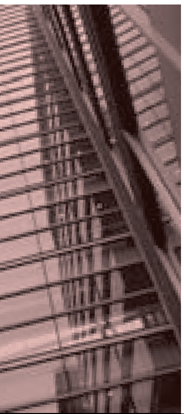
IPF Research Programme 2006-2009

Real Estate's Role in the Mixed Asset Portfolio: A Re-examination




Working Paper 2
Private Commercial Real Estate Returns and the Valuation Process

April 2012

This research was commissioned by the IPF Research Programme 2006–2009

IPF Investment Property Forum

This research was funded and commissioned through the IPF Research Programme 2006–2009, funded by a cross-section of 24 businesses, representing key market participants, together with a contribution from the Barkshire Committee.

This Programme has supported the IPF's wider goals of enhancing the knowledge, understanding and efficiency of property as an investment class. The initiative has provided the UK property investment market with the ability to deliver substantial, objective and high-quality analysis on a structured basis. It will enable the whole industry to engage with other financial markets, the wider business community and government on a range of complementary issues.

The IPF gratefully acknowledges the support of the following contributing organisations to the Research Programme 2006–2009.

Addleshaw Goddard
British Land
Credit Suisse
Deloitte.
DLA Piper
DTZ
GIC Real Estate
Grosvenor
GVA
Hammerson
Helical Bar plc
IPD
Kenmore property group
Knight Frank
LandSecurities
LaSalle Investment Management
Legal & General
Aviva Investors
Nabarro Clarity Matters
PRUPIM
Quintain
Standard Life Investments
Strutt & Parker
Scottish Widows Investment Partnership

Working Paper 2

IPF Research Programme 2006–2009

April 2012

Research team

Colin Lizieri, *University of Cambridge*

Jamie Alcock, *University of Cambridge*

Steve Satchell, *Trinity College, Cambridge and the University of Sydney*

Eva Steiner, *University of Cambridge*

Warapong Wongwachara, *University of East Anglia*

Research steering group

Asli Ball, *GIC*

Russell Chaplin, *Aberdeen Asset Management*

Pam Craddock, *Investment Property Forum*

Sue Forster, *Investment Property Forum*

Guy Morrell, *HSBC Global Asset Management (UK) Limited*

Ben Sanderson, *Hermes Fund Managers Limited*

CONTENTS

1. EXECUTIVE SUMMARY

- This paper is the second of four working papers re-examining the role of real estate in mixed asset portfolios for the Investment Property Forum. In it the behaviour of valuation-based measures of the commercial property market are examined. In particular, the extent to which the behaviour of real estate returns and the valuation of property vary in different economic states is investigated.
- The thinly traded commercial real estate market relies on periodic valuations to construct market performance measures. Valuers draw on historic transaction data and prior valuations as a basis for their appraisals. As a result, valuation-based return series will tend to lag the underlying market and dampen reported volatility in the market – valuation smoothing. Smoothing effects are much more pronounced in high-frequency return series such as monthly indices, where valuers tend to undertake desk-based valuations and update prior valuations. Over longer time periods, the effects diminish.
- Uncritical use of valuation-based series in portfolio allocation models could lead to sub-optimal weightings to property. Techniques exist to **desmooth** property indices – attempting to estimate the true underlying pattern of returns in the market. However, standard desmoothing techniques typically assume that smoothing effects are constant over time and make strong assumptions about return processes.
- Research in real estate and other asset markets suggest that both underlying market behaviour and valuer behaviour may vary over the market cycle. This suggests that analysis based on the existence of distinct market regimes – states of the world determined by particular economic conditions – may be helpful in understanding the dynamics of property returns.
- The research uses econometric approaches to test whether both the return process and the valuation smoothing process vary over time, dependent on the state of the economy or wider market conditions. The technique used is a **Threshold Autoregression** or TAR model. These models test whether the returns can be better characterised as deriving from processes which differ according to economic state – for example, if the economy is in recession or is booming.
- The results of two TAR models are reported: a model where valuation smoothing is assumed to be constant across time but the return process varies according to market conditions; and a second model, where both valuation smoothing and underlying return processes are assumed to vary according to market conditions.
- Commercial real estate performance is measured using the IPD Monthly Index. To match with some of the aggregate macro-economic variables, this was aggregated to quarterly returns. Initially, data from 1986 to 2008 were analysed, to take in the onset of the property market correction. They were then reanalysed the data to mid-2011, to provide robustness checks and to assess the continuing impact of global financial instability.
- A number of factors thought to drive commercial property returns were tested. An output measure of GDP and changes in service employment was used to test whether behaviour varied over the economic cycle. Returns from the FT All Share Index were used to investigate linkage between equity returns and the property market. The impact of interest rates was analysed, using three-month LIBOR as a reference value. ONS's RPIX index was used to test property–inflation linkages. Given the growing importance of foreign investment in real estate, the research included an exchange rate variable, the US$ rate against sterling. Finally, as an **internal** indicator of the property market, a yield or cap rate measure was included: after testing, IPD's All Property initial yield figure was utilised.

