.9	24.1	*63.4*	44

Part C: Long Holding Periods Only

Error Range	All Suburbs# Mean	All Suburbs# Med	All Suburbs# *S*	All Suburbs# N	Scarborough Mean	Scarborough Med	Scarborough *S*	Scarborough N	Maylands Mean	Maylands Med	Maylands *S*	Maylands N	Como Mean	Como Med	Como *S*	Como N	South Perth Mean	South Perth Med	South Perth *S*	South Perth N
Total sample	-4.1	-4.8	*7.0*	6,345	-3.4	-4.3	*7.3*	2,010	-5.2	-5.7	*7.3*	1,844	-4.6	-5.3	*6.0*	1,348	-3.2	-5.	*6.7*	1,143
e < - 0.10	-2.2	-3.8	*8.8*	1,448	-1.2	-3.2	*9.2*	418	-3.4	-4.6	*8.7*	478	-2.1	-4.0	*9.2*	247	-1.8	-2.9	*8.1*	305
-0.10 < *e* <0	-5.	-4.9	*6.1*	1,275	-3.4	-5.	*6.5*	460	-5.1	-5.4	*6.7*	353	-4.8	-5.3	*4.4*	268	-3.7	-4.7	*5.6*	194
0 < *e* < + 0.10	-4.5	-4.7	*5.9*	1,463	-3.8	-3.9	*6.0*	544	-6.1	-6.4	*6.4*	364	-4.7	-5.1	*5.0*	357	-2.9	-4.0	*5.7*	198
e > + 0.10	-5.2	-5.5	*6.4*	2,159	-4.6	-5.3	*6.9*	588	-6.0	-6.1	*6.7*	649	-5.7	-5.9	*5.1*	476	-4.0	-4.8	*6.2*	446

This table provides results for excess returns estimated with a cross-sectional trading rule for repeat-sales. Four sample suburbs were selected. Results are given for each individual suburb sample and for a pooled sample of all suburbs. Properties are divided into portfolios based on the size of the estimation error (actual transaction price less price predicted by most recent regression prior to sale). Excess return for each property is measured as annualised property appreciation less the yield at the time of the initial purchase on a government bond of similar duration to the holding period between property transactions. Short holding periods are one year or less. # Tests of statistical significance using Sharpe ratios are completed for long holding periods (all suburbs) in Table 5.

One fact that is immediately evident is the lower standard deviation of excess returns than that reported for the aggregate data. For ‘all suburbs’, the mean of -1.4% indicates that on average excess returns are close to zero. The standard deviation of 35.8% confirms significant variation in individual property returns although this is much lower than the 88.9% standard deviation reported for the aggregate data.

The greatest variation in excess returns is within the $e < -0.10$ ‘undervalued’ portfolio where the ‘all suburbs’ mean excess return is 3.8% and the standard deviation is 65.5%, again much lower than for the aggregate sample. All other portfolios confirm lower level negative excess returns and lower relative standard deviations. In general, this trend is consistent for all of the individual suburb samples excepting South Perth where three of the portfolio groups have positive excess returns.

This confirms the results from the analysis of the aggregate data where there are significant different levels of risk between portfolios. As with the aggregate data, the main cause of the variation in excess returns becomes evident when Parts B and C of Table 4 are analysed. Here the sample is further divided into short holding periods of one year or less, and longer holding periods of more than one year. For ‘all suburbs’, the short holding period mean excess return is 31% and when the $e < -0.10$ ‘undervalued’ portfolio is used it is 63%. These returns are accompanied by standard deviations of 121% and 205% respectively. These returns are similar to those for the aggregate data shown in Table 2 however the standard deviations are much lower.

When examining short holding periods only, the other portfolios are also accompanied by positive excess returns and high standard deviations. This result is consistent for all individual suburb samples. The median excess return figures are much lower for all groups but still significantly positive. This confirms higher excess returns and positive skewness in the excess returns for short holding periods.

In Part C of Table 4 it is evident that when only long holding periods are considered, the mean excess returns are negative for all portfolios, there is less positive skewness and standard deviations are very much lower. If the implicit rental dividend were included, then on average the long-term investment returns shown in Part C would be slightly positive or very close to zero.

