# Real Interest Regimes and Real Estate Performance: A Comparison of U.K. and U.S. Markets

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***Abstract.*** **Linear models of market performance may be misspecified if the market is subdivided into distinct regimes exhibiting different behavior. Price movements in the United States real estate investment trusts and United Kingdom property companies markets are explored using a threshold autoregressive (TAR) model with regimes defined by the real rate of interest. In both U.S. and U.K. markets, distinctive behavior emerges, with the TAR model offering better predictive power than a more conventional linear autoregressive model. The research points to the possibility of developing trading rules to exploit the systematically different behavior across regimes.**

## Introduction

This article analyzes the behavior of publicly traded United States and United Kingdom real estate performance using non-linear regime-based modeling techniques. Such techniques have been applied in areas of economics and finance with some success (Engel, 1991; and Dacco' and Satchell, 1995). They are particularly useful in trying to conceptualize situations where behavior differs in distinct market states. Under such circumstances, the conventional linear model, which allows for just one market state, will not be able to explain fully the movement of prices and returns and hence fails to generate useable trading rules or informed portfolio allocation decisions.

Real estate markets are generally considered to be cyclical in nature. It is plausible that the structure of market behavior differs across boom and bust phases. In a downturn, property values may fall more sharply, and with less volatility, than they rise in an upturn. In equity markets, it is known that falling prices are more volatile than rising prices, the so-called leverage effect (Black, 1976). A regime-switching model may be able to capture these behavioral differences. Knowledge of the state

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variable, the variable or set of variables that determine the regimes, might point to distinct investment strategies.

One approach to regime modeling is based on the use of Markov switching models, as popularized by Hamilton (1989).[1] This technique treats the state variable as unobservable which, from a forecasting viewpoint, leads to serious difficulties (see Dacco' and Satchell, 1995). Accordingly, this article explores threshold autoregressive (TAR) models, which have the advantage that the state variable is observable in many of the possible specifications. The real rate of interest is used as a state variable. While this is only one of many possible variables defining regimes, there are strong a priori reasons for anticipating interest rate effects. This intuition is confirmed by the results.

This research tests for the existence of distinct interest-rate regimes in the U.S. real estate investment trust (REIT) and U.K. property company markets and compares the behavior of these investments over time. An earlier U.K. study using a TAR approach (Lizieri and Satchell, 1997b) found distinct regimes related to real interest rates. However, the results are hard to interpret due to the trending nature of the price series. This article addresses the trending issue directly in the model specification. Although there are some dissimilarities between REITs and property companies, both are considered as highly liquid real estate investments in their respective countries and might be seen as complementary assets in an international diversification strategy. Thus, it will be interesting to determine whether or not these two publicly traded real estate investment vehicles exhibit similar behavioral traits.

The remainder of the article is structured as follows. Next, the influence of the real rate of interest on the commercial real estate sector is discussed. Then the underlying fundamentals of TAR modeling are reviewed. The fourth section describes the data employed. Next, empirical results comparing U.S. and U.K. markets are presented. Finally, the conclusion points to future research directions.

## Commercial Real Estate and the Real Rate of Interest

It is contended that the real rate of interest is a major driver of commercial real estate markets. It is not suggested that the real interest rate is the *only* exogenous variable influencing real estate behavior. Other macro variables may be significant and could be used to segment the data series. Nonetheless, interest rates are considered to be of major significance: thus, the investigation of non-linear structures is anchored upon them. In conventional appraisal models, rents are capitalized using a rate that is dependent, inter alia, on nominal interest rates. In high interest rate environments, increased yields lead to a decrease in the capital value of commercial property. This impact is magnified due to the extensive use of financing for real estate investments. Conversely, inflation is often seen as having a beneficial effect on real estate investments, as owners benefit from increasing income and capital growth, while the real value of their historic debt is eroded.

For simplicity, define the real rate of interest as $R_t = (N_t - F_t)$. $N_t$, the nominal rate, has a negative effect on capital values. $F_t$, the expected inflation rate, has a positive effect on income but is removed from $R_t$. It can be seen that the real rate has an unequivocally negative impact on real estate values.

