14th Pacific-Rim Real Estate Society Conference

Kuala Lumpur, Malaysia, 20 to 23 January 2008

LIQUIDITY IN HOUSING MARKETS - MARKET MOMENTUM AND MARKET REVERSION

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*The authors advise that this is a preliminary version of the paper and should be considered as work in progress. The results of this paper should not be quoted without the express permision of the authors. (Corresponding author; Greg Costello: G.Costello@Curtin.edu.au).

**The authors gratefully acknowledge the Western Australian Valuer General's Office for providing the data used in this research. We also acknowledge Curtin University and The University of Melbourne for providing the sabbatical funding that enabled this collaboration.

Abstract: This paper examines how the price discovery process responds to periodic variations in liquidity (sales volumes) and information provided from past prices within own sub-markets and the aggregate market. In our empirical study, we analyze relationships between geographically defined housing sub-markets and a large aggregate housing market (Perth, Australia). The study is designed to test for general market momentum or reversion patterns in prices. We select a specific set of sub-markets that are not spatially contiguous. For each sub-market and the aggregate market we calculate weekly time-series for sales prices and volumes and individual capital returns series. Finally, we fit a *panel* VAR model that relates the capital returns and sales in each suburb with lagged values of the same and correction terms for differences between sub-markets and the aggregate market. The results confirm significant variations in temporal patterns of influence for liquidity and past price information both within specific sub-markets and according to varying lag structures.

1. Introduction

This paper examines the short run dynamics of a resale housing market. The analysis relates weekly data on housing returns and housing sales (liquidity) for thirteen housing submarkets in Perth, Australia. We use weekly data because the residential resale market tends to follow a weekly pattern of activity. Properties are open for inspection on weekends, with offers and acceptance made then and over the rest of the week. The weekly inspection sequence allows both buyers and sellers to update their prior information about the state of the market. To our knowledge, this is the first paper to examine ‘high frequency’ residential pricing and sales behavior.

The research uncovers the responses for local residential submarket prices and sales to price and sales innovations within the local market and in the broader Perth market. One of the key questions we ask is whether price or sales shocks are persistent, so that high returns today mean higher returns for the immediate future and high sales volumes today mean higher sales volumes in the future. Our analysis also attempts to answer questions such as; if prices increase sharply in a submarket do sales rise in the following week?

We also examine whether the resale market exhibits error correction processes. Care is needed in defining error correction in the short run since housing returns and sales are stationary and, in this sense, will always exhibit some error correction processes. What we are interested in is whether residential submarkets correct toward the broader markets trend. For example, if housing prices rise more rapidly in a submarket than they do in the whole market, do buyers shun this market and force returns back toward the market norm?, or do buyers add momentum to the submarket hoping to capitalize on the higher returns? In this respect, the paper makes a contribution towards the established body of urban economic theory related to price discovery in and between market segments within housing markets (for a concise summary see DiPasquale and Wheaton (1996)).

Finally, we are interested n whether there is persistence in volatility in either residential returns or sales and whether this persistence (if any) varies across residential submarkets. We use simple generalized autoregressive conditional heteroskedasticity (GARCH) modeling to answer these questions.

The paper is organized as follows. Section 2 presents our review of the literature. Section 3 develops out econometric model. It also explores the nature of error correction in these models. Section 4 describes out data and section 5 presents our econometric results. Section 6 concludes.

2. Literature Review

DiPasquale and Wheaton (1996) concisely summarised the established body of urban economic theory related to price discovery in and between market segments within housing markets. They described 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. In this environment, 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 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. This proposition has also been tested in a number of empirical studies that relate to the broad analysis of sub markets (Watkins (1998) summarised twenty papers of this type).

This paper examines to what extent these market movements might also be influenced by sales volumes (liquidity) in housing markets. The simultaneous movements in prices and sales within housing markets have also been analysed in a number of empirical studies. Most of the early studies are based on data for U.S. housing markets and in most cases the evidence suggests that prices and the number of sales are positively correlated (Berkovec and Goodman 1996; Fu 1996; Stein 1995). This however is not a consistent result. In contrast, Follain and Velz (1995) established evidence of a negative relationship between house prices and sales. A similar result was achieved by Hort (2000) in a study of Swedish housing markets.

Hort (2000) examined the Swedish housing market during the boom and bust phase of the 1980's and 1990's and observed that in the early phase of both the boom and the bust the number of sales changed markedly. The standard stock-flow model of the housing market assumes that short-run price effects of demand shocks occur instantly and without friction. With perfect price adjustment, the number of sales would be unaffected during the adjustment process. In real estate markets, however, the heterogeneity of housing and the fact that most market participants (agents) trade infrequently implies that information is not perfect.

Starting with the premise that informational imperfections in the housing market imply that the adjustment of house price expectations following a shock to demand is likely to be slow, Hort (2000) tested whether there were also asymmetries in buyers' and sellers' responses such that the market exhibited some quantity adjustment processes. These propositions were tested using a search theoretic model where buyers were assumed to respond prior to sellers, and sales were expected to respond prior to prices. The impulse-response functions calculated from a VAR model of the after-tax mortgage rate, house prices and sales provided empirical support for these propositions.

An important empirical result from Hort's study is that agents are likely to be slow in recognizing market wide price changes. Hort suggests that this implies that initial price changes occur gradually as sellers and buyers revise their expectations. If buyers and sellers are equally slow in adjusting their expectations, sales will remain unaffected by shocks to housing demand. However, should the adjustment process differ between buyers and sellers, (where one side of the market adjusts more rapidly to changing market conditions than the other), it is likely that the transactions market (sales or liquidity) would display some short run quantity adjustment patterns.

Hort (2000) suggests several reasons to expect sellers to lag buyers in this adjustment process. First, while buyers' behaviour is guided by the direct effect of the demand shock on their individual budget constraint, sellers' decisions are based on estimates of the effect on the distribution of bids. Since information on the aggregate housing market is likely to arrive more slowly, it is likely that buyers adjust their reservation prices prior to sellers. In addition, during the search process buyers are more likely than sellers to search in precisely the segment of the market in which they intend to trade. Hort argues that it is for this reason buyers are likely to be better informed of recent transactions in their target markets. Hort concludes from these observations that it is reasonable to assume that sellers lag buyers in the adjustment of their price expectations.

3. The Model

We assume that buyers and sellers form their expectation of the gain to buying and selling using the return and sales information from their preferred housing submarket and return and sales information from the broader market. Here we argue that the broader market should be all of Perth because, without balkanization, submarkets returns should tend toward aggregate return over time.[1] Buyer and seller expectations are complicated by the technology of information release in Western Australia. The public is officially notified that a property has sold on a particular date at a particular price when the sale is final, on the date of closing. Thus, there is lag between the time a buyer and seller reach an agreement and the time the public is notified of this agreement. Typically, the closing date is between 30 and 90 days (4 to 13 weeks) after the agreement of sale. Buyers use the intervening time to solidify their mortgage funding and both parties to the sale arrange for legal transfer of the property. Market participants are also informally notified of a sale by 'SOLD' sign placed on the property at the time a sale agreement is reached. Generally, the agreed price is known to the

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[1] One could define the market more narrowly, as a collection of related submarkets. While this assumption is intuitively appealing, it opens the questions such as: How does one define the collection submarkets? and, How is this collection of submarkets related to the aggregate urban market? These questions are beyond the scope of this paper. We adopt the simpler view of what constitutes the broader market.

seller's agent and hence to the local community of real estate agents.[2] Thus, there is considerable information leakage about the sale in the local submarket prior to the information being made public. This is an important aspect of our research, and relates to the expanding interest in the characteristics of information sets used by agents in housing markets and the different information diffusion processes that may apply. In our companion paper, Costello and Schwann (2007) we expand on the characteristics of the search environment for both buyers and sellers.

Our description of the technology of information release suggests that some buyers and sellers will have short run information about sales and sale prices in their local submarket that may influence their expectations. Other buyers and sellers will find our about these sales later when the information is released publicly and will act on it at that time. Thus, we expect both short and long run information effects in the local market. In contrast, it is unlikely that any buyers and sellers, or their agents, will grasp the full range of information from the broader market until it is released publicly.[3] Hence, we expect only a long run information effect from the broader market.