This is a consistent trend for all of the suburb samples. Consistent with results for the aggregate sample, there are quite clearly incentives to investors in short-term trading for some housing units.

In Part B the $e < -0.10$ 'undervalued' portfolio shows clearly the highest level of returns, which suggests that knowledge of an individual housing unit's estimation error is useful information. The accompanying high standard deviations confirm a corresponding higher level of risk. As noted previously, there is likely to be considerable capital expenditure involved with these short-term transactions. The likely scenario is that many of these short-term transactions are housing units that are purchased, substantially renovated and quickly re-sold.

The results for Part C are interesting in that they display a clear hierarchy in longer run returns based on levels of estimation error. The highest levels of excess returns (lowest negative numbers) all apply to the $e < -0.10$ 'undervalued' portfolios, and the excess returns decrease as expected with the changes in estimation error, a clear pattern for the majority of suburb samples. It is notable that the same pattern is not so evident for similar tests with the aggregate data summarised in Table 2.

It is quite clear that there are patterns of varying levels of return but there are also varying levels of risk, as confirmed by the variations in the standard deviations. Are these differences in returns significant on a risk-adjusted basis? Consistent with analysis of the aggregate data the Sharpe ratio (reward-to-variability ratio) tests are presented in Table 5. The data used for these tests consists of the 'all suburbs' data for long holding periods only (see Table 4) as results for the aggregate data confirm that there is too much volatility in returns caused by the influence of short holding periods for there to be any statistically significant differences between portfolios. As with the analysis of the aggregate data in Table 3, none of the individual portfolio Sharpe ratios is significantly different from the Sharpe ratio for the total property portfolio at even a 10% level. The null hypothesis that the risk-adjusted return performance of all portfolios was the same could not be rejected. While it is clear that individual properties identified as 'undervalued' according to their estimation error earn on average higher excess returns, the higher risk associated with these portfolios indicate that it is difficult to achieve 'abnormal' risk-adjusted profits.

Table 5: Spatial Regions - Sharpe Ratio Analysis for Different Portfolios

Range of Estimation Error at Time of Purchase	Sharpe Ratio All Suburbs Long Holding Periods 1989-1998	z_{Sh} Compared with Portfolio of Total Sample for Same Time Period	P-value
Total sample	-0.61	–	–
$e < -0.10$	-0.16	0.45	(0.65)
$-0.10 < e < 0$	-0.72	0.12	(0.90)
$0 < e < +0.10$	-0.72	0.11	(0.91)
$e > +0.10$	-0.86	0.25	(0.80)

Notes: The Sharpe ratio is calculated as the mean excess return earned by properties in the portfolio divided by the standard deviation of the excess returns for properties in the portfolio. Z_{Sh} is a test statistic to measure whether the Sharpe ratio for each portfolio is significantly different from the Sharpe ratio for the portfolio of all properties. None of the test statistics is statistically significant, leading to the conclusion that the risk-adjusted performance is the same for all portfolios, including those of 'undervalued' properties.

Concluding Summary and Opportunities for Further Research

In general these results are consistent with Linneman (1986) and Londerville (1998) in that they confirm that the estimation error for a property can be used to identify properties that may be 'undervalued' and will on average earn higher excess returns than other properties. The ability to effectively identify under-valued properties is improved with smaller spatial region data sets. While the Sharpe ratio tests indicate that this information cannot be used consistently to earn abnormal returns these results provide some important information and directions for further research.

These results make it clearly evident that there are incentives to short-term trading and the results of this trading are improved by identifying 'undervalued' properties based on estimation error. There is a lot of 'noise' present with the data in the form of unidentified capital expenditure, and debt financing but it is clear that this short-term trading is an important segment of activity within the market. As much of this is likely to be renovation activity it is clear that these short-term transactions carry higher levels of risk.