The links between private and public (in the U.K., the direct and indirect) real estate markets are complex and are subject to lags. The performance of the REIT and property company sectors will, ultimately, be based on the performance in the underlying direct market. U.K. property investment companies are valued by equity analysts on a discounted net asset value (NAV) basis. Hence, their share prices will reflect changing property values. As rising real interest rates depress capital values, so NAV will be marked down. The actual price will vary on a day by day basis depending upon the amount of the discount and on general stock market movements. Returns on individual properties and developments will be affected by interest rate impacts on project-specific borrowing. The impact of corporate borrowing (the gearing ratio) will magnify any changes. Developer-Trader companies will, in similar fashion, be affected by capital growth and the cost of borrowing and their share price will vary accordingly. Most credit-driven markets will be subject to real interest rate effects, and the property sector should be no exception. As a result of valuation inertia, it is possible that the response to interest rate changes will be more rapid in the property equity[2] market than in the underlying direct investment market.

Recent North American studies have indicated that interest rates have a significant impact on real estate markets. Ling and Narnjo (1995) sought to identify key macroeconomic risk factors or ‘state variables’ that affect US real estate returns. Using both fixed-coefficient and time-varying models, they report that interest rates were significant, albeit dominated by growth in consumption. The real interest rate was particularly significant for real estate stocks. McCue and Kling (1994), using a VAR approach, find significant links between U.S. real estate stock prices, inflation and U.S. three-month Treasury bills, with nominal rates explaining over 36% of the variation in the real estate series.

Mueller and Pauley (1995:324) found weak negative correlations between REIT prices and short, medium and long-term interest rate variables in the period 1972–93. However, in examining sub-periods, they reported inconsistent betas and suggested that this implies that ‘‘REIT price movements cannot be adequately explained by interest-rate movements.’’ Their conclusion, however, hints that there may be different effects on REIT prices from periods of rising and falling interest rates. Liang, McIntosh and Webb (1995) present results of a two-index model analysis of REIT portfolios that suggest both market and interest rate betas are time varying. Finally, Liang and Webb (1995), using a similar methodology, argue that a large part of the market risk associated with mortgage REITs is derived from interest rate uncertainties.

From a different perspective, Hendershott’s (1995) analysis of rental determination in the Sydney office market is based on a model where changes in the real (risk free) interest rate drive equilibrium real rents. His dynamic adjustment model is thus strongly dependent upon real interest rate changes. This result suggests strong a priori grounds for examining the linkage between interest rates and property performance.

Given the likely impact of interest rates, an initial autoregressive model might relate price changes to current and lagged values of the price level of property $Y_t$ and the real interest rate $X_t$. We formulate this below as:

$$\Delta Y_t = \alpha_0 + \Sigma\alpha_j Y_{t-j} + \Sigma\beta_j X_{t-j} + \upsilon_t, \tag{1}$$

where $\upsilon_t$ is assumed, for convenience, to be independent and identically distributed normal with mean 0, variance $\sigma^2$ or $\sim$ iid $N(0,\sigma^2)$.[3]

Since the price level is measured in nominal terms, $Y_t$ is likely to be trending upwards. Equation (1) could thus be augmented to include a time-trend variable. While this is a perfectly plausible model of $\Delta Y_t$, it may not capture the periods where $Y_t$ is highly volatile, where $Y_t$ is either trending up or down or where $Y_t$ is mean-reverting. From a financial perspective, it is important to isolate such behavior as each regime can be associated with different investment strategies. For example, in a world where values are trending up or down, portfolio insurance would seem appropriate, while in a mean-reverting state it might be profitable to follow some form of contrarian strategy, such as rebalancing. The disadvantage of the formulation in Equation (1) is that it admits only one such state owing to its linearity. For this reason, a TAR formulation is examined.

## TAR Modeling

Threshold models were introduced by Tong and Lim (1980) and are discussed extensively by Tong (1983, 1990). The basic idea may be explained as follows. A linear model for a series $Y_t$ is defined then the parameters of the model are allowed to vary according to the values of a finite number of past values of an associated series $Z_t$. In many applications, the associated series coincides with the series under investigation, resulting in a self-exciting threshold autoregressive (SETAR) model.

To find the threshold value, $z$, separating regimes, Tong (1983) proposed a grid-searching algorithm based on the use of the Akaike (1973) information criterion. Tong argues that the Akaike criterion should be used as a guide to select a small subclass of plausible models which may then be examined by diagnostic checks to assess whether the fitted model shares the main characteristics of the data.[4] Chen (1995) discusses other techniques to locate and determine thresholds. Applications of TAR models can be found in Cao and Tsay (1994), Peseran and Potter (1994), Potter (1995), Tiao and Tsay (1994) and Yadav, Pope and Paudyal (1994).