We now formalize our model. Let $y_t = (r_{it}, s_{it})'$ be the vector of return and sales volume information available for housing submarket *i* at time *t* and let $x_t = (r_{mt}, s_{mt})$ be the vector of return and sales information for the aggregate housing market at time *t*. Since the aggregate information is not known for at least four weeks, x_t contains the four week lagged return and sales. Also, let $y_t^* = E_t(y_t \mid I_{t-1})$ and $x_t^* = E_t(x_t \mid I_{t-1})$ be the expected values of y_t and x_t, respectively, conditional on the information *I* available at time *t*. We further assume that the joint process for (y_t, x_t) can be approximated by the vector autoregressive moving average (VARMA) representation:

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \mu^y \\ \mu^x \end{pmatrix} + \begin{pmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} B_{11} & B_{12} \\ 0 & 0 \end{pmatrix} \begin{pmatrix} y_t^* \\ x_t^* \end{pmatrix} + \begin{pmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{pmatrix} \begin{pmatrix} \varepsilon_t^y \\ \varepsilon_t^x \end{pmatrix} \tag{1}$$

This specification incorporates our idea that returns and sales (liquidity) in a housing submarket are inter-dependent. This interdependence is captured by the autoregression coefficients in the p^{th} order lag polynomial $A_{11}(L)$ and the moving average coefficients in the q^{th} order lag polynomial $\Phi_{11}(L)$. The specification also incorporates our idea that sales in a housing submarket depend on the state of the aggregate housing market. This is captured by the coefficients in the lag polynomials $A_{12}(L)$ and $\Phi_{12}(L)$. Finally, we suggest that the returns and sales in a housing submarket might depend on buyers and sellers expectations about the

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[2] Agents are not legally bound to secrecy concerning agreements for sale.

[3] If the submarkets follow common cycles in sales and returns, short run local information may be used as a proxy for the broader market information. In this case, the broader market information may have no effect on release because the information is already fully incorporated in the market.

returns and sales in the submarket and the aggregate market. We build this into the equation by introducing the *2×2* coefficient matrices B_{11} and B_{12}. The coefficients in the first matrix give the effect of y_t^* on y_t and the coefficients in the second matrix give the effect of x_t^* on y_t.

The system of equations (1) allows for a connection between submarkets returns and sales and aggregate market returns and sales through the lag polynomials $A_{21}(L)$ and $\Phi_{21}(L)$. The estimation of the model would be simplified considerably if we could assume that this connection is negligible. In this case, x_t^* would be conditionally exogenous to y_t^* and the returns and sales equations for the aggregate market could be estimated separately. Despite this simplification, we maintained the connection between submarkets and aggregate market because the *a priori* evidence suggests that individual submarkets and the aggregate market are related. In principle, y_t is a component of x_t and therefore the coefficients in $A_{21}(L)$ and $\Phi_{21}(L)$ depend on the coefficients in the equations for y_t. Nevertheless, if the submarket is relatively small and there is no common cycle between submarkets, one might still assume that $A_{21}(L)$ and $\Phi_{21}(L)$ are zero with little damage to the model. Unfortunately, the evidence does not support the conjecture of no relationship. Later in the paper (Data section, Table 2), we show that there are significant correlations between submarket returns and aggregate market returns and between submarkets sales and aggregate market sales.

The equations in (1) can not be estimated directly because y_t^* and x_t^* are not predetermined. We must first solve for the conditional expectations of these variables as functions of the predetermined variables and substitute these expectations back into equation (1). Taking the conditional expectations of y_t, and x_t, we get:

$$\begin{pmatrix} I-B_{11} & -B_{12} \\ 0 & I \end{pmatrix}\begin{pmatrix} y_t^* \\ x_t^* \end{pmatrix}=\begin{pmatrix} \mu^y \\ \mu^x \end{pmatrix}+\begin{pmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{pmatrix}\begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix}+\begin{pmatrix} \Phi_{11}(L)-I & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L)-I \end{pmatrix}\begin{pmatrix} \varepsilon_t^y \\ \varepsilon_t^x \end{pmatrix} \quad (2)$$

We solve for y_t^* and x_t^* by pre-multiplying (2) by the inverse of the lead matrix of coefficients on the left hand side of (2), which is:

$$\begin{pmatrix} (I-B_{11})^{-1} & (I-B_{11})^{-1}B_{12} \\ 0 & I \end{pmatrix}$$

Substituting this solution into (1), we arrive at VARMA model:

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix}=\begin{pmatrix} \tilde{\mu}^y \\ \mu^x \end{pmatrix}+\begin{pmatrix} \tilde{A}_{11}(L) & \tilde{A}_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{pmatrix}\begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix}+\begin{pmatrix} \tilde{\Phi}_{11}(L) & \tilde{\Phi}_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{pmatrix}\begin{pmatrix} \varepsilon_t^y \\ \varepsilon_t^x \end{pmatrix} \quad (3)$$

with coefficients in the top row defined by:

$$\begin{aligned}
\tilde{\mu}^{y} &= \left(I + B_{11}(I - B_{11})^{-1}\right)\left(\mu^{y} + B_{12}\mu^{x}\right) \\
\tilde{A}_{1i}(L) &= \left(I + B_{11}(I - B_{11})^{-1}\right)\left(A_{1i}(L) + B_{12}A_{2i}(L)\right),\ i = 1, 2, \\
\tilde{\Phi}_{1i0} &= I,\ i = 1, 2 \\
\tilde{\Phi}_{1ij} &= \left(I + B_{11}(I - B_{11})^{-1}\right)\left(\Phi_{1ij}(L) + B_{12}\Phi_{2ij}\right),\ i = 1, 2,\ j = 1, \dots, q
\end{aligned}$$

In equation (3), each of the coefficients in the submarket equation for y_t is the combination of the direct effect of a variable on y_t and the induced effect *via* the variables effect on the conditional expected value. These two effects cannot be separated without additional identifying restrictions and must be interpreted accordingly. In the following discussion we will refer to this specification as a rational expectations model.

(a) Error correction interpretations

The submarket equation may be re-written as an error correction in several ways. The variants depend on how the submarket variables adjust to their aggregate market counterparts. It is easier to describe these models using model (1) and then to give the rational expectations interpreation, so our presentation follows this route.

In our first variant, buyers and sellers may move the submarket toward the market average using recent evidence as their guide. We can express this model as:

$$y_t = \mu^{y} + A_{11}(L)(y_{t-1} - x_{t-1}) + \varepsilon_t^{y} + \Phi_{11}(L)(\varepsilon_{t-1}^{y} - \varepsilon_{t-1}^{x}) \tag{4}$$

which is achieved by setting $A_{12}(L) = -A_{11}(L),\ \Phi_{12}(L) = -\Phi_{11}(L)$ and $B_{11} = B_{12} = 0.$ When the restrictions for this model are imposed, the rational expectations version is fully identified because $\tilde{\mu}^{y} = \mu^{y},\ \tilde{A}_{1i}(L) = A_{1i}(L), i = 1, 2$ and $\tilde{\Phi}_{1i}(L) = \Phi_{1i}(L), i = 1, 2$. Thus, the estimates may be interpreted as coming from the error correction model (4) or the rational expectations model (3), depending on ones viewpoint. A previously noted, only further identifying restriction will enable one to differentiate the models.

This model would be plausible if buyers and sellers shun submarkets with above average returns in favor of submarkets with below average returns, thereby driving submarket returns toward the aggregate return. The submarket will converge to the aggregate market if the eigenvalues of companion matrix for $A_{11}(L)$ are negative. This specification is restrictive, however, as it requires all submarket dynamics to be driven by differences between the submarket and the broader property market. One feature implicit in this specification is that the submarket reacts to both permanent and transitory fluctuations in y_t and x_t. A looser specification would allow unrestricted submarket dynamics but still have the submarket variables adjust to their aggregate market counterparts.