1. EXECUTIVE SUMMARY

- As with prior research, the high autocorrelation and low relative risk of the valuation-based IPD total return index gives credence to suggestions that the series is smoothed due to valuer behaviour. The models provide strong evidence of smoothing behaviour, with almost all variables generating high values of alpha, the smoothing parameter.
- Examining, first, variation in return processes with constant smoothing, the best models used GDP, LIBOR or FT returns, with the FT regimes best able to capture periods of poor real estate performance. The LIBOR regime model suggests that when interest rates rise above a threshold value, property returns become negative with strong downward momentum, emphasising the downside risk inherent in leverage.
- With FT returns defining real estate market behaviour, it appears that property returns are positive and stable when equity markets are positive. However, falling equity prices are linked to sharply falling property returns. Fortunately these low regimes tend to be short-lived.
- The second set of models provide evidence that valuer behaviour is also time-varying, with smoothing more evident and stronger in the poorly performing down market states. Equity returns provide the best indicator of valuer behaviour, with very high levels of smoothing occurring when the equity market is in a 'bad' regime of sharply falling prices. This coincides with falling underlying property returns.
- The results from the analysis from 1987 to 2008 and those of the models that include the post-market correction period from 2009 to mid-2011 are broadly consistent, with similar outcomes. However, it does appear that, after including the period following the onset of the global financial crisis, the commercial property market has become more sensitive to interest rates shocks.
- Examining the smoothing coefficients in the models using FT as a regime indicator gives some support for the suggestion that valuers marked capital values down more sharply in the 2007–2008 correction than in the 1990 downturn and were prepared to use evidence external to the market.
- The findings have implications for risk management and portfolio strategy. First, they suggest that the dynamics of real estate returns must be considered carefully. Second, the results suggest that return distributions are asymmetric and, critically, that the relationship between equity markets and property markets is asymmetric and time-varying. Third, the results again highlight the importance of the relationship between real estate risk and interest rates.

2. INTRODUCTION

This is the second working paper from the Investment Property Forum funded project re-examining the 'case for property' in multi-asset portfolios. The project seeks to explore the nature of commercial real estate returns in the light of the performance of the asset class over the recent financial turmoil and the apparent failure of property to provide the diversification gains hoped for in mixed-asset portfolios. The project focuses on the dimensions of risk in property markets, the factors that drive returns, the relationship between real estate and other investment assets and the extent to which those relationships vary over time and are asymmetric in nature. This paper focuses on the valuation process and its impact on the measurement of risk and return. In particular, the research tests whether there are distinct smoothing regimes – periods in the market where the return processes and the behaviour of valuers are distinct and significant.