A two-regime TAR model may be estimated by fitting each of the two components separately to the appropriate subset of observations and using standard least squares exactly as in the case of a linear autoregressive model.[5] The estimation of coefficients presents little difficulty. However, evaluating the significance of the threshold parameter is more problematic since standard asymptotic theory is inapplicable.[6] There are also difficulties associated with forecasting. Multi-step ahead forecasts are influenced by whether one stands at a peak or a trough at time $t$.[7]

For all these notes of caution, the TAR approach offers potential gains in the understanding of the operation of markets. This will be particularly true where the price behavior in different regimes is distinctive since the conventional linear formulation will be misspecified and fail to capture the underlying characteristics of the market. The TAR model may thus improve both our understanding of market processes and our forecasting ability.

The analysis that follows is restricted to a situation where there is a single period lag and two regimes. It is possible to include more lags in the model and consider more regimes but this is likely to introduce more complexity than clarity. A one period lag is used on the assumption that REIT and property equity prices will quickly adjust to changing interest rate environments. In the direct investment market, inertia may mean that there will be a slower adjustment process and a longer lag.

Now consider a TAR model that accounts for an underlying time trend. In this structure, it is assumed that:

$$\Delta Y_t = \alpha_i + \beta_i Y_{t-1} + \gamma_i T + \sigma_i \upsilon_t \quad \text{if } X_{t-1} \in R_i, \tag{2}$$

where $Y_t$ is the log of the price index, $T$ is a time trend ($T = 1, 2, 3 \ldots n$), $i = 1, 2$, ($\alpha_i$, $\beta_i$, $\gamma_i$, $\sigma_i$) are the parameters associated with the regime $R_i$ and $\upsilon_t$ is the error term at time $t$. There may be two regimes, the $R_i$ need to be mutually exclusive and exhaustive and the errors, $\upsilon_t$, are iid $\sim N$ (0,1). The underlying linear time-trend is captured by the $\gamma$ coefficient, while the $\beta$ coefficient relates to the autoregressive response.

The above model is simple and admits a wide range of different behavioral characteristics. Some possible states include:

| | |
|---|---|
| $\alpha_i = 0$, $\beta_i = 0$, | A random walk; |
| $\beta_i < 0$, | A mean-reverting process around a trend; |
| $\beta_i > 0$, | A mean-averting process around a trend; |
| $\gamma_1 > 0$, $\gamma_2 < 0$, | Regimes which alternately trend up and down; and |
| $\sigma_1$ large, $\sigma_2$ small, | A world with high and low volatility states around the trend. |

It is assumed that the regimes $R_1$ and $R_2$ will be determined by real interest rates. Regime 1 will hold where $X_{t-1} <$ some threshold value $z$: if $X_{t-1} > z$, then the market is in Regime 2.

The individual regression equations for the two regimes are estimated by conditional least squares, which is consistent and gives estimates that are asymptotically normal with the usual covariance matrix. The only complexity comes from the estimation of $z$, the threshold coefficient. This value is estimated by carrying out a grid search on the total residual sum of squares. For the reasons outlined, standard errors for the threshold estimate $\hat{z}$ are not reported.

The TAR formulation is contrasted with a standard autoregressive linear formulation:

$$\Delta Y_t = \alpha + \beta Y_{t-1} + \gamma T + \upsilon_t. \tag{3}$$

To some extent, the simple autoregressive formulation is a ''straw man'' that does not represent a state of the art model. It might be possible to construct a model based on fundamental analysis principles that would give better data fits and predictions. Such a causal approach would be preferable in private, direct real estate markets. When dealing with publicly traded real estate securities with relatively high frequency data, the simple linear form seems more appropriate. Autoregressive models in this form are frequently used in equity analysis. The linear autoregressive formulation provides us with a benchmark to evaluate the existence of regimes. Although further research could examine regimes within the context of a multifactor model, this lies outside the scope of the present analysis and may introduce more noise than clarity.

In different regimes, different trading rules may apply. If prices follow a random walk with positive trend, then a rule of buy and hold will dominate any rule that involves changes in portfolio weighting. The proportion of investible wealth placed in commercial real estate would depend upon that investor's utility function, the time horizon, the competing asset classes and the statistical properties of the errors in the random walk. In a mean-reverting autoregressive regime, prices above the trend would revert to the trend. The same process would hold for prices below the trend. In this market, one would buy when prices were below trend and sell when they were above trend—a contrarian strategy. By contrast, in a mean-averting, explosive, environment one might buy (sell) on a trend.