The following specification allows this:

$$y_t = \mu^y + A_{11}(L)y_{t-1} + A_{12}(L)x_{t-1} + B_{11}(y_t^* - x_t^*) + \Phi_{11}(L)\varepsilon_t^y + \Phi_{12}(L)\varepsilon_t^x \qquad (5)$$

which is obtained by setting $B_{12} = -B_{11}$. In this equation, the expected value of the submarket variables moves toward the expected market average. Because of the expectations, the submarket does not react to purely transitory shock to y_t or x_t. Equation (5) will converge if the eigenvalues of B_{11} are negative. Imposing these restrictions gives the rational expectations coefficients:

$$\begin{aligned}
\tilde{\mu}^y &= \left(I + B_{11}(I - B_{11})^{-1}\right)\left(\mu^y - B_{11}\mu^x\right) \\
\tilde{A}_{1i}(L) &= \left(I + B_{11}(I - B_{11})^{-1}\right)\left(A_{1i}(L) - B_{11}A_{2i}(L)\right),\ i = 1, 2, \\
\tilde{\Phi}_{1ij} &= \left(I + B_{11}(I - B_{11})^{-1}\right)\left(\Phi_{1ij}(L) - B_{11}\Phi_{2ij}\right),\ i = 1, 2,\ j = 1, \ldots, q
\end{aligned}$$

These equations have *6+4×(p+q)* unknown coefficients in *2+4× (p+q)* equations. Hence, two of the four coefficients in B_{11} may be determined. We may identify the remaining two coefficients by setting $B_{11}(1,2) = B_{11}(2,1) = 0$, so that submarkets returns adjust only to market returns and sub market sales adjust only to market sales and there are no cross-effects.

Finally, we can always decompose the submarket equations as:

$$y_t = \mu^y + A_{11}(L)y_{t-1} + A_{12}(L)x_{t-1} + C(y_{t-1}^* - x_{t-1}^*) + C_{11}y_{t-1}^* + C_{12}x_{t-1}^* + \Phi_{11}(L)\varepsilon_t^y + \Phi_{12}(L)\varepsilon_t^x \qquad (6)$$

where $B_{11} = C_{11} + C$ and $B_{12} = C_{12} - C$. The equation is over-parameterized and cannot be estimated directly. Yet, it shows that the term $C(y_t^* - x_t^*)$ is an error correction component and the terms $C_{11}y_t^*$ and $C_{12}x_t^*$ are momentum adjustments originating within the housing submarket or the general housing market, respectively. The error correction model in equation (5) results from assuming no momentum and the model in equation (4) results from restricting further the dynamics of market adjustment.

4. Data

Our model assumes that search activity in housing markets occurs within a system of dynamic submarkets. Typically, these submarkets are defined by location, price and housing quality criteria. In order to research variations in returns and sales (liquidity) these important determinants (variables) of submarkets need to be present within the data to be analysed. Since we focus on search liquidity within specific sub-markets it is necessary to select sample submarkets that display market density within fine (weekly) time increments so as to identify variations in liquidity and prices in a manner consistent with the information that would be available to market participants engaged in active search behavior.

The primary data for this study is generated from a dataset of all transaction in Perth occurring between July 1998 to December 2005 that was provided by the Western Australian Valuer General's Office. The data is classified by week of sale and the median price and total sales are calculated on a weekly basis for thirteen submarkets. The capital return for a submarket is calculated as the difference in log median price. The submarkets were selected to minimize spatial auto correlation. No two submarkets are adjacent and in an effort to eliminate spatial auto correlation issues, sub-markets were selected to be as geographically remote from each other as was possible. We focus only on strata-title sales in our simulations in order to provide market density for quality attributes and provide a tighter specification of individual submarkets. The strata-title market segment is rich in data for quality attribute variables, the most important being the area of the building and age of structure at time of sale.

The descriptive statistics for the weekly residential property returns in our thirteen postcode-submarkets and the property sales by postcode are given in Table 1, together with the comparable figures for the entire Perth market. The top panel records the statistics for the capital return to housing. The mean return for each postcode is given in column 2 of the table. The mean returns for the sample ranges from a low of 0.073 percent per week (3.8% per year) in postcode 6009 to 0.363 percent per week (18.9% per year) in postcode 6155. The average return in the submarkets is 0.168 percent per week (8.7% per year). This average is comparable to the return for Perth, which is 0.15 percent per week (7.9% per year). Thus, our sample contains a wide range of submarkets as defined by returns but these submarkets fit nicely within the aggregate market. The standard deviation of the returns is given in column 3. The statistics reveal the submarket returns are extremely variable. The average volatility is 21.174 percent per week. In comparison, the average volatility for Perth as a whole is 3.188 percent per week. The difference between these averages highlights the potential power of diversification in the residential housing market. Averaging across submarkets reduces the volatility by 85%. Unfortunately, individual buyers and sellers cannot diversify in this way. Columns 3 and 4 contain the Jarque-Bera test statistic and its p-value for each submarket and Perth. These summary statistics show that the uncontrolled returns distribution is non-normal for most of the markets and Perth.

Table 1
Descriptive Statistics for Weekly Residential Property Returns and Sales by Postcode for July 1988 to December 2005, inclusive (886 observations)

Submarket/ Postcode	Mean	Std. Dev.	Jarque-Bera	JB Probability
Returns				
6008	0.073%	32.078%	52.318	0.000
6018	0.122%	15.162%	34.775	0.000
6027	0.157%	13.903%	5.190	0.075
6050	0.161%	46.947%	1.165	0.559
6056	0.109%	18.140%	1894.516	0.000
6064	0.145%	17.378%	40.361	0.000
6100	0.285%	29.015%	150.286	0.000
6110	0.104%	10.987%	121.290	0.000
6148	0.152%	27.971%	172.479	0.000
6152	0.116%	21.490%	1.134	0.567
6155	0.363%	13.554%	172.973	0.000
6163	0.204%	16.514%	191.794	0.000
6210	0.192%	12.126%	1.954	0.376
Average	0.168%	21.174%	218.480	
Perth	0.152%	3.188%	66.527	0.000
Sales				
6008	7.2	3.3	51.8	0.000
6018	14.9	6.2	41.4	0.000
6027	23.7	7.3	14.7	0.001
6050	7.9	3.6	43.2	0.000
6056	14.5	6.3	49.0	0.000
6064	14.0	5.6	34.3	0.000
6100	8.2	4.1	11.9	0.003
6110	14.2	5.3	65.7	0.000
6148	7.9	3.5	23.1	0.000
6152	13.5	5.4	88.5	0.000
6155	12.2	5.9	35.0	0.000
6163	14.5	5.3	51.5	0.000
6210	31.7	14.0	65.6	0.000
Average	14.2	5.8	44.3	
Perth	718.9	205.1	3.0	0.227

The bottom panel of Table 1 contains statistics on weekly sales volume for each submarket and Perth. On average, 14.2 houses sold in the submarkets each week as compared to 718.9 sales per week in all of Perth. Thus, the submarkets in this paper represent 2.0% of the total market. As with returns, there is considerable variation in the means (column 2) between the submarkets. Sales rate ranged from 7.2 sales per week on average for postcode 6008 to postcode 31.7 sales per week for postcode 6210. It is important to note that in using these fine (weekly) time increments there are numerous periods where there are no sales (zero liquidity) in some postcode areas sub-markets. The inter-week variation in sales rates is measured by the standard deviations in sales in column 3. The average inter-week variation is 5.8 sales, with the individual postcode variation ranging from 3.3 to 14.0 sales per week. In summary, the results show a wide divergence in the sales rates both within and between submarkets. Since sales are counts and the number of sales in a submarket is truncated below by zero, the distribution of sales should not be normal. The Jarque-Bera tests in columns 3 and 4 confirm this. We can reject the null hypothesis of normality in all cases.

