# UK housing market: time series processes with independent and identically distributed residuals

**Abstract**
The paper examines whether a univariate data generating process can be identified which explains the data by having residuals that are independent and identically distributed, as verified by the BDS test. The stationary first differenced natural log quarterly house price index is regressed, initially with a constant variance and then with a conditional variance. The only regression function that produces independent and identically distributed standardised residuals is a mean process based on a pure random walk format with Exponential GARCH in mean for the conditional variance. There is an indication of an asymmetric volatility feedback effect but higher frequency data is required to confirm this. There could be scope for forecasting the index but this is tempered by the reduction in the power of the BDS test if there is a non-linear conditional variance process.

**Keywords** UK house prices, independent and identically distributed residuals, iid.

## Introduction

This paper examines the distribution of the residuals from various fairly simple time series data generating processes that may describe the UK housing market, in particular whether those residuals are independent and identically distributed. The basis for this is the BDS test developed by Brock et al (1996), with the generally accepted assumption that independent and identically distributed residuals imply that the proposed data generating process fully explains the time series. The lack of independent identically distributed residuals is normally expressed as 'indicating that there is still something there'. This approach is not uncommon in the analysis of share indices (see Al-Loughani and Chappell, 1997) or other economic time series data but we are not aware of its UK application to a house price index. As a comparison, the exercise is repeated on the US market, but with no significant outcome.

Empirical papers in finance that focus on real estate are normally concerned with non-domestic property, or tend to consider listed firms linked to the property sector. The summer 2007 volatility in the cash and financial markets, triggered by the sub-prime lending in the USA, does however bring domestic housing more into focus. Research in house prices has to an extent mirrored equity-based research in a variety of ways. For instance, Marathe and Shawky (2003) examine the structural relationship between mortgage rates and short/long term interest rates and Jud and Winkler (2003) apply the Q Theory to housing. Volatility of house prices is considered by Miller and Peng (2006) whilst Hui and Yue (2006) study house price bubbles and Lorenz et al (2006) analyse property valuation's risk and uncertainty.

Also mirroring the equity market, there are several studies of property as an asset class in a portfolio. Glascock and Kelly (2007) test the merit of international diversification of real estate portfolios, McGreal et al (2006) look at private real estate diversification by region within the UK/Ireland, Leung (2007) considers optimal portfolio weights and Lee and Stevenson (2006) find that there are increasing benefits from real estate in a mixed asset portfolio. Links between equity and property markets (stationarity and cointegration) are investigated by Liow (2006). In contrast to the benefit of including property in a portfolio, Cauley et al (2007) study how home ownership acts as a constraint on frequent adjustment of asset allocations. There is additionally a growth in studies of appropriate derivatives for real estate portfolios, for instance Quigley (2006) and the consideration of behavioural finance in relation to housing (see for example Farlow, 2005).

This paper does not follow a structural, sectoral or macro economic method, but is univariate in its analysis, (see also Tsolacos, 2006, on forecasting house prices via time series models). The most common time series data generating processes, with constant or conditional variances, are in turn examined to establish if they produce independent identically distributed residuals and hence 'explain' the historic data, or if the postulated process is inefficient in explaining all the features of the time series. The residuals that are independent and identically distributed (iid) will be a series of random variables $\varepsilon_t$ with: $E\{\varepsilon_t\} = \mu_x$, a constant that may equal zero; $\sigma^2(t)=\sigma^2$, a constant that is independent of time; and $\varepsilon_t$ independent of all $\varepsilon_s$ for $t \neq s$.

## Data and Method

*Data*

One of the issues with applying equity based research methods to housing is the problem of the selection of an index that attempts to describe price changes in an illiquid non-fungible asset class. A comparison of UK house price indices is given by Wood (2005), highlighting "significant conceptual and practical problems". Alternatives are few, such as the sales price appraisal ratio described by Bourassa et al (2006), hence the comment of Thwaites and Wood (2003) to be "careful to match the measure …with the concept of house price". For this study, quarterly data is taken from Communities and Local Government (Office of Deputy Prime Minister as was), specifically "Table 590, Housing market: mix-adjusted house price index, by region". This index measures the prices of properties transacted, rather than the value of the housing stock. Unlike indices reported by mortgage providers it is not based on provider-specific properties. The data covers Quarter 2:1968 to Quarter 2:2007, resulting in 157 observations. The use of almost 40 years of data is in step with empirical research documenting long cycles in property markets, with Leung (2004) referring to cycles of 20 to 30 years. The series is neither smoothed nor adjusted to allow for seasonality.