Given the above, it is possible to define a (not necessarily unique) trading strategy depending upon the states of the markets. If Regime 1 were a random walk and Regime 2 were mean-reverting, one would buy and hold in Regime 1 and buy or sell in Regime 2 depending on the behavior of prices relative to the trend. Furthermore, one could use forecasts of what regime is likely to apply next period to make adjustments to portfolio weightings. It should be emphasized that the efficacy of such trading rules are conditional on there being a liquid market with comparatively low information and transaction costs.[8] The ability to implement such a strategy in the private, direct-ownership real estate market is questionable. In public-traded securities markets as those of U.S. REITs and, in particular, U.K. property company shares, market conditions may permit the development of such techniques.

The presence of successful trading rules or autoregressive patterns in returns might seem to contravene market efficiency. The literature on market efficiency in the 1970s broadly treated efficiency as synonymous with (log) prices following a random walk. However, research in the last twenty years has evolved considerably. The question of efficiency has been broadened to address the question: are returns consistent with an intertemporal representative agent equilibrium in the asset markets? Discussions may be found in Fama and French (1988, 1989), Poterba and Summers (1986, 1988) and McQueen and Thorley (1991).

A number of articles have shown theoretically that such markets may have risk premia that are time-varying, autoregressive or predictable (*e.g.*, Abel, 1988; and Balvers, Cosimano and McDonald, 1990; and, for empirical evidence, Whitelaw, 1994). Since the optimal trading strategies of investors in such economies are, typically, extremely complex—far more complex than investors use in practice—contrarian and other trading strategies may be interpreted as robust approximations to the true dynamic trading strategy. These rules do not lead to ‘‘excess’’ returns since, in equilibrium, there will be a risk adjustment just as there occurs with the dynamic CAPM.

## Data Issues: Analyzing the Public Real Estate Market

A major difficulty facing real estate research is the absence of timely and reliable indicators of direct market activity. The benchmark portfolio indices available in the U.K. are based on appraisals (valuations) rather than on transactions—as are published U.S. indices such as the NCREIF index. The reliability of those valuations has been questioned (Brown, 1992; Lizieri and Venmore-Rowland, 1993; and Matysiak and Wang, 1995). There is evidence of smoothing and autocorrelation due to asynchronicity of valuations, temporal aggregation and the valuation process (Blundell and Ward, 1987; Brown, 1991; Geltner, 1991, 1993; Newell and MacFarlane, 1994; Barkham and Geltner, 1995; and Brown and Matysiak, 1996). Although it is possible to ‘‘unsmooth’’ the direct indices, there remains a coverage problem. In the U.K., the only generally available monthly indices (the IPD Monthly Index and the Richard Ellis Monthly Index) both start in 1986. These indices are dominated by valuations of properties held in pooled unitized trusts, which may not be fully representative of the typical commercial real estate investment market.

The use of stock market property indices to measure real estate performance is also problematic. U.S.-based research indicates that REITs are strongly correlated with common stock indices. This has led some authors to question whether they measure real estate performance at all. Similar results have been found for U.K. property company share prices (see Mengden and Hartzell, 1986; Gyourko and Keim, 1992; McCue and Kling, 1994; and Campeau, 1995). In both U.S. and U.K. markets, strong contemporaneous correlation between real estate stocks and equity prices have been found.

Nonetheless, there must be a logical link between the performance of real estate in the direct and indirect markets. Real estate stock indices have the advantage that they are publicly traded, transaction-based, transparent and reported on a frequent basis. As a result, a model based on interest rate regimes should prove more useful for investment strategies for indirect real estate markets. Accordingly, price series for property company shares in the U.K. and REITs in the U.S. were used in this study.

Since the focus is on real estate equity performance itself, and not on the links between equity real estate and the underlying commercial real estate market, no attempt was made to remove the effects of leverage (gearing) from the equity real estate indices. Barkham and Geltner (1995) found that their unleveraged U.K. property company series had a *higher* contemporaneous correlation with the stock market than the leveraged series (0.74 compared to 0.62). Campeau (1995) obtained similar results. These results confirm the contention that the real estate sector of the stock market is more interest-rate sensitive than the stock market in general.

### *U.K. Data*

Although it would be possible to construct a real interest rate series using U.K. government index-linked securities, practical difficulties (including the lack of coverage prior to 1983 (*i.e.*, Robertson and Symons, 1994) led to use of a real interest rate series based upon current inflation and short-term interest rates. Inflation was measured by the change in the headline Retail Price Index (RPI).[9] The daily closing three-month Treasury bill rate was used an indicator of nominal interest rates. This constitutes the market's benchmark interest rate indicator. While a longer duration bond may be more appropriate for analyzing direct equity investment in real estate, the short-term indicator seems more appropriate for real estate stock performance.