The research starts with a review of the literature on the impact of valuation methods on the measurement of real estate performance and the ways in which smoothing can be removed and the underlying market performance be recovered. It is argued that many of the conventional smoothing models do not deal explicitly with the fact that individual property transaction prices are noisy signals of the 'fundamental value' of the asset and smoothing models must deal simultaneously with the return process and any smoothing. The research then briefly examines the literature on time varying return behaviour which points to the existence of 'regimes' – states of the market with distinct real estate return behaviour. Next, an intuitive description of the models used in the paper is provided (with full mathematical details available in an appendix), and the choice of variables that might drive regime behaviour in commercial property is discussed. The research then examines UK commercial real estate returns, analysing IPD returns on a quarterly basis from 1986 to 2008. The results indicate the presence both of return regimes and smoothing regimes where the regimes can be defined either in terms of equity market or interest rate behaviour. The results have strong implications for asset allocation and risk management in mixed-asset portfolios and point to the possibility of asymmetric relationships between real estate and equity markets, affecting the diversification benefits of commercial property.

3. REVIEWING THE LITERATURE

Reported private property performance derives from valuations rather than actual sales transactions. It is argued that this 'smoothes' the reported returns as a result of valuer behaviour. This section reviews the research on valuation smoothing and its implications.

Reported property returns differ from those of financial assets in that they rely on valuations to measure periodic capital growth and income return. It has been argued that this practice results in 'smoothing' of the reported returns. Temporal aggregation (the spread in the timing of valuations around the quoted valuation date) and lagging effects (both from anchoring on prior valuations and from use of comparables from before the valuation) produce serial correlation in return series, and dampen reported volatility measures. In turn, this has implications for the use of real estate indices in asset allocation and performance measurement applications (Quan and Quigley 1991, Geltner et al. 2003). Reliance on a smoothed measure of real estate performance in the asset allocation process could lead to excess weights in property, distorting performance metrics and, critically, providing misleading information for risk management systems.

As it is often ignored in discussions on valuation smoothing, it is worth stressing that, in the original Quan and Quigley paper, it was argued that appraiser behaviour in smoothing was not irrational. In their model, the price paid for an individual asset is a noisy signal of the true, underlying value of that property (as a result of the heterogeneity of property and the nature of private markets where buyers do not have complete information on the assets they are considering and have less information than sellers for any individual property – information asymmetry). As a result, valuers cannot rely on the most recent sale price since that price might reflect random errors made in the sale process. As a result their valuation, rationally, will be a blend of the most recent and older sales information, creating a lagging effect. This process interacts with sales activity. In general, since commercial property is thinly traded, smoothing effects will be greater than in more actively traded markets. More particularly, smoothing effects will be greater in states of the market where there are few deals and less where there are many transactions to aid the valuation process. As a result, smoothing processes might be time-varying.[1]

While there is a rational component to valuation smoothing, behavioural factors are also likely to play a part. Experimental studies provide evidence that valuers exhibit 'anchoring' – that is, the valuation of an asset is influenced by a prior valuation such that the full information available to the valuer is not used in the appraisal. This is likely to be significant where there are repeated valuations of the same property at regular intervals with the prior valuation known to the valuer – as would be the case with monthly or quarterly valuations on the IPD index. Smoothing effects are thus likely to be more pronounced with higher-frequency data. Confirmation of this effect can be seen empirically: the serial correlation in returns for the IPD monthly All Property Total Return Index (from December 1986 to May 2011) falls from 0.903 with a lag of one month, to 0.760 with a three-month lag, 0.511 with a six-month lag to just 0.176 with a one-year lag – which could, in large measure, be attributed to the impact of stable rental income as much as a valuation effect (monthly income return has a correlation of 0.748 with income return 12 months earlier, suggesting that capital value change dominates volatility in commercial property).

[1] Analysing the evidence in the IPD/RICS (2010) Valuation and Sales Report suggests that valuation error is negatively correlated with sales rate, sales volume and capital return.