Time series analysis using 157 observations (the maximum available for UK data) can give rise to two sets of problems. If the identified process has GARCH for the conditional variance, then Hwang and Pereira (2006) suggest that 150 data points is too small and could result in bias in the estimated parameters. In addition, combining a GARCH process with use of the BDS test has a second factor to contend with, in that Caporale et al (2005) discuss how small sample sizes may distort the BDS test. This is tempered to an extent by Fernandes et al (no date) who show that the distribution of the BDS test statistic does approximate to normality for samples of 100. This serendipity being the inter-reaction of two opposite forces, the finite sample bias and the nuisance parameter effect which cancel each other out. Irrespective of the sample size, it should also be noted that BDS tests of non-linear models do not always produce correct results (see Brooks and Heravi, 1999).

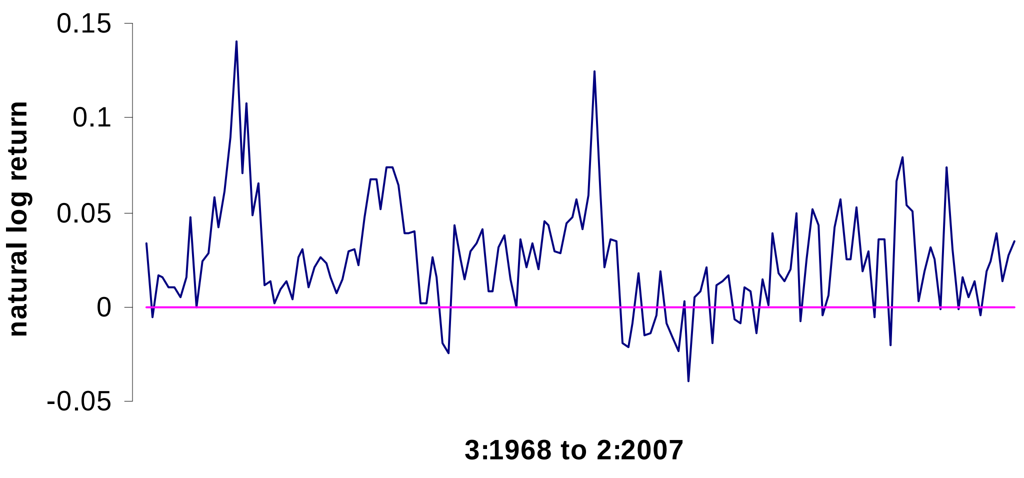
For differencing purposes and to allow for continuous compounding in returns the index is converted to natural logarithms. The first difference of the series produces quarterly returns at time t ($R_t$) using the continuously compounded formula:

$$R_t = Y_t - Y_{t-1} \tag{1}$$

where $Y_t$ is the natural logarithm of the index. In time series analysis of share price indices there is sometimes an adjustment to the return by deducting an estimate of the risk free rate. This analysis does not make that adjustment on pragmatic grounds; firstly as there is no obvious proxy for a housing market risk free rate (although the rate could be argued as common for all investment asset classes) and secondly as any suitable data generating process could contain a constant which may include the risk free rate. Thus the series is total return rather than a housing risk premium.

The return series set out in Figure 1 has a mean of 0.025, standard deviation of 0.028, skewness of 0.0871 and kurtosis of 4.968. The JB test statistic of 44.911 (Jarque and Bera, 1980, 1987) indicates very strongly that the data are not normally distributed so no use is made of the coefficients of possible spurious regressions, although non-normality is common in financial data where ARCH is present. Similarly, the lack of normality does not impact the unit root or BDS tests as critical values are derived by simulation. The autocorrelation coefficients (not given here) are significant for up to four lags and the partial autocorrelation coefficients decline and cease to be significant after six lags.