For U.K. real estate performance, the Datastream International U.K. Property Price Index was used. This index includes the share prices of UK property companies (excluding property agents) listed on the London Stock Exchange, weighted by market capitalization. It is similar in construction to the more commonly used FT Property Index but was preferred since the FT Index was reorganized in 1994, necessitating the merging of two series. Monthly data for the period January 1975 to August 1995 were collected. Earlier data would be distorted by legislative and planning controls on real estate in the early 1970s. Market capitalization as a share of the overall equity market has varied over time, although not as markedly as U.S. REIT data. The average share of the total stock market for a consistent subsample of major companies over the period 1980–95 was 2.9%. In mid-1995, the estimated market capitalization of the sample was approximately £16.1 billion (U.S. $24.5 billion).

The data shows that there was a spectacular fall and subsequent rise in the property index around December 1990, which seems to be associated with the property slump. Thereafter, the high real interest rate environment would be expected to adversely affect the property sector. However, the performance of the property companies in the 1991–95 period appears to be driven largely by the general rise in equity prices, disguising the effects of interest rate structures. Nonetheless, tests on the data excluding the 1991–95 period generated similar results to tests for the full period of analysis.

### *U.S. Data*

As our index of real estate performance for the U.S., the NAREIT share price and return index for equity REITs (excluding healthcare) was used. Equity REITs are those whose primary investment (over 75%) are in direct ownership of the real estate asset. The type of properties and forms of ownership held by these constituent REITs are similar to the portfolios of U.K. property companies.

There has been an explosive growth of the REIT market, particularly in the equity REIT market, in the last five years (Corgel, McIntosh and Ott, 1995; Han and Liang, 1995; and Pagliari and Webb, 1995). The market capitalization of the industry has gone from $1.88 billion in 1972 to $44.31 billion in 1994. In particular, the last two years have seen a much higher number of new equity REIT security offerings than in previous years. This makes the index difficult to use as a proxy for real estate investments. Additionally, there is a survivorship bias—Glascock and Hughes (1995) found that only 16 of the 245 REITs in the NAREIT Index existed for their entire study period (1972–91). Nevertheless, the NAREIT series is the most widely used by those investing in the U.S. public real estate market[10] and is used in this study.

Current U.S. inflation was measured by the change in the Consumer Price Index. The three-month T-bill return series (annualized and for new issues) reported by the Department of the Treasury was used to proxy nominal interest rates. Monthly data from December 1972 to March 1995 were used in the analysis.

## Results

To provide a benchmark for analysis of the TAR models, linear models were investigated. Results for the full U.S. data set from December 1972 to March 1995 were:

$$\begin{aligned} \Delta Y_t = {} & \underset{(1.7)}{0.0866} - \underset{(-1.5)}{0.0174 Y_{t-1}} + \underset{(1.4)}{0.0002 T} \end{aligned} \tag{4}$$

Figures in parentheses are $t$-Statistics, Adj. $R^2 = .004$ and RMSE $= 0.041$.

Results for the full U.K. data set from January 1975 to August 1995 were:

$$\begin{aligned} \Delta Y_t = {} & \underset{(2.1)}{0.2125} - \underset{(-2.0)}{0.0333 Y_{t-1}} + \underset{(1.3)}{0.0002 T} \end{aligned} \tag{5}$$

Figures in parentheses are $t$-Statistics, Adj. $R^2 = .011$ and RMSE $= 0.067$.

These results suggest at best a weak autoregressive process with limited forecasting ability. None of the U.S. coefficients are significant. The U.K. results tentatively indicate mean reversion about the upward drifting trend line. The generated equations do not seem to point to effective trading rules. Can a TAR formulation provide stronger results and usable trading rules?

The full sample U.S. REIT two-regime TAR results are shown in Panel A of Exhibit 1. We observe two regimes separated by a threshold real interest rate of 2.9%. The market is in Regime 1, the lower interest rate regime, 64% of the time. The regimes are persistent, the probability of remaining in Regime 1 is 0.96 and of remaining in Regime 2 is 0.95. The behavior of the market is quite distinct across the two regimes.