Does this indicate that the market for these properties is inefficient? In terms of Fama's (1970) discussion of market efficiency this activity is probably closest to the strong-form of market efficiency. It is likely that 'inside' operators, full-time housing market participants who possess an intimate knowledge of local markets undertake much of this short-run trading activity. In many cases they might be investing their full time labour as well as capital, confirming higher levels of risk. Past price and publicly available information on property characteristics can be used effectively to identify under-valued properties and these properties can be effectively traded to yield excess returns.

It is also likely that capital expenditure impacts on longer-term transactions. The individual properties that are identified as under-valued are likely to have higher levels of physical obsolescence associated with the buildings. This will require higher levels of capital expenditure to maintain the buildings in the longer term. The varying levels of capital expenditure for longer holding periods is likely to influence the standard deviations and therefore it is likely that the under-valued segments of the market will exhibit higher levels of risk.

As this has been a 'desktop' analysis without any field inspections, it remains unclear whether these returns are higher on a risk-adjusted basis. It is likely that the explanatory power of pricing models could be further improved by traders with the aid of physical inspection of properties and detailed local knowledge of specific regions. This knowledge could be used in specifying additional independent variables such as specific sub-regions with access to views or influential factors operating within the region.

It is possible that some parts of this methodology can be further adapted to examine the present value relationship (PVR) within housing markets and also to construct some new variables that can be used in further time series analysis of housing markets. The present value relation for housing (PVR) examines the influence of the user cost of housing over time. An implication of the efficient markets hypothesis is that in an efficient housing market, prices are correctly capitalised rents.

The calculation of excess returns in equation (4) is derived from house price changes excluding any implicit housing dividend accruing to the homeowner or investor. The results indicate that in general for holding periods of longer than one year, excess returns for individual properties calculated on this basis are negative. In an efficient housing market, if the dividend to housing *D* were to be added to the left hand side of equation (4) then excess returns would be zero.

$$ER + D = R - Rf + D = 0 \tag{5}$$

Under the PVR, this would be the expectation for an efficient housing market as prices would reflect correctly capitalised rents and opportunities to exploit excess returns would not exist. If it is assumed that housing markets are efficient and that excess returns do not exist, $ER = 0$, then we can abbreviate equation (5) to:

$$D = R - Rf \tag{6}$$

With equation (6) we are able to 'back out' an assumed implicit annual rental dividend, *D* for individual properties from a pair of repeat-sales. This variable *D* is related to a specific holding period for an individual property within a specific time period and provides a number of opportunities for further research. Initially this variable can be used with aggregate city-wide data in time series analysis to examine how the implicit rental dividend might vary over time in periods of varying demand for housing. The results in this study suggest that varying levels of informational efficiency exist within housing markets and some of these variations are explained by spatial influences. If this variable is used to analyse specific market segments the results in this study suggest that there will be systematic variations that will provide useful further insights as to the nature of informational efficiency in housing markets.

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.

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

Clapp, JM., Tirtiroglu, D. (1994). "Positive Feedback Trading and Diffusion of Asset Price Changes: Evidence from Housing Transactions," *Journal of Economic Behaviour and Organization*, 24:3, 337-355.

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.

Fama, E. F. (1970). "Efficient Capital Markets: A Review of Theory and Empirical Work", *Journal of Finance* 25, 383-420.

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.

Gau, G. W. (1985). "Public Information and Abnormal Returns in Real Estate Investment", *Journal of American Real Estate and Urban Economics Association*, 13, 15-31.

Gau, G.W. (1987). "Efficient Real Estate Markets: Paradox or Paradigm?" *Journal of the American Real Estate and Urban Economics Association* 15, 1-15.

Gillen, K., Thibodeau, T., and Wachter, S., (2001)). "Anisotropic Autocorrelation in House Prices", Journal of Real Estate Finance and Economics, (23) pp5-30.

Linneman, R (1986). "An Empirical Test of the Efficiency of the Housing Market", *Journal of Urban Economics* 20, 140-154.

Londerville, J. (1998). "A Test of a Buying Rule for "Underpriced" Apartment Buildings", *Real Estate Economics*, Vol. 26, No 3, pp537-553.

Meese, R., Wallace, N., (1994). "Testing the Present Value Relation for Housing Prices: Should I Leave My House in San Francisco?" *Journal of Urban Economics* 35(3): 254-266.