**Figure 1 Quarterly Returns**



*Method*

Firstly, the time series is formally examined for stationarity by Augmented Dickey Fuller tests. (Phillips-Perron tests for a unit root were also examined but produced the same conclusions.) Secondly, and assuming stationarity, an appropriate data generating process is sought that produces iid residuals. The starting point will be an ARMA process where information criteria are used to consider if there is an autoregressive or moving average explanation in the style of equation 2.

$$Y_t = \mu+\Phi_1 Y_{t-1}+\Phi_2 Y_{t-1}+\ldots+\Phi_p Y_{t-p}+\theta_1 u_{t-1}+\theta_2 u_{t-2}+\ldots+\theta_q u_{t-q}+\varepsilon_t \qquad (2)$$

If this does not produce iid residuals then the three versions of a random walk format (pure, with drift and/or with trend) will be utilised, as set out in equations 3, 4 and 5, but differenced once for returns.

$$Y_t = Y_{t-1} + \varepsilon_t \qquad (3)$$

$$Y_t = \mu + Y_{t-1} + \varepsilon_t \qquad (4)$$

$$Y_t = \mu + Y_{t-1} + \beta t+ \varepsilon_t \qquad (5)$$

These four maintained regressions are performed initially with a constant variance and then for a GARCH process. Stevenson (2004) finds considerable evidence of heteroscedasticity in hedonic models, which more than justifies this approach and likewise Lee (2006) reports on the "temporal instability" of covariances. The assumption is of basic GARCH as the starting version, then TGARCH and EGARCH, and then the same three versions but additionally with an In Mean component. (The data in Figure 1 suggests that the analysis could also consider component GARCH, but the number of observations invalidates that option.) In each of the 28 possible data generating processes (ARMA and three random walk formats; each with constant variance and three versions of GARCH with/without in mean) the maintained regression's standardised residuals are tested for iid, as verified by the BDS test. If the test shows that the residuals are iid, then that particular process will be regarded as explaining the quarterly return of the housing index. Rejection of the null of iid via the BDS test will show that the process does not describe the series well, as the residuals indicate the data are still unexplained.

## Results

*Stationarity*

Table 1 shows the Augmented Dickey Fuller statistics for the natural logarithms of the index (the level series) and the quarterly return of the series (the first difference). ADF(4) is used, based on the autocorrelations identified above, and critical values are derived from Cheung and Lai's response surface coefficients. The trend obviously present in the level series suggests a testing framework commencing with the $\Phi_3$ test for drift and trend but none of the ADF statistics are significant. The non-rejection of $\Phi_3$'s unit root null and a trend coefficient not significantly different from zero makes $\Phi_1$ the next test (just drift). In this case only one statistic is significant, namely ADF(1) which does reject the null, but the rejection is very marginal (4.750 compared to a critical value of 4.740) so both options are considered. The $\tau$ test (as if $\Phi_1$'s null was not rejected) shows non-rejection of the null of I(1) and the alternate critical value for the $\tau_\mu$ test (as if $\Phi_1$'s null was rejected) likewise does not reject that onesided null. Thus it is assumed that the level series is not stationary. Following the same process for the first differenced series, the statistics shows non-rejection of the nulls for both drift and trend and just drift formats, but are significant at 5% for a pure random walk format. Hence the natural log first differenced quarterly return series is assumed to be stationary. A result that is common with many financial/economic series and also house prices (see for example Meen, 2002).

Table 1 ADF test statistics

| | ADF(0) | ADF(1) | ADF(2) | ADF(3) | ADF(4) |
|---|---|---|---|---|---|
| Level series | | | | | |
| $\Phi_3$ | -3.090 | 4.621 | 0.738 | 1.256 | 2.527 |
| $\Phi_1$ | -1.499 | 4.750* | 0.633 | 1.089 | 2.012 |
| $\tau$ | 1.681 | 5.192 | 0.879 | 1.308 | 2.241 |
| First difference | | | | | |
| $\Phi_3$ | -4.234 | -1.814 | -0.995 | 0.176 | 3.728 |
| $\Phi_1$ | -4.069 | -2.016 | -1.134 | 0.081 | 3.663 |
| $\tau$ | -2.439* | -4.005* | -2.498* | -0.825 | 3.024 |

* 5% significance

*Autoregressive moving average as the data generating process*

Time series analysis often uses information criteria to assist in selection of an appropriate data generating process. Table 2 sets out the Schwarz criterion for consideration of an ARMA (p,q) structure.