**Exhibit 1**
**TAR Results for the Full Sample**[11]

| | Regime 1 | *t*-Statistic | Regime 2 | *t*-Statistic |
|---|---|---|---|---|
| Panel A: U.S. Results 1973–95 | | | | |
| $\alpha$ | 0.225 | 3.4 | −0.056 | −1.0 |
| $\beta$ | −0.005 | −3.3 | 0.020 | 1.6 |
| $\gamma$ | 0.001 | 3.3 | $<-0.001$ | −2.8 |
| $\sigma$ | 0.045 | | 0.029 | |
| P(S1) = .643 | $P_{11}$ = .965 | $P_{12}$ = .035 | $P_{21}$ = .053 | $P_{22}$ = .947 |
| Correlations | S1 = 0.229 | S2 = 0.355 | AR = 0.090 | |
| Panel B: U.K. Results 1975–95 | | | | |
| $\alpha$ | 0.294 | 2.9 | 0.119 | 1.2 |
| $\beta$ | −0.048 | −2.8 | −0.005 | −0.3 |
| $\gamma$ | $<0.001$ | 2.5 | −0.001 | −3.9 |
| $\sigma$ | 0.069 | | 0.057 | |
| P(S1) = .747 | $P_{11}$ = .931 | $P_{12}$ = .069 | $P_{21}$ = .203 | $P_{22}$ = .797 |
| Correlations | S1 = 0.199 | S2 = 0.342 | AR = 0.148 | |

This exhibit shows the coefficients and *t*-Statistics for the TAR model for Regime 1 (below threshold real interest rates) and Regime 2 (higher interest rates). P(S1) is the proportion of time spent in Regime 1 and therefore P(S2) = 1 − P(S1). $P_{11}$ shows the probability of remaining in Regime 1 in the next period, given that one is in Regime 1 now, $P_{12}$ shows the probability of moving from Regime 1 to Regime 2, and so on. The correlations shown are between the forecast values and the actual values for TAR Regime 1 (S1), Regime 2 (S2) and for the linear autoregressive model (AR). Real interest rate threshold value separating regimes in Panel A is 2.9%. Real interest rate threshold value separating regimes in Panel B is 5.5%.

Regime 1 is characterized by mean reverting behavior about a positive trend—that is positive and significant values of $\alpha$ and $\gamma$ and a negative and significant value of $\beta$. The market moves upward around its trend line with slower or faster growth corrected the next period. By contrast, in the second, higher, interest rate regime, random walk behavior around a negative trend is observed: only the $\gamma$ coefficient is significant and values fall with little volatility about the trend line. The magnitude of the intercept and the steepness of the slope of the trend are sufficient that the overall price volatility in the second regime is greater than in the first, capturing the leverage effect well known in equity markets since the work of Black (1976). Volatility around the trend line (measured by the sigma coefficient) is, however, lower in the second regime.

The two regimes differ with respect to the fit between forecast and actual values. For Regime 1, the correlation between actual and forecast values is 0.229; for Regime 2, the correlation rises to 0.355. Both offer higher correlations than the linear model's 0.090. These results strongly suggest that the linear model is misspecified and that

**Exhibit 2**
**TAR Results for the Subperiod 1980–95**

| | Regime 1 | *t*-Statistic | Regime 2 | *t*-Statistic |
|---|---|---|---|---|
| Panel A: U.S. Results | | | | |
| $\alpha$ | 0.354 | 2.8 | −0.088 | −1.0 |
| $\beta$ | −0.060 | −2.8 | 0.019 | 1.2 |
| $\gamma$ | 0.001 | 3.0 | <0.001 | −2.3 |
| $\sigma$ | 0.041 | | 0.029 | |
| P(S1) = .429 | $P_{11}$ = .944 | $P_{12}$ = .056 | $P_{21}$ = .042 | $P_{22}$ = .958 |
| Correlations | S1 = 0.263 | S2 = 0.331 | AR = 0.141 | |
| Panel B: U.K. Results | | | | |
| $\alpha$ | 0.724 | 3.8 | 0.034 | 0.2 |
| $\beta$ | −0.102 | −3.7 | 0.001 | <0.1 |
| $\gamma$ | <0.001 | 2.5 | −0.001 | −3.6 |
| $\sigma$ | 0.064 | | 0.060 | |
| P(S1) = .585 | $P_{11}$ = .872 | $P_{12}$ = .128 | $P_{21}$ = .179 | $P_{22}$ = .821 |
| Correlations | S1 = 0.319 | S2 = 0.336 | AR = 0.185 | |