In the preceding section, we were confronted with the question of whether one might assume that the aggregate market is conditionally exogenous from a submarket; that is, whether the lag polynomials $A_{21}(L)$ and $\Phi_{21}(L)$ are zero. We address this question with the results in Table 2. In column 2 we present the simple correlations between the returns in each submarket and the returns in the Perth market. Ten of the thirteen correlations are statistically significant at the 5 percent level of significance, indicating that submarket and market returns are related. This is surprising because we calculate the return to housing a submarket from the median home price in this market and the aggregate return to housing from the median home price in the entire market and hence, there is no linear connection between them. The results are suggestive of a common cycle between the returns in the submarkets of Perth. In columns 3 to 6 of the table, we present several views of the relationship between submarket sales and aggregate sales. In principle, sales in the local housing submarket are connected to those in the entire market. Aggregate sales are the sum of all the individual market sales; that is, $s_{mt} = \Sigma_i s_{it}$. However, our submarkets are small relative to the entire market and the statistical impact unimportant. Column 3 gives the size of each submarket relative to the aggregate

Table 2
Correlations of Submarket Returns and Sales with Perth Market Returns and Sales

Submarket/ Postcode	Correlation of Returns with Market Return	Percent of Market	Correlation of Sales with Market Sales	Correlation of Sales Cycle with Market Sales	Correlation of Sales Trend with Market Sales
6008	0.101 *	1.0%	0.535 *	0.355 *	0.415 *
6018	0.105 *	2.1%	0.748 *	0.464 *	0.606 *
6027	0.172 *	3.3%	0.645 *	0.569 *	0.387 *
6050	0.096 *	1.1%	0.557 *	0.422 *	0.390 *
6056	0.025	2.0%	0.758 *	0.370 *	0.695 *
6064	0.054	2.0%	0.683 *	0.405 *	0.570 *
6100	0.088 *	1.1%	0.623 *	0.386 *	0.505 *
6110	0.006	2.0%	0.611 *	0.468 *	0.425 *
6148	0.070 *	1.1%	0.550 *	0.412 *	0.390 *
6152	0.164 *	1.9%	0.662 *	0.466 *	0.493 *
6155	0.054	1.7%	0.756 *	0.382 *	0.683 *
6163	0.165 *	2.0%	0.591 *	0.546 *	0.336 *
6210	0.193 *	4.4%	0.825 *	0.423 *	0.740 *

market and shows that all of the submarkets are small relative to the entire market. In column 4, we present the simple correlations between the sales in each submarket and the sales in the Perth market. The correlation is statistically significant in all cases. These correlations may simply reflect a common positive trend in sales. To address this, we filter the time series on sales using a Hodrick-Prescott and extract the trend and cycle components. The correlations between the sales cycle and trend in each submarket and the sales in the Perth are given in columns 5 and 6. All of the submarket correlations are statistically significant for both the cycle and the trend. Thus, the coefficients in $A_{21}(L)$ and $\Phi_{21}(L)$ are unlikely to be zero.

5. Econometric Results

We present our preliminary estimates of the model (3) in this section. To fit this model, we must first determine the order of the autoregression, the order of the moving average and the number of periods to lag the market information. We attacked the determination of these values with a combination of Box-Jenkins identification and brute force.

We started the process of identification by using the well known Box-Jenkins identification procedures to determine the AR and MA orders for each of the univariate return and sales time series. Our work showed that all of the univariate series had an MA(1) component. The order of the AR component was generally between one and five. However, some submarket returns and sales series displayed much AR higher orders. We suspected that the higher lags in the autoregression where picking up the influence of the general market. When we included market return or market sales variables, the higher lags became statistically insignificant. This result supports our conjecture concerning the influence of the general market. It also indicated that we need to estimate the full model in order to identify the AR order.

We fit the model with the order of the autoregression varying between zero and five and a market lag varying between four and eighteen weeks. A market lag of four weeks corresponds to the first release of closing prices and sales figures (one month closing) and might be viewed as 'fast price discovery.' A lag of 18 weeks corresponds to the release of closing prices and sales figures for a three month closing period *plus* one further month for price discovery. This can only be viewed as 'slow price discovery.' The model with the smallest ratio of the Schwarz criteria to the number of observations is used as the model selection criteria. This ratio is widely used when the number of observations varies across models.

Our brute force search always indicated that a VARMA(1,1) model was the best fit. Higher order models did not improve the fit enough to overcome the addition of the 16 parameters per AR order. The market lag varied between 15 and 18 weeks, with 9 of 13 submarkets at 18 weeks. We record the market lag for each market in Table 3. Our search result suggests that it takes a very long time for market data to be incorporated into market expectations.

Table 3: Market Lags

Submarket/ PostCode	Market Lag
6008	-18
6018	-15
6027	-18
6050	-18
6056	-15
6064	-18
6100	-16
6110	-18
6148	-18
6152	-15
6155	-18
6163	-18
6210	-18

Our final set of estimates consists of thirteen models, one for each submarket in our data set. The estimation results are given in table A1 in the appendix. We will not discuss each model separately. Instead, we treat the thirteen submarkets as a panel of independent markets and summarize the results by presenting panel estimates and tests. These estimated are presented in Table 4.

Table 4 consists of four panels, one panel for each equation in the model. In each panel, the first column of numbers contains the average of the coefficients across the 13 submarkets. The average is a valid panel estimate for each coefficient. Column two gives Fisher's (1932) test of the null hypothesis coefficients for all of the submarkets are zero. It is a robust nonparametric test. The test is based on the p-values, π_i, from each market and the test statistic $-2\Sigma_{i=1}^{n}\ln(\pi_i)$ is distributed as a χ^2 random variable with *2n* degrees of freedom. Column three gives the p-value for this χ^2 test.

The submarket return equation in Panel A is dominated by the moving average coefficient on innovations to submarket returns. The estimate indicates 93.7% of a returns shock is reversed in the following week so that, for the most part, a shock to the submarket return averages out over two weeks. This looks like an arbitrage result but we do not believe it is. The speed of the response is too fast for a search market. Instead, we suggest that a week of hot sales in a residential submarket removes both buyers and sellers from the market because they have struck their deals. It then takes time for more buyers and sellers to enter the submarket and prices slump during this brief quiescent period. The submarket sales equation in Panel B lends support to this conjecture. We examine the nature of this support later. One other coefficient has power in this equation. The moving average coefficient on innovations to market returns is 0.140, which indicates that on average 14% of shocks to the Perth market are transferred to the individual submarkets after they are revealed to the public.

The Fisher tests show that most of the coefficients in the equation are statistically significant. The coefficient on the market return in the autoregression is an exception, but the influence of this variable is already captured through the moving average. The moving average coefficient on market sales is also insignificant.

To further interrogate the estimates, we test three composite hypotheses based on the coefficients in both the AR and MA components. These test results are given in the table 5. Again, to save space, the full set of hypothesis tests is given in the appendix as Table A2. The first null hypothesis is that sales have no effect on submarkets returns and the coefficient on the sales variables are jointly zero. The panel test of this hypothesis rejects the null. Thus, sales matter even though the size of the coefficients on the sale variables suggests a minor effect. The second null hypothesis is that the market variables have no effect on returns. Again, the null hypothesis is rejected in the panel test. Therefore, one cannot treat submarket returns as balkanized and analyze them independently from the rest of the market. The third test is a combination of the two preceding tests. The null hypothesis is that there are no cross-variable effect; that is, submarket returns only depend on themselves. This null is easily rejected in the panel. Caution is needed in reviewing these results because they apply in aggregate but do not apply to each market individually.

The submarket sales equation in Panel B is more complex than the submarket returns equation and initially, it is difficult to interpret the estimates. The hypothesis tests in Table 5 give the best indication about the dynamic behavior of submarket sales. The first null hypothesis is that submarket and market returns have no effect on submarket sales. Surprisingly, we cannot reject this null. Returns do not lead to sales even though sales do lead to returns. This is a Grainger causality result. In the second null hypothesis, we test whether market variables have no effect on returns and we reject this null. Submarket sales cannot be disentangled from the market trend.