Table 2 Schwarz criterion for consideration of an ARMA(p,q) structure.

| ARp / MAq | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | -4.603 | -4.571 | -4.596 | -4.567 | -4.622 |
| 2 | -4.574 | -4.545 | -4.596 | -4.547 | -4.588 |
| 3 | -4.553 | -4.744 | -4.734 | -4.838 | -4.812 |
| 4 | -4.567 | -4.832 | -4.739 | -4.710 | -4.713 |

The statistics indicate that the best choice should be ARMA (3,4). Such lags are expected and are supported by empirical research such as Devaney et al (2007) who report serial persistence in UK property returns. This regression is run and the process successfully produces residuals with much of the serial correlation removed. Coefficients (t statistics in brackets) are:

$$R_t = .0255 + .7198\,R_{t-1} - .9963R_{t-2} + .7370R_{t-3} - .3604\varepsilon_{t-1} + 1.3381\varepsilon_{t-2} - .3737\varepsilon_{t-3} + .3605\varepsilon_{t-4} \quad (6)$$
$$(4.477)\ (8.745)\ (-174.)\ (8.897)\ (3.616)\ (8.745)\ (-3.839)\ (4.275)$$

The BDS test statistics for the residuals from this ARMA (3,4) process are given in Table 3. The assumptions underlying the tests are firstly of dimensions up to 5, as this more than encompasses the autocorrelations, and secondly a correlation integral (epsilon) ranging from 0.5 to 0.9, so that each test is based on consideration of 12 BDS statistics.

Table 3 BDS test statistics for an ARMA(3,4) mean process with constant variance

| | Dimension | | | |
|---|---|---|---|---|
| Epsilon | 2 | 3 | 4 | 5 |
| .5 | 0.0044 | 0.0093 | 0.0122* | 0.0112* |
| .7 | 0.0076 | 0.0214* | 0.0349* | 0.0424* |
| .9 | 0.0043 | 0.0162* | 0.0297* | 0.0407* |

* 5% significance

The BDS test has a null of iid which is rejected at 5% in the higher dimensions. Therefore it is assumed than the ARMA mean process with constant variance does not explain the housing index return series. The LM test is now used to establish if there is an ARCH or GARCH process indicating a conditional variance. With one lag the F-statistic is 1.385031 (with probability 0.2411) and $TR^2$ is 1.390657 (probability 0.2383). The LM's null is no ARCH and this is not rejected. Thus it is also assumed that an ARMA mean process with non-constant variance does not explain the index return series either. Failure of an ARMA process to describe UK house price returns is paralleled by (say) Stevenson (2007) who highlights various limitations in the use of ARIMA modelling, albeit in the office sector.

*Random walk as the data generating process*

A common approach in finance is to test for randomness as a special case of an autoregressive process. This is performed for a random walk with drift and then with trend. The resulting mean equation is:

$$R_t = .029074 - .000079Y_{t-1} + \varepsilon_t \quad (7)$$
$$(8.579)^*\ \ (-1.568)$$

The coefficient for the lagged log index is not significant at 5%, supporting the random walk format, and so can be dropped. Rerunning the regression without this gives:

$$R_t = \underset{(11.222)^*}{0.025145} + \varepsilon_t \qquad (8)$$

with the t statistic indicating a constant that is significantly different from zero at 5%. Table 4 shows the BDS test statistics for this regression's residuals. All dimensions for all correlation intervals reject the null of iid, so the format does not explain the series.

Table 4 BDS test statistics on residuals from $R_t = 0.025145 + \varepsilon_t$

| | Dimension | | | |
|---|---|---|---|---|
| Epsilon | 2 | 3 | 4 | 5 |
| .5 | 0.045* | 0.050* | 0.042* | 0.036* |
| .7 | 0.050* | 0.084* | 0.102* | 0.110* |
| .9 | 0.018* | 0.043* | 0.063* | 0.080* |

* 5% significance

If a trend is included then:

$$R_t = \underset{(3.268)^*}{0.055821} - \underset{(-1.382)}{0.014411}\, Y_{t-1} + \underset{(0.952)}{0.000241}t + \varepsilon_t \qquad (9)$$

Only the constant is significant at 5% so this format collapses to the earlier random walk with drift, fails the same BDS test and does not explain the series.

If the use of a random walk with drift as the data generating process is not producing residuals that are iid, then it may be the case that the variance is not constant and that some form of ARCH process can be considered. Replicating the earlier ARMA-based LM test for the presence of ARCH, but in the random walk with drift format, gives an F statistic of 12.53757 (pr 0.0005) and $TR^2$ of 11.73947 (pr 0.0006), which indicate strongly the presence of a conditional variance. Interestingly, the use of GARCH to establish a data generating process that has iid residuals could be viewed as unexpected, given the use of quarterly data, in that Joseph (2003) observes that in much financial literature conditional heteroscedasticity is "substantially reduced at lower data frequency", finding it almost minimal in monthly data.