This exhibit shows the coefficients and *t*-Statistics for the TAR model for the sub-period 1980–95. Regime 1 has below threshold real interest rates and Regime 2 has higher interest rates. As before, P(S1) is the proportion of time spent in Regime 1: P(S2) = 1 − P(S1). $P_{11}$ shows the probability of remaining in Regime 1 in the next period, given that one is in Regime 1 now, $P_{12}$ shows the probability of moving from Regime 1 to Regime 2, and so on. The correlations shown are between the forecast values and the actual values for TAR Regime 1 (S1), Regime 2 (S2) and for the linear autoregressive model (AR). Real interest rate threshold value separating regimes in Panel A is 2.7%. Real interest rate threshold value separating regimes in Panel B is 5.4%.

the TAR model offers superior forecasting ability. Although the relatively low $R^2$ values indicate that the model will not provide accurate point estimates of price changes, the correlations are such that it should theoretically be possible to generate useable trading rules. Given the high persistence of regimes, one might adopt a contrarian strategy in regime one and sell in regime two. The effectiveness would depend on the holding period, which possibly requires further analysis. Operationalizing rules would require a forecast of interest rates (perhaps using the yield curve or, in the U.K., the spread between index-linked and conventional gilts). These, and related, questions will be the subject of a further article.

The full sample U.K. property company results (shown in Panel B of Exhibit 1) are remarkably similar to the U.S. REIT behavior. The threshold value separating regimes is higher at 5.5% with 75% of observations falling into the first, lower real rate regime. The first regime is persistent (with a probability of remaining in the regime being 0.93), while the probability of remaining in Regime 2 is lower at 0.797.

The behavior in the two regimes follows the same pattern as U.S. REITs. Regime 1 shows mean reversion about a positive trend with significant $\alpha$ and $\gamma$ coefficients and a significant and negative $\beta$ coefficient. Regime 2 follows a random walk around a negative trend: the $\gamma$ coefficient is strongly negatively significant. In the U.K. case, the absolute value of the $\gamma$ trend coefficient is larger in Regime 2 than in Regime 1. In aggregate, prices fall more sharply in Regime 2 than they rise in Regime 1—again consistent with the Black (1976) leverage effect.

In the UK, the correlation between forecast and actual values is higher for Regime 2 (0.342) than for Regime 1 (0.199) although both are higher than for the linear model (0.148). Furthermore, the root mean square error in Regime 2 is lower than that for Regime 1. This implies that knowledge of regime tells us when price changes may be forecastable. This, once again, points to the possibility of developing operational trading rules.

The early part of the analysis period coincides with considerable instability in financial markets with the impact of oil price shocks and the breakdown of the Bretton Woods currency framework being reflected in global interest rates and inflation. To test the stability of the results, both U.S. REIT and U.K. property company performance were reanalyzed for a subsample of the data beginning in January 1980. The results, shown in Panels A and B of Exhibit 2, are remarkably consistent with the findings over the whole time series. In both cases, the same distinct patterns of behavior are observed across high and low interest regimes.

## Conclusion

This article has presented two models of commercial real estate performance. The interest rate regime-based TAR model seems to offer advantages over the more conventional linear autoregressive process. First, in both markets, the correlation between forecast and actual values is higher for the TAR model than for the linear autoregressive model. Second, and perhaps more significantly, the TAR model identifies distinct patterns of behavior in each regime. This implies that the linear model may be prone to misspecification errors. The results largely confirm the contention that the real rate of interest plays a significant role as an indicator of real estate performance in both the U.K. and the U.S.

A major advantage of the TAR model is that it does not require a forecast of the real interest rate, performing well while only using the lagged interest rate $X_{t-1}$. While the $R^2$ values from the model are not high, it should be recalled that we are working with price changes, not levels. The observed correlations within regimes of 0.3 or above may be sufficient to develop trading rules. Since the behavior across regimes is so different, and since the regimes are highly persistent, knowledge of the likely regime could point to the adoption of distinct investment strategies.

In the high interest rate regimes, it seems that indirect property indices fall sharply down their trend line. In lower interest rate environments, prices exhibit mean-reverting behavior around an upward trend. In general, the results suggest that the price/return falls in high real interest environments are sharper than the rises associated with lower real rates. If this pattern can be translated to the underlying private real estate ownership market, it may imply that there are asymmetries in real estate performance. This would impact upon the way in which researchers should approach the analysis of real estate cycles. The results fit an intuitive view of the property boom and bust cycle with a rapid and severe downward ‘‘correction’’ being followed by a longer and more erratic climb back to a local peak.