Table 4: Panel Estimates of VARMA Model

	Ave. Coef.	Fisher Stat	Prob.	Ave. Coef.	Fisher Stat	Prob.
	Panel A			**Panel C**		
	Submarket Returns			**Market Returns**		
Constant	0.00178	155.963	0.000	0.00150	226.021	0.000
AR Terms						
Submarket Return	0.04051	67.380	0.000	-0.00512	38.188	0.058
Submarket Sales	-0.00059	59.341	0.000	-0.00017	48.793	0.004
Market Return	0.00666	22.058	0.686	-0.01044	5.566	1.000
Market Sales	0.00001	39.933	0.040	0.00001	72.789	0.000
MA Terms						
Submarket Return	-0.93726	299.336	0.000	0.00973	76.872	0.000
Submarket Sales	0.00094	55.769	0.001	0.00017	41.524	0.027
Market Return	0.14010	67.391	0.000	-0.71263	239.469	0.000
Market Sales	-0.00002	33.005	0.162	-0.00001	21.554	0.713
Standard Error	0.15688	299.336	0.000	0.02599	239.469	0.000
	Panel B			**Panel D**		
	Submarket Sales			**Market Sales**		
Constant	13.97941	231.348	0.000	704.27732	239.469	0.000
AR Terms						
Submarket Return	-0.57281	21.473	0.717	7.71570	19.484	0.815
Submarket Sales	0.93231	239.469	0.000	9.01454	235.310	0.000
Market Return	6.06046	26.415	0.441	-189.85390	29.338	0.296
Market Sales	0.00118	88.717	0.000	0.82497	239.469	0.000
MA Terms						
Submarket Return	0.73904	43.893	0.016	-5.77679	17.565	0.891
Submarket Sales	-0.79640	239.469	0.000	-8.27873	212.209	0.000
Market Return	-2.26723	29.029	0.310	74.50836	10.995	0.996
Market Sales	-0.00289	71.917	0.000	-0.24236	239.469	0.000
Standard Error	4.50334	239.469	0.000	105.53154	239.469	0.000

Our finding in the hypothesis tests show that submarket sales are driven the dynamics of sales within a submarket and by the impact of market sales trends on the submarket. In Table 1, the average coefficients show that submarket sales have a strong positive first order autocorrelation (0.932) and a strong negative first order moving average (-0.796). In combination, these coefficients give an impulse response that follows the damped oscillation shown in Figure 1. The high-low sales pattern displayed by submarket sales supports our conjecture that periods of strong sales leave the market temporarily depleted of buyers and sellers and that it takes time to replenish the stock of agents willing to trade. The slow damping of this effect is evidence of considerable market inertia. We find that on average an increase in market sales decreases submarket sales. The negative sign on market sales is consistent with error correction in sales as described by equation (5).

Table 5: Panel Hypothesis Tests

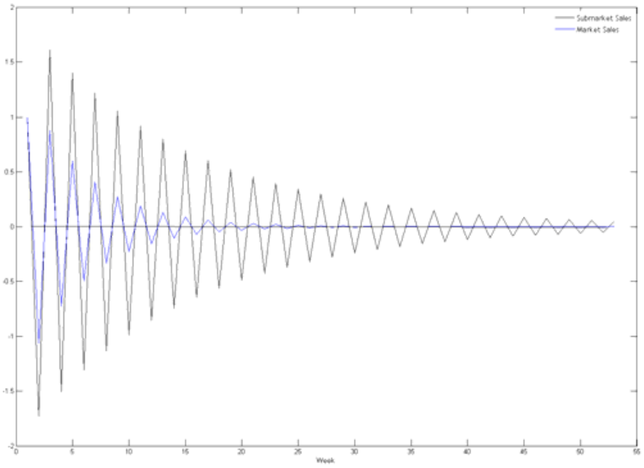
Equation	Test	Fisher Test	Prob.
Submarket Equations			
Returns	No sales effect	115.567	0.000
	No market effect	119.342	0.000
	No cross-variable effect	172.192	0.000
Sales	No return effect	35.590	0.099
	No market effect	61.253	0.000
	No cross-variable effect	61.991	0.000
Market Equations			
Returns	No sales effect	95.800	0.000
	No submarket effect	78.593	0.000
	No cross-variable effect	132.740	0.000
Sales	No return effect	18.405	0.861
	No submarket effect	270.005	0.000
	No cross-variable effect	261.231	0.000
Cross-Equation Tests			
	Submarket Exogeneity	139.419	0.000
	Market Exogeneity	276.392	0.000
	Joint Submarket & Market Exogeneity	294.731	0.000
Correlation Structure			
	Submarket Innovations Uncorrelated	42.033	0.024
	Market Innovations Uncorrelated	13.725	0.976
	Submarket Uncorrelated with Market	27.049	0.407
	All Innovations Uncorrelated	28.909	0.315
ARCH LM Tests			
Submarket Returns	No ARCH (lags 1-4)	97.490	0.000
Submarket Sales	No ARCH (lags 1-4)	299.336	0.000
Market Returns	No ARCH (lags 1-4)	290.126	0.000
MarketSales	No ARCH (lags 1-4)	299.336	0.000

We turn now to the market return and sales equations given in Panel C and D on the right hand side of Table 4. The market return equation is similar to the submarket return equation. Market returns have dominated by the moving average coefficient on innovations to market returns, with 71.3% of a returns shock is reversed in the following week. All of the other coefficients are small in magnitude. Nevertheless, we reject the null hypothesis that sales have no effect and reject the null hypothesis that submarket returns and sales have no effect on market returns. Thus, while the effects of the other variables are numerically small, they are statistically important.

Similarly, in panel D the market sales equation is similar to the submarket sales equation, although some of the coefficients are numerically larger because there are more sales. The coefficient of 0.825 for market sales shows that a shock to sales are persistent, while the coefficient of -0.242 for innovations in market sales shows that a shock to sales in partially offset in the next period. Figure 1 shows that the dynamic behavior of market sales follows a damped oscillation, like that for submarket sales, but the effect decays much faster. In addition, we find that, on average, a one sale increase in a submarket induces 8.015 sales in other submarkets for at total increase of 9.015 sales in the market. Unfortunately, this spillover effect implies an almost unstable dynamic system for sales and market sales, with an eigenvalue close to the unit disk. We need to evaluate this aspect of our model more closely in future work. In the panel hypothesis tests, we cannot reject the null hypothesis that market sales are independent from submarket and market returns, while we can reject the null hypothesis that the market sales are independent from submarket returns and sales.

We complete our evaluation of the coefficient estimates with a Grainger causality test and tests of the correlation structure. We can reject both the null hypothesis that submarket returns are exogenous and the null hypothesis that market returns are exogenous. Therefore, the model exhibits bi-directional causality. This finding validates our earlier decision not to assume market exogeneity and set $A_{21}(L)$ and $\Phi_{21}(L)$ equal to zero. The test on the correlation structure shows that most of the innovations are independent. The exception is correlation between submarket returns and submarket sales, which are positively and significantly correlated.

Figure 1
Impulse Response for Sales



(b) ARCH Effects

So far, we have focused on the means of the return and sales generating processes. In this section, we shift our focus to the variance of the innovations and examine these innovations for ARCH effects. The principle question is whether there is persistence in volatility in one or more of the four innovations. Our first task is to determine whether the existence of ARCH effects is evident in our data and, if it exists, our second task is to characterize the persistence in volatility.

We test for existence of persistence in volatility using ARCH LM tests with four lags of the residuals included in the auxiliary regression. We also include the contemporaneous number of sales to capture the possible effect of a decrease in the bid-ask spread resulting from a concentration of market activity in any period. The results of the ARCH LM tests are recorded in the last section of table 5. The panel tests reject the null hypothesis of no ARCH effect for each of the innovations. Thus, there is persistence in volatility in the residential resale market in Perth. The tests are conclusive for the innovations to submarket sales, the innovation to market returns and the innovation to market sales. ARCH effects are detected for every submarket for these series. The results are not as conclusive for the innovations to submarket returns. We reject the null for six of the thirteen submarkets but not for the seven remaining submarkets. There does not appear to be any systemic reason for persistence in some but not all submarkets.

Normally, the next set would be to re-fit the model with ARCH variances. Unfortunately, none of the available econometric packages will fit a multivariate model with moving average errors with ARCH variances. The procedure for doing so has been known for some time (Harvey, Ruiz and Sentana 1992) but has not been implemented. Instead of refitting, we have estimated our ARCH models directly on the innovations from the VARMA model. Consequently, these estimates are consistent but not efficient. Our estimates are given in Table 6. The orders of the ARCH and GARCH components are determined by minimizing the Schwarz criterion over the plausible value for these components.