Since its initial development, GARCH has expanded to encompass a range of formats, each with a financial rationale. These are now followed with the residuals in each case tested for iid via the BDS test. Results for the various maintained regressions are not given at this stage, but the allied BDS statistics are shown in Table 5. The regressions assume GARCH (1,1) as p=q=1 is the most common structure in financial research. The tests start with GARCH, then TGARCH and EGARCH and are repeated to include In Mean.

Table 5 BDS test statistics on residuals from three GARCH and three GARCH in mean regressions on a random walk with drift

| | Dimension | | | |
|---|---|---|---|---|
| Epsilon | 2 | 3 | 4 | 5 |
| GARCH .5 | 0.007 | 0.003 | 0.001 | 0.002 |
| .7 | 0.009 | 0.013 | 0.017 | 0.024* |
| .9 | 0.001 | 0.003 | 0.005 | 0.014* |
| TGARCH .5 | 0.007 | 0.003 | 0.002 | 0.002 |
| .7 | 0.011* | 0.018* | 0.024* | 0.032* |
| .9 | 0.001 | 0.004 | 0.009 | 0.018* |
| EGARCH .5 | 0.013* | 0.008 | 0.004 | 0.003 |
| .7 | 0.017* | 0.025* | 0.029* | 0.031* |
| .9 | 0.003 | 0.007 | 0.010 | 0.016 |
| GARCHM .5 | 0.007 | 0.003 | 0.002 | 0.003 |
| .7 | 0.010* | 0.017* | 0.022* | 0.028* |
| .9 | 0.002 | 0.004 | 0.008 | 0.015* |
| TGARCHM .5 | 0.006 | 0.005 | 0.003 | 0.006 |
| .7 | 0.009 | 0.013 | 0.015 | 0.024* |
| .9 | 0.003 | 0.008 | 0.010 | 0.017 |
| EGARCHM .5 | 0.003 | 0.003 | 0.001 | 0.004 |
| .7 | 0.006 | 0.010 | 0.012 | 0.019 |
| .9 | 0.003 | 0.007 | 0.009 | 0.013 |

* 5% significance

The first four sets of tests all reject the BDS null at 5% significance for two or more correlation intervals and dimensions. Threshold GARCH in mean only rejects the null at 5% in one test and Exponential GARCH in mean does not reject the iid null in any test. This version will now be followed up.

The two regressed equations are the mean (an alternative representation not used here could be to include the conditional variance in the mean equation, rather than standard deviation) and the conditional variance (use of Exponential GARCH results in the conditional variance being expressed as a natural logarithm).

$$\text{mean: } R_t = c + \delta\sigma_t + \varepsilon_t \quad (10)$$

$$\text{conditional variance: } \log\sigma^2_t = \omega + \beta \log\sigma^2_{t-1} + \alpha \left| \varepsilon_{t-1} / \sigma_{t-1} \right| + \gamma\, \varepsilon_{t-1} / \sigma_{t-1} \quad (11)$$

The resultant mean regression (with z rather than t statistics) is:

$$R_t = \underset{(-1.784)}{-0.066464} + \underset{(2.331)^*}{3.962464}\sigma_t + \varepsilon_t \quad (12)$$

where the constant is not significant but the "in mean" coefficient is significant at 5%. The log of the conditional variance is:

$$\log\sigma^2_t = \underset{(-2.210)^*}{-1.737533} + \underset{(7.490)^*}{0.778208}\log\sigma^2_{t-1} + \underset{(1.327)}{0.071796}\left| \varepsilon_{t-1}/\sigma_{t-1} \right| + \underset{(3.013)^*}{.175255}\varepsilon_{t-1}/\sigma_{t-1} \quad (13)$$

with only the absolute term not significantly different from zero. The BDS test statistics in Table 5 have already shown that, in this random walk with drift format for the mean and with EGARCH in mean for the conditional variance, the residuals are iid, so the first difference of the UK Housing market mix-adjusted house price index time series is explained. Of the 28 possible data generating processes considered here, 27 failed to produce standardised residuals that were independent and identically distributed but this final version does have iid residuals indicating that 'there is nothing else left'.

This result for UK house prices aligns well with the findings of Bond and Patel (2003) who examined real estate markets that were securitized, finding evidence that UK property companies followed an AR(1) mean process and GARCH for the conditional variance. Their focus was on skewness in the conditional distribution and so this study's rejection of only one epsilon/dimension BDS test for TGARCH and non-rejection of all the EGARCH BDS tests gives support to the possibility of asymmetries as both of these GARCH versions include a volatility feedback effect. This effect is only very light as equation 13's conditional variance shows that the coefficient for the absolute value $\left|\varepsilon_{t-1}/\sigma_{t-1}\right|$ is not significantly different from zero. A news impact curve was produced (not shown here) but there was no obvious evidence of good/bad news having an asymmetric impact on volatility.