It is quite feasible that there may be more than two interest rate regimes. The TAR approach can attempt to identify such regimes and incorporate longer lag structures. Similarly, there might be other state variables that define relevant regimes for real estate. These might include other, non-interest rate macro-variables influencing demand and supply. TAR models do not require a single variable in defining regimes. The threshold variable could, for example, be derived from a vector of variables identified as relevant to price formation. Other extensions of the work might include investigation of regime-based structures in the direct, private ownership market. This poses problems in terms of data frequency and data reliability. Another avenue to explore might be to work with an unleveraged real estate equity market series or with an index with overall common stock market effects removed (see Lizieri and Satchell, 1997a, for a critique of such an approach). We leave these for later research.

Our main intention was to investigate whether regime-switching models can provide useful insights into the performance of publicly traded real estate. The fact that our TAR model identified clear regimes for both the U.S. and U.K. data sets—and that the behavior patterns observed in high and low interest rate regimes were remarkably similar in both countries—is highly persuasive. Although the two-regime real interest rate model examined above may not fully describe changes in property prices, the very different behavior observed across regimes casts doubt on the applicability of linear, one-state models and their ability to generate usable, reliable and robust trading rules.

## Notes

[1] For a real estate example see Maitland-Smith (1996).

[2] In this article, when we refer to the property or real estate equity market we refer to the U.K. property company and U.S. REIT markets that are publicly traded on stock markets, also known as the indirect or public markets. These markets differ from private ownership of land and buildings (sometimes known as equity ownership in the U.S.). It is the indirect market, traded on the stock exchange, that is the focus of our study.

[3] Equation (1) could be rewritten in terms of an error-correction formulation. This would leave all variables in differences except for the levels components of I(1) variables that correspond to a ‘‘long-run’’ equilibrium.

[4] Tsay (1986, 1989) proposed a test based on that of Petrucelli and Davis (1986). Both are based on arranged autoregression and predictive recursive residuals. A TAR model is transformed into a regular change point problem in linear regression, using the concepts of

arranged autoregression. Instead of using the time index to control the flow of data, this uses the magnitude of the threshold variable. The advantage of the Tsay procedure over Tong's algorithm is that it does provide diagnostic statistics to assess the need for a threshold model. However, there is a strong assumption that the only conceivable non-linearity is a TAR model. See Tsay (1989) for a discussion and Brock, Hseih and LeBaron (1991) for some simulation results. We follow the Tong procedure.

[5] Tong (1990) showed that for an ergodic SETAR model, the set of estimated coefficients has an asymptotic multivariate normal distribution. This result does not take into account the sampling properties of the threshold parameter, but assumes that it is known a priori. In the case of Gaussian errors, the log likelihood function is equivalent to the conditional sum of squares.

[6] Attempts to avoid this difficulty have been made by Petrucelli and Davis (1986), Moeanaddin and Tong (1988), Chan and Tong (1990) and Chan (1991).

[7] Moeanaddin and Tong (1988) demonstrate that multi-step-ahead SETAR models outforecast linear models over ''troughs'' although the reverse was true over ''peaks.'' Dacco' and Satchell (1995) show that a small misclassification when forecasting which regime the world will be in loses any advantage from knowing the correct model specification relative to (incorrectly) assuming a random walk. De Goojer and Kumar (1992) and Pemberton (1987) provide further discussion.

[8] It would also require a model with sufficiently high $R^2$ and with limited noise.

[9] The more consistent time series available for the headline rate proved persuasive in rejecting use of the underlying rate that excludes mortgage costs and certain tax items.

[10] There are two other REIT indices available in the U.S., the Wilshire Index and the Lehman Brothers Index [see Giliberto and Sidoroff (1995) for a comparison of the three indices]. The NAREIT Index has the longest series (it starts in 1971, Wilshire in 1977 and Lehman Bothers in 1991) so we can attempt to analyze the shifts in the interest rate regimes over a longer time period. Second, this Index covers the most REITs and has the largest market capitalization.

[11] It may be thought that, in testing for a random walk, appropriate tests are of the Dickey-Fuller (DF) kind with non-standard asymptotic distributions and critical values nearer three than two. That this is *not* the case is due to the result of West (1988) who shows that, in an AR(1) model with drift, a *t*-test of the hypothesis $\beta = 1$ will be asymptotically standard normal as long as the intercept (or trend, if the trend is being modeled) is non-zero under the null. Thus the appropriate *t*-Statistic for a one-sided test would be $-1.645$. If we wished to parameterize the trend $\gamma$ as $\gamma = \gamma_0 (1 - \beta)$ such that the intercept under $H_0$ would also be zero then it follows that the *t*-tests would have DF type distributions of great complexity. Simulation would be required to determine the critical values in this case. However, we do not assume such a parameterization here.

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