3. REVIEWING THE LITERATURE

Nonetheless, evidence exists to suggest that there is a behavioural component to valuation behaviour that helps to explain observed smoothing and serial correlation. In particular, it has been argued that valuers are subject to 'anchoring' behaviour – well-described by the founders of behavioural finance, Tversky and Kahneman (1974):

> *'In many situations, people make estimates by starting from an initial value that is adjusted to yield the final answer. The initial value, or starting point, may be suggested by the formulation of the problem, or it may be the result of a partial computation. In either case, adjustments are typically insufficient. That is, different starting points yield different estimates, which are biased toward initial values.' (Tversky and Kahneman, 1974, p. 1174)*

Experimental evidence suggests that anchoring is widespread among professional real estate valuers when they assess both commercial and residential property. Diaz and Hansz (2007) present a recent summary of this literature. Gallimore (1994, 1996) finds significant evidence of heuristic-driven behaviour among residential valuers including a general tendency to form an early judgement and subsequently seek evidence to justify it. Diaz and Wolverton (1998) find evidence of anchoring based on previous estimates and insufficient updating of estimates in the light of new information, known as appraisal smoothing, a direct confirmation of the anchoring-and-adjustment mechanism proposed by Tversky and Kahneman. Diaz (1997) suggests that where valuers were experts making valuations in areas familiar to them, anchoring biases are significantly reduced or even eliminated.

Conventional valuation-based unsmoothing methodology (Geltner 1991, 1993, Fisher, Geltner and Webb 1994, Cho, Kawaguchi and Shilling 2003, Booth and Marcato 2004, Marcato and Key 2007a,b) has proved successful in the sense that it generates higher volatility in the unsmoothed returns than in the observed 'smoothed' returns, and tends to reduce lagging effects when compared to public listed real estate indices. These results have influenced investor attitudes on the risk of property as an asset class. Further confirmation of this is provided by the development of repeat sales transaction-based indices such as the MIT series for the US, which show significantly higher variance of returns (see eg Fisher et al. 2003) with standard deviations broadly comparable to those generated by desmoothing processes.

Nevertheless, a number of studies have shown that private commercial property returns still appear to have significantly better risk-hedging characteristics than other asset classes (eg Hudson-Wilson, Fabozzi and Gordon 2003, Worzala and Sirmans 2003, Bond et al. 2007b). Measures of volatility for unsmoothed series still seem too low in relation to the returns of financial assets and the use of unsmoothed data in conventional asset allocation optimisers still produces weightings that out of line with professional investor practice. This has been attributed to an additional ex ante liquidity premium that is not accounted for in conventional returns (IPF, 2004; Bond et al. 2007a), to investors' inability to diversify away specific risk fully due to large lot size (Baum, 2009) or to the distributional characteristics of real estate returns (Young 2007).

3.1 Desmoothing and Regime-Switching Behaviour

In this paper, it is argued that the conventional unsmoothing methodology is not completely satisfactory because it ignores non-linearity in the data and regime-switching behaviour in particular. The underlying concept behind regime-switching models is straightforward. The model assumes that there are two or more distinct regimes – market states – between which the behaviour of an investment asset differs. For example, for a two-regime state there might be high-volatility and low-volatility regimes or market states or, for a three-regime state, there might be distinct periods when asset values are falling sharply, rising slowly or rising rapidly. The term market state here denotes a set of economic conditions that are thought to influence the return series under investigation, so might relate to aggregate economic measures such as GDP or an individual economic variable such as the real interest rate. In principle, it would be possible to define the market states 'internally' – that is, in relation to the returns themselves. However, this masks the underlying factors driving returns.

From a real estate market perspective, the regimes might relate to the factors that drive stages in the property cycle – in particular where a 'bad' regime identifies a period when there are rapid falls in real estate prices – for example where there is a market correction following prolonged (and unsustainable) growth in the economy feeding into rapidly rising asset values followed by an economic shock such as a sharp increase in interest rates. In such a regime, given that real estate is a private market, it is likely that transaction activity will fall sharply (property purchases on the IPD databank in 2008 were 80% below the number of acquisitions in 2006). As a result, valuers have less transaction-based information to inform their appraisals and may draw on earlier sales or rely more heavily on prior valuations as a result. While, anecdotally, valuers in the 2007–2008 downturn used wider information than in previous corrections, it is still possible that reported property market behaviour will vary by market regime or environment.

The empirical tasks, then, are:

- (a) to identify whether or not distinct regimes exist;
- (b) to determine asset behaviour within each regime; and
- (c) to estimate the probability that the asset remains in its current regime in the next period.