Bond and Patel attributed the securitized market's skewness to a possible mix of differences of capitalization and upward-only rent reviews, although this does not immediately seem a likely driver for domestic house prices. Alternatively Ortalo-Magne and Rady (2004, 2006) suggest a model for the housing market where potential first-time buyers experience income volatility that acts as a factor in house price excess volatility. This combined with their credit constraint parameter, and in particular its relaxation in the UK in the early 1980's, could go some way towards explaining the time varying volatility identified here. Benito (2005) applied the Ortalo-Magne and Rady model to UK house prices by district-level housing markets, finding evidence of significant difference by district.

**The US market**

The purpose of this paper is to establish if a fairly simple univariate data generating process produces iid residuals, so explaining the UK housing market: this has been achieved. As a comparison, the process is now replicated for the US market to consider if wider conclusions can be drawn. Quarterly data for a similar period is obtained from the Freddie Mac Conventional Mortgage Home Price Index and is subject to the same analysis, however, the results are very different. Using log values the level series is not stationary and neither is the first differenced return series, when tested via the ADF process. First difference stationary is indicated by the Phillips-Perron test so the results are contradictory. Schwartz Information Criteria indicate an ARMA(5,4) process but both the constant and conditional variance processes reject the null of iid residuals. Similarly, all other processes, with and without the various forms of GARCH and with and without an in-mean component, fail to produce residuals that are independent and identically distributed. In every process utilised, the BDS test indicates that the data are not fully explained. (Resultant statistics are not given here.)

There could be numerous reasons why the US market results differ from those of the UK. One possibility is triggered by Miller and Peng's 2006 study of US house price volatility by metropolitan area. They examined 277 metropolitan areas and found time varying volatility in 17% of them, thus aggregate indices in both the UK and the USA may hide significant differences in processes at the regional level let alone for trans-national comparison. Miller and Peng also identified two further issues that could be applicable to the UK statistics. Firstly, that volatility Granger-causes additional volatility in later periods, as paralleled by the UK results in equations 12 and 13 above; thus the US and UK markets may be more similar at a regional level than indicated by this paper's country-wide analysis. Secondly, they suggest that asymmetry exists in the US metropolitan markets; again giving similar conclusions to the equation 13 suggestion of asymmetry in the UK.

**Concluding Remarks**

Earlier reference to three issues surrounding sample size and the combination of GARCH with BDS tests casts some doubt on this analysis. The Brooks and Heravi paper (1999) suggests that rejection of the null can occur more frequently than is appropriate. This problem can be minimised by limiting the dimensions m to 5 or less, as assumed here, but it is still possible that use of GARCH has not captured all of the data's non-linearity. Thus, one or more of the rejected GARCH-based processes may explain the data as well as or better than that of the identified EGARCH in mean. Secondly the concerns of Hwang and Pereira (2006) relate to small samples, which may result in the parameters in equation 13 having a negative bias. Their study was on GARCH and not the Exponential version, and not in mean, so it is possibly not applicable to the explaining format identified here. Thirdly, Caporale et al (2005) were particularly concerned with mildly explosive processes, but identification of a random walk as the process which explains the data removes this problem.

The purpose of the study was to establish if the UK housing index series or the differenced return series could be modelled by one of the fairly common time series univariate data generating processes and produce residuals that were independent and identically distributed. This was achieved using a mean process of random walk with drift, supported by an EGARCH in mean conditional variance, which produces a variety of further observations. The only significant coefficient in the mean process is for the standard deviation, indicating that increases (decreases) in volatility generate increased (decreased) returns. This combined with the significant coefficients for the log version of the conditional variance could be seen as inferring inefficiency in the market, although this would need to be studied further to establish the forecasting power of the data generating process. The need to include GARCH to obtain iid residuals for quarterly data warrants further consideration, possibly via a comparison with more high frequency data, although that would be difficult given the current availability of UK housing indices. The 'hint' of asymmetry could also be followed up with higher frequency data as this may make it more visible and significant. Finally, the availability of the same data set as used here, but at a regional level, could allow replication of the process to establish commonality or differences by region.

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