The ARCH models for the innovations from the submarket returns equations are recorded in the top panel of Table 6. The dominant specification for these innovations is an ARCH(1,1) model, although higher order ARCH and/or GARCH terms appear for some submarkets. The ARCH(1) coefficients are small in magnitude for all of the submarkets; the average coefficient is 0.034. This indicates that large innovations are required to increase the volatility of submarket returns. In comparison, the average GARCH(1) coefficient is 0.756, so volatility is persistent. Thus, it takes large innovations to change the volatility significantly, but once changed, the volatility persists for a number of weeks. We included the contemporaneous sales in the submarket in the models to capture the possible effect of a decrease in the bid-ask spread resulting from a concentration of market activity. If the bid-ask spread decreases the volatility should drop. We find that this is the case for twelve of the thirteen submarkets and the coefficient in the remaining submarket is statistically insignificant. However, the effect is small. On average, each sale reduces the volatility .0005, which is about 1% of the steady-state volatility.

The ARCH models for the innovations from the submarket sales equations are all ARCH(1,0) models. In these models, the average ARCH(1) coefficient is 0.938. Hence, even small fluctuation in sales innovations cause large changes in sales volatility but this volatility is persistent. As in the submarket returns equation, we have included the contemporaneous sales in the submarket as a volatility regressor. We interpret the coefficient on this variable as a market scale effect. We expect higher sales volume to be associated with high volatility and, therefore, the coefficient should be positive. Our expectation is realized. The average coefficient across the submarkets is 0.957 and most of the coefficients are statistically significant. The Fisher test statistic for joint significance is 182.4 with a p-value less than 0.001. To put this figure in perspective, 0.957 is approximately 6% of the steady-state volatility.

The ARCH models for market returns are similar in structure to those for submarket returns. The dominant model is again an ARCH(1,1). However, the coefficients on the ARCH terms are numerically larger in the market equations. The average ARCH(1) coefficient is 0.071, which is about twice as large as the 0.034 recorded for the submarkets. The average GARCH(1) coefficient is 0.970 as compared 0.756 for the submarkets. Hence, the market returns are more responsive to innovations and more persistent than the component returns from the submarkets. This is what one expects from aggregation. The figures given for the coefficients suggest that the volatility is not covariance stationary because .071+0.970>1. However, when we include the higher order ARCH and GARCH terms, we get 0.976 as the sum of the coefficients and, in addition; all the component submarket equations are stationary. Again, we include a sales term as a contemporaneous regressor. However, since this is a market equation, we include market sales rather than submarket sales. The signs of the estimated coefficients are mixed across the submarkets, but the coefficients are statistically insignificant in all but one submarket. The joint test of significance has a χ^2 with 26 degrees of freedom of 25.853, which has a p-value of 0.471. We interpret the insignificance of sales for market volatility as an aggregation result. Sales are relevant for the local submarket bid-ask spread but when added together, asynchronous timing between submarkets obscures the effect.

Table 6: ARCH Estimates

Submarket / Postcode

Variable	6008		6018		6027		6050		6056		6064		6100	
	Coef.	z-Stat.	Coef.	z-Stat.	Coef.	z-Stat.	Coef.	z-Stat.	Coef.	z-Stat.	Coef.	z-Stat.	Coef.	z-Stat.
Submarket Returns														
Constant	0.046 **	8.210	0.006 **	2.983	0.005 **	3.141	0.008	2.147	0.002 **	3.479	0.001	2.220	0.021 **	5.231
RESID(-1)^2	0.013	0.887	-0.025	-1.195	-0.015	-0.861	0.002	0.222	0.040 **	5.053	0.134 **	2.967	0.107	2.203
RESID(-2)^2											-0.113	-2.526		
GARCH(1)	0.874 **	10.126	0.711 **	6.966	0.689 **	5.440	0.950**	34.721	0.918 **	3.518	0.944 **	36.162	0.549 **	7.455
GARCH(2)	-0.573 **	-5.458							-0.884 **	-5.019			-0.657 **	-5.255
GARCH(3)									1.144 **	6.482			0.584 **	4.917
GARCH(4)									-0.285	-1.095				
Submarket Sales	-0.002 **	-9.699	0.000 **	[illegible]	0.000 **	[illegible]	[illegible]	[illegible]	[illegible] **	[illegible]	[illegible]	[illegible]	[illegible] **	-1300.743
Submarket Sales														
Constant	8.080 **	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.048
RESID(-1)^2	0.775 **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	66.100
Submarket Count	0.173 **	[illegible]	[illegible]	[illegible]	[illegible] **	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible] **	[illegible]	[illegible]	1.280
Market Returns														
Constant	0.000 **	-735.261	0.000	1.910	0.000	2.317	0.000	1.974	0.000 **	-370.700	0.000 **	49.786	[illegible]	2.027
RESID(-1)^2	0.085 **	4.279	0.071 **	3.782	0.048 **	3.034	0.062 **	3.298	0.101 **	4.150	0.127 **	3.368	0.067 **	3.272
RESID(-2)^2											-0.122 **	-3.296		
GARCH(1)	0.906 **	49.324	0.896 **	34.783	0.923 **	44.079	0.916 **	41.599	0.890 **	39.461	1.727 **	18.488	0.895 **	30.926
GARCH(2)											-0.734 **	-8.150		
Market Sales × 10^8	1.370 **	2.841	0.000	0.047	-0.327	-0.215	-0.000	-0.042	1.480	2.037	-0.037	-0.254	-0.137	-0.065
Market Sales														
Constant × 10^{-3}	133281.800 **	-8.874	-2.298	-0.273	48.663 **	4.196	-23.890 **	-2.812	-2.979	-0.359	-7.869	-0.928	66.002 **	5.770
RESID(-1)^2	0.900 **	43.320	0.885 **	49.672	0.898 **	24.148	0.874 **	20.916	0.879 **	49.383	0.874 **	47.980	0.926 **	60.014
RESID(-2)^2														
GARCH(1)					-0.049	-0.930	0.018	0.347						
Market Sales	-116.298 **	-3.955	88.838 **	4.192	40.328	1.360	116.897 **	4.834	93.839 **	4.606	104.845 **	4.936	-40.308	-1.806

Table 6 (cont.): ARCH Estimates

Submarket / Postcode

Variable	6110		6148		6152		6155		6163		6210	
	Coef.	z-Stat.	Coef.	z-Stat.	Coef.	z-Stat.	Coef.	z-Stat.	Coef.	z-Stat.	Coef.	z-Stat.
Submarket Returns												
Constant	0.000	-0.321	0.031 **	-4.685	0.006	1.965	0.061 **	10.876	0.041 **	3.167	0.004	1.908
RESID(-1)^2	0.029 **	3.202	-0.030	-1.979	-0.070	2.064	0.070	2.486	0.080	1.278	-0.032	-1.691
RESID(-2)^2												
GARCH(1)	0.964 **	21.361	0.557 **	2.765	0.697 **	5.217	0.791 **	19.876	0.507 **	2.987	0.692 **	3.936
GARCH(2)												
GARCH(3)												
GARCH(4)												
Submarket Sales	0.000	0.689	-0.001 **	[illegible]	[illegible]	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible]	[illegible]
Submarket Sales												
Constant	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RESID(-1)^2	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]
Submarket Count	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]	[illegible] **	[illegible]
Market Returns												
Constant	0.000	2.113	0.000 **	-136.450	0.000	1.995	0.000	2.263	0.000	2.318	0.000	[illegible]
RESID(-1)^2	0.054 **	3.335	0.086 **	4.127	0.059 **	3.560	0.050 **	2.871	0.055 **	3.402	0.061 **	3.675
RESID(-2)^2												
GARCH(1)	0.910 **	36.190	0.902 **	44.176	0.913 **	41.518	0.907 **	30.263	0.916 **	43.213	0.914 **	42.235
GARCH(2)												
Market Sales × 10^8	-0.542	-0.296	1.380	1.886	-0.066	-0.043	-0.901	0.474	-0.362	-0.239	-0.037	-0.023
Market Sales												
Constant × 10^{-3}	-12.666	1.552	-10.065	-1.187	134.922 **	-8.452	43.384 **	4.030	-21.755	-2.561	-18.935	-2.046
RESID(-1)^2	0.784 **	19.733	0.886 **	20.247	0.898 **	40.283	0.846 **	17.528	0.868 **	47.223	0.840 **	20.548
RESID(-2)^2			0.001	0.024							0.033	0.730
GARCH(1)	0.109	2.259					0.054	0.947				
Market Sales	99.029 **	4.289	98.738 **	4.432	-116.470 **	-3.628	10.035	0.418	131.525 **	6.055	122.781 **	5.078

Finally, consider the volatility models for market sales in the last panel of Table 6. The predominant model is an ARCH(1,0) with an average ARCH(1) coefficient of 0.874. This is similar to the 0.938 average found in the submarket sales models. Some of the submarkets have ARCH(2) or GARCH(1) terms but the coefficients are small in all cases. The market sales variable is positive and statistically significant in all but one submarket. The average effect is 48.752. Although this appears large, it amounts to only 0.05% of the steady-state volatility. Thus, while aggregation has not marred the statistical significance of sales on volatility, it has weakened its economic impact.