Application of regime-switching models in financial markets is not uncommon (for example there are applications to stock returns (Li and Lam 1995), to exchange rate changes (Alba and Park 2005), and to property returns (Lizieri et al. 1998). Regime-switching behaviour seems highly plausible for real estate returns which exhibit episodes of booms and busts due to the cyclical nature of property and credit markets. The strategy used here is to employ a family of Threshold Autoregressive (TAR) models (Tong 1978, 1990), in effect, allowing for some non-stationarity. The regimes will be determined by variables that, from prior research, are known to influence real estate returns: candidates include macro-economic indicators such as GDP, returns from other asset markets, interest rate variables and inflation. TAR models have been used in real estate applications previously (Lizieri et al. 1998, Brooks and Maitland-Smith 1999): the research provides an extension and application to return measurement.

The prior expectation is that the unsmoothing methodology based on TAR models will provide evidence of additional 'built-in' volatility in real estate returns. In earlier research, Chaplin (1997) attempted to incorporate regimes into the unsmoothing methodology. He assumed that real estate returns were normally distributed, and divided them into six regimes with predetermined unsmoothing parameters (his theoretical framework follows Quan and Quigley's approach, but the values are asserted not estimated). The methodology is more general in two main aspects. First, regimes may be defined in terms of property returns themselves (eg into periods of high, average and low returns as Chaplin (1997) does) or in terms of exogenous variables driving property performance such as macroeconomic factors, credit conditions and similar factors. Second, the threshold value can be estimated, rather than imposed.

3.2 Summary

- The thinly traded commercial real estate market relies on periodic valuations to construct measures of market performance;
- Valuers draw on historic transaction data and prior valuations as a basis for their appraisals;
- As a result, valuation-based return series will tend to lag the underlying market and dampen reported volatility in the market – valuation smoothing;
- Smoothing effects are much more pronounced in high frequency return series such as monthly indices;
- Uncritical use of valuation-based series could lead to sub-optimal portfolio allocations to property;
- Techniques exist to 'desmooth' property indices – attempting to estimate the true underlying pattern of returns in the market;
- Standard desmoothing techniques typically assume that smoothing effects are constant over time;
- Both underlying market behaviour and valuer behaviour may vary over the market cycle;
- This suggests that analysis based on the existence of distinct market regimes may be helpful in identifying the underlying nature of risk in property markets and the conditions where risk is most pronounced.

4. THE MODELS EXPLAINED

In this brief section, the basic statistical ideas underlying the TAR models that are used to test for the existence of return and smoothing regimes in commercial property are introduced. Full technical details are available in an appendix.

Appendix A in this paper sets out mathematically the nature of the models employed. This short section attempts to provide an intuitive understanding, first, of the 'standard' Quan and Quigley model and, second, of the various TAR regime approaches analysed in the report.

In the absence of regimes or asymmetries, the essential return process in real estate markets can be described as an autoregressive process where today's return consists of three components: a trend component (that is, over the long-run, returns grow at a particular steady rate); an autoregressive component (that is, today's return is linked to the previous period's return – as would be the case if there were cycles or periods of boom and bust); and a random component that is specific to the time period. This can be written as:

Equation 4.1:

$$r_t = \gamma + \phi r_{t-1} + \varepsilon_t$$

where r_t is this period's return, γ is the drift or trend term, ϕ is the autoregressive term and ε is the error term.

In general, the constant term, γ, might be expected to be zero (if the series is stationary) or positive (if it is believed there is long-run growth). While very long run data sets typically indicate that real estate values do no more than keep pace with inflation, for shorter periods, the expectation is that the constant will be positive for nominal returns, that is, average property returns are expected to be positive. The momentum term, ϕ, should be less than one, more than –1 and will be positive if returns are 'sticky' – that is, if there is a cycle or prolonged periods of positive and negative returns or momentum effects – or negative if returns that are above trend are followed by negative returns to correct back to trend). The error terms are unpredictable and, on average, zero.