6. Conclusion

In summary, we have found that there is persistence in the volatility of returns and sales at both the submarket and market level. In all cases, the persistence may be modeled by low order ARCH models. The evidence suggests an ARCH(1,1) model for returns and an ARCH(1,0) model for sales. While returns are persistent, the coefficient estimates indicate that it takes large shocks to move the volatility of returns, after which the volatility is reasonably persistent. On the other hand, sales respond strongly to shocks and are very persistent. This characterization of the relative volatility of returns and sales agrees with the established wisdom among real estate agents that market fluctuations are manifest in mostly sale volumes and only sluggishly in market prices. Last, we have shown that sales volume has an important role in the volatility processes for submarket returns and sales. Our estimates suggest that an increase in sales volume results in a decrease in the volatility of returns. This is consistent with a reduction in the bid-ask spread during times of high market activity. Our estimates also show that an increase in sales volume increase the volatility of sales. We interpret this as a scale effect. Higher sales volumes give greater scope for volatility. Both of these contemporaneous sales effects are muted in the market equations due to aggregation bias.

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Appendices

Table A1: Estimates of VARMA Model

	Submarket/Postcode												
	6008	6018	6027	6050	6056	6064	6100	6110	6148	6152	6155	6163	6210
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Panel A: Submarket Returns Equation													
Constant	0.00057	0.00145 **	0.00144 **	0.00136 **	0.00142 **	0.00149 **	0.00501	0.00140 *	0.00196 **	0.00094	0.00279	0.00163 **	0.00173 **
AR Terms													
Submarket Return	0.06507	0.01192	0.06639	0.00228	0.04809	0.10511 **	0.02180	0.04890	-0.02229	-0.01955	0.24050 **	-0.07564 *	0.03405
Submarket Sales	-0.00290	0.00014	0.00049	0.00193	0.00069	0.00084	-0.00370 **	0.00019	-0.00433 **	-0.00061	-0.00096	0.00024	0.00036 **
Market Return	-0.10935	-0.07487	-0.11479	0.76450	0.17917	0.18975	0.19043	-0.17304	-0.90444 *	-0.06322	0.14435	0.02858	0.02957
Market Sales	0.00003	0.00000	0.00000	-0.00002	-0.00001	-0.00001	0.00003	0.00001	0.00005 **	0.00002	0.00001	0.00000	-0.00002 *
MA Terms													
Submarket Return	-0.89848 **	-0.95674 **	-0.96931 **	-0.97803 **	-0.97023 **	-0.95237 **	-0.86715 **	-0.95232 **	-0.96152 **	-0.88379 **	-0.87864 **	-0.97499 **	-0.94086 **
Submarket Sales	0.00457	0.00038	-0.00090	-0.00319	-0.00147 *	-0.00105	0.00523 *	0.00017	0.00512 *	0.00148	0.00198 *	0.00039	-0.00046
Market Return	0.18822	0.13964	0.14473 *	0.03280	0.01658	0.06103	0.00064	0.12190	0.51415 **	-0.03953	0.19987	0.24184 **	0.19940 **
Market Sales	-0.00011	0.00001	-0.00002	0.00013	0.00004	0.00002	-0.00012	-0.00003	-0.00018 **	-0.00005	-0.00001	0.00001	0.00004
Standard Error	0.24565 **	0.11025 **	0.10298 **	0.33463 **	0.13620 **	0.13227 **	0.22146 **	0.08169 **	0.19818 **	0.15896 **	0.11368 **	0.11377 **	0.08978 **
Panel B: Submarket Sales Equation													
Constant	6.95010 **	14.32958 **	23.63849 **	7.83672 **	14.54032 **	14.29833 **	7.03292 **	14.49617 **	7.88253 **	13.19895 **	11.51879 **	14.53523 **	31.47418 **
AR Terms													
Submarket Return	-0.23005	-0.45638	-4.17863	0.16165	-1.95812	-0.55967	-1.07782 *	-0.19174	-0.02071	0.47609	-0.06715	0.84426	-0.18829
Submarket Sales	0.92888 **	0.96464 **	0.87153 **	0.97207 **	0.97687 **	0.91167 **	0.96799 **	0.90721 **	0.93936 **	0.96034 **	0.99182 **	0.81687 **	0.91081 **
Market Return	3.20408	11.81081	7.49952	7.82047	2.28819	-0.44425	9.53854	4.67194	6.05911	20.94904 *	6.64150	-2.16588	0.91284
Market Sales	0.00056 **	0.00069	0.00185 *	0.00029	0.00054	0.00155 *	0.00040	0.00142 **	0.00052	0.00052	0.00017	0.00192 **	0.00493 **
MA Terms													
Submarket Return	0.11218	0.22147	4.01213 *	-0.40446 **	-0.86409	0.53153	0.40792	2.90845 *	0.27650	0.02641	0.89991	-0.06969	1.54931
Submarket Sales	-0.88273 **	-0.87157 **	-0.64360 **	-0.90318 **	-0.85239 **	-0.76354 **	-0.87330 **	-0.80740 **	-0.85470 **	-0.88478 **	-0.88390 **	-0.59541 **	-0.53670 **
Market Return	-3.57600	-4.56275	-0.77644	-1.58748	3.27396	2.35042	-0.27118	-3.23019	-6.77943 *	-8.56192 *	-4.98791	0.46091	-1.22591
Market Sales	-0.00237 *	-0.00256	-0.00226	-0.00188 *	-0.00154	-0.00172	-0.00234 *	-0.00350 *	-0.00187	-0.00222	-0.00063	-0.00460 **	-0.01007 **
Standard Error	3.03141 **	4.85473 **	6.25821 **	3.22903 **	4.34112 **	4.46870 **	3.36767 **	4.66230 **	3.18002 **	4.59151 **	4.12283 **	4.65643 **	7.77947 **
Panel C: Market Returns Equation													
Constant	0.00147 **	0.00141 **	0.00148 **	0.00142 **	0.00146 **	0.00154 **	0.00138 **	0.00161 **	0.00152 **	0.00147 **	0.00164 **	0.00157 **	0.00155 **
AR Terms													
Submarket Return	-0.00891 *	0.01233	-0.01598	-0.00372	-0.00909	-0.00870	-0.00067	-0.02201	-0.00287	-0.00199	0.00372	0.00828	-0.01696
Submarket Sales	-0.00020	-0.00014	0.00007	-0.00064 **	-0.00013	-0.00030	-0.00070 **	0.00032	-0.00027	-0.00014	-0.00029	0.00006	0.00011
Market Return	-0.01296	-0.01878	-0.00605	-0.00694	-0.00920	-0.01340	-0.00573	-0.00012	-0.00446	-0.01448	-0.01569	-0.01872	-0.00915
Market Sales	0.00001	0.00001	0.00000	0.00001 **	0.00001	0.00001	0.00001 **	0.00000	0.00001 *	0.00001	0.00001 *	0.00000	0.00000
MA Terms													
Submarket Return	0.00560	0.00454	0.01857 **	0.00511 **	0.01232 *	0.02138 **	-0.00070	0.01178	0.00249	-0.00158	0.01376	0.00713	0.02616 **
Submarket Sales	0.00060	0.00016	-0.00025	0.00082 *	0.00006	0.00024	0.00083 **	-0.00053	0.00016	-0.00004	0.00025	0.00010	-0.00022
Market Return	-0.71011 **	-0.69928 **	-0.71886 **	-0.73015 **	-0.71380 **	-0.72280 **	-0.72837 **	-0.71571 **	-0.71076 **	-0.70070 **	-0.69691 **	-0.69758 **	-0.71918 **
Market Sales	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	0.00000
Standard Error	0.02595 **	0.02605 **	0.02596 **	0.02585 **	0.02604 **	0.02582 **	0.02587 **	0.02599 **	0.02611 **	0.02608 **	0.02614 **	0.02608 **	0.02591 **
Panel D: Market Sales Equation													
Constant	696.82080 **	691.09460 **	710.20790 **	710.29770 **	713.66420 **	725.61780 **	645.94420 **	732.94140 **	712.05730 **	702.33760 **	693.57020 **	713.32570 **	707.72580 **
AR Terms													
Submarket Return	-20.22301	-12.77609	73.46090	-3.79583	-1.10690	22.14639	-2.82800	86.18839	-2.20164	13.72736	-89.97832	17.79034	19.90045
Submarket Sales	22.84513 **	8.16143 **	3.37254 **	9.70983 **	6.65207 **	10.80805 **	9.91450 **	8.80937 **	11.09583 **	10.57342 **	6.93417 **	6.03685 **	2.27583 **
Market Return	-385.70240	-183.99190	-233.98860	-1.85238	-0.29361	-326.91140	-350.80850	-214.36650	-4.79808	-43.81031	-368.67980	-82.02426	-270.87300
Market Sales	0.80610 **	0.79109 **	0.88362 **	0.87071 **	0.78880 **	0.75755 **	0.83840 **	0.82982 **	0.86309 **	0.80290 **	0.79215 **	0.87925 **	0.82110 **
MA Terms													
Submarket Return	31.46800	40.70356	-35.47508	3.25185	-0.12160	-55.41123	7.57508	-62.42131	-13.41192	-13.60370	38.26991	23.09639	-39.01824
Submarket Sales	-23.63095 **	-6.95619 **	-2.79774 *	-8.12033 **	-5.53142 **	-11.00948 **	-10.02492 **	-8.16415 **	-9.19466 **	-9.49200 **	-5.45803 **	-5.18955 **	-2.05414 **
Market Return	212.51350	19.94055	44.08559	0.16490	-0.05607	200.51810	305.65580	-43.24501	-0.89890	-23.24270	220.05490	-24.06862	57.18658
Market Sales	-0.24524 **	-0.21864 **	-0.26706 **	-0.29090 **	-0.22324 **	-0.17707 **	-0.27120 **	-0.24083 **	-0.28048 **	-0.21910 **	-0.20784 **	-0.27375 **	-0.23529 **
Standard Error	103.87721 **	104.73030 **	107.22758 **	106.51992 **	104.86701 **	104.70601 **	105.17846 **	105.86943 **	106.44900 **	104.83225 **	104.77833 **	107.21654 **	105.65800 **

* means statistically significant at the 5% level of significance, while ** means statistically significant at the 1% level of significance.

Table A2: Hypothesis Tests

		Submarket/Postcode												
		6008	6018	6027	6050	6051	6064	6065	6066	6148	6152	6155	6156	6210
Equation	**Test**	**Chi-square**	**Chi-square**	**Chi-square**	**Chi-square**	**Chi-square**	**Chi-square**	**Chi-square**	**Chi-square**	**Chi-square**	**Chi-square**	**Chi-square**	**Chi-square**	**Chi-square**
Submarket Equations														
Returns	No sales effect	2.835	13.415 **	12.889 *	3.378	12.327 *	6.327	15.350 **	31.583 **	8.321	9.582 *	14.326 **	16.542 **	20.610 **
	No market effect	2.628	13.208 *	12.189 *	13.201 *	3.695	6.000	2.752	6.102	17.164 **	2.622	25.454 **	62.129 **	40.491 **
	No cross-variable effect	4.197	24.746 **	23.201 **	14.854 *	18.304 **	12.759 *	17.025 **	37.208 **	18.859 **	10.653	43.498 **	76.929 **	57.096 **
Sales	No return effect	6.083	1.622	7.352	8.949	6.749	0.809	9.018	7.384	6.063	6.144	3.602	0.459	0.333
	No market effect	9.653 *	4.218	8.716	7.470	2.345	7.773	8.218	9.526 *	8.850	8.517	1.906	10.603 *	12.964 *
	No cross-variable effect	11.691	4.584	16.244 *	15.546 *	7.638	7.899	13.886 *	13.681 *	9.594	9.180	3.872	10.960	13.093 *
Market Equations														
Returns	No sales effect	10.813 *	8.023	8.821	12.134 *	8.177	9.769 *	20.496 **	14.834 **	8.034	10.363 *	6.861	10.901 *	14.526 **
	No submarket effect	8.351	4.617	11.924 *	18.032 **	7.738	16.149 **	10.282 *	8.920	1.982	2.690	9.128	6.199	14.922 **
	No cross-variable effect	15.561 *	12.143	18.647 **	26.124 **	17.620 **	28.186 **	20.523 **	22.084 **	8.395	10.860	11.481	15.122 *	25.640 **
Sales	No return effect	5.119	2.589	5.536	0.098	0.002	4.485	2.924	6.071	0.626	0.419	5.791	1.596	4.088
	No submarket effect	42.120 **	50.311 **	17.951 **	22.584 **	55.571 **	36.844 **	35.999 **	35.863 **	23.713 **	37.720 **	55.933 **	18.672 **	50.369 **
	No cross-variable effect	46.412 **	53.162 **	20.952 **	24.022 **	56.286 **	42.314 **	45.473 **	39.228 **	23.755 **	40.037 **	62.525 **	19.538 **	55.211 **
Cross-Equation Tests														
	Submarket Exogeneity	11.348	15.830 *	23.825 **	26.225 **	12.964	8.233	11.390	13.572	31.595 **	9.152	39.412 **	63.033 **	43.229 **
	Market Exogeneity	53.702 **	54.571 **	30.021 **	35.144 **	61.425 **	50.010 **	38.815 **	45.762 **	25.631 **	39.928 **	63.021 **	28.502 **	68.064 **
	Joint Submarket & Market Exogeneity	71.392 **	71.558 **	54.833 **	73.041 **	76.411 **	55.251 **	49.531 **	61.593 **	57.146 **	47.849 **	100.537 **	86.986 **	103.362 **
Correlation Structure														
	Submarket Innovations Uncorrelated	0.281	2.345	2.849	0.031	5.622 *	7.466 **	0.129	0.218	0.018	3.404	0.096	1.200	1.608
	Market Innovations Uncorrelated	0.327	0.292	0.388	0.012	0.099	0.006	0.234	0.868	0.153	0.136	0.007	1.196	0.973
	Submarket Uncorrelated with Market	2.980	2.200	7.152	6.924	1.177	3.703	4.852	7.168	7.797	4.518	1.036	0.978	3.702
	All Innovations Uncorrelated	3.603	4.936	9.848	7.141	6.847	11.123	5.092	8.853	8.375	8.777	1.155	3.310	6.249
ARCH LM Tests														
Submarket Returns	No ARCH (lags 1-4)	0.612	0.171	0.604	0.807	1.348	13.458 **	4.180 **	0.542	1.318	6.152 **	108.385 **	3.270 *	1.313
Submarket Sales	No ARCH (lags 1-4)	4930.459 **	5319.684 **	814.647 **	2881.944 **	4595.422 **	2945.099 **	2714.205 **	3141.164 **	3401.057 **	3004.974 **	7354.196 **	629.849 **	888.897 **
Market Returns	No ARCH (lags 1-4)	7.479 **	6.704 **	6.533 **	8.245 **	7.575 **	6.698 **	8.975 **	5.730 **	7.628 **	6.891 **	6.485 **	6.922 **	6.126 **
MarketSales	No ARCH (lags 1-4)	1329.709 **	1023.539 **	1033.933 **	1273.042 **	860.278 **	966.601 **	1228.337 **	1063.192 **	1251.961 **	1132.414 **	865.396 **	1103.646 **	730.175 **

* means statistically significant at the 5% level of significance, while ** means statistically significant at the 1% level of significance.