The valuation-based series reported (r^*_t) is a weighted average of the 'true' return from the previous equation and the previously reported valuation return, for the reasons discussed above:

Equation 4.2:

$$r^*_t = \alpha r_t + (1 - \alpha)\, r^*_{t-1}$$

In conventional desmoothing approaches, 'recover' the underlying true return is 'recovered' by assuming or estimating a value for alpha (the 'smoothing parameter') and then rearranging the equation to isolate the 'true' return. However, given the existence of the error term in the return process equation, this is not a complete process and, strictly, the research should account for the noise in the true return series simultaneously. This is done iteratively: an estimate of alpha, fixing phi and gamma is obtained aiming to minimise the residual or sum of squared errors (SSE) in the equation, then fix value of alpha and estimate a new phi and gamma and continue recursively until the change in the model residual error stabilises. The regime-based approach builds on this standard model by allowing one or more of the parameters to vary by market state or economic conditions. Suppose, first, that the underlying return process is regime based (for example, that returns generally rise, but that there are periods of downward 'correction') but the valuation-smoothing process is constant over time. This is described as an AR-TAR process. Thus, the values of gamma (the trend term) and phi (the return auto-regression) are estimated for each state from the reported, valuation-based, series, while keeping the smoothing parameter, alpha, constant. The regimes are defined in terms of the value of a 'state variable' – as an example, this might be economic growth: for a two-regime model the research separates observations into a 'high state' and a 'low state', again finding the boundary by searching for the solution that minimises estimation error.

The AR-TAR model assumes that valuation smoothing does not vary by market environment: however, there is evidence that this may not be the case. Therefore, a double-regime model is estimated – which is described as a TAR-TAR process. Here, both the underlying market processes and the valuation process are regime based. The two sets of regimes may be defined by the same state variable or different state variables (for example return regimes may relate to general economic growth but smoothing regimes may be determined by interest rates). The estimation procedures are the same as for the AR-TAR approach, if more complex to undertake. In principle, there might be a TAR-AR process (where smoothing varies by regime but the return process is constant). This is considered unlikely, and empirical tests are unsatisfactory, so those results are not reported here.

4.1 Summary

- Fundamental, underlying property returns should follow a regular process where each return reflects long-term growth, the immediate prior return (due to momentum and cyclical effects) and random, 'noise' effects particular to an individual time period – an autoregressive or AR process;
- Reported valuations blend the true underlying price with prior valuation(s) such that the reported series is smoothed and exhibits lower volatility than the underlying returns;
- Conventional desmoothing methods aim to remove valuation effects and 'recover' the underlying price series but rely on assumptions about the underlying return process;
- Regime-based approaches suggest that the return process and/or the smoothing process vary over time, dependent on the state of the economy or wider market conditions;
- Two threshold autoregressive (TAR) regime-based models are to be estimated: an AR-TAR process where valuation smoothing is assumed to be constant across time but the return process varies according to market conditions; and a TAR-TAR process, where both valuation smoothing and underlying return processes are assumed to vary according to market conditions.

5. THE CHOICE OF STATE VARIABLES

To test for the existence of regimes, it is necessary to specify the variables that might define the different states of the world. These could simply relate to property returns – but it is more helpful to think of external factors such as economic growth or interest rates. Here the research considers which variables are most appropriate for testing in the TAR models. The data employed in this study is then detailed.

To investigate the possible existence of return and smoothing regimes using TAR models, one or more regime indicators are required. The variables tested were reselected based on prior research on the drivers of private real estate return behaviour. The underlying rationale is, first, that the real estate return-generating process may be time-varying, dependent on (exogenous or endogenous) market conditions; and, second, that appraiser behaviour may vary in different market environments, influenced, for example, by transaction volumes, volatility, uncertainty and a variety of other information-linked factors. Specifically, interest rate variables, demand indicators, performance measures from the real estate market, a measure of inflation and an exchange rate variable were examined. These were used to test explicitly whether the return-generating processes and valuers' smoothing behaviour varied by regime, with the error terms from the models and the plausibility of the coefficients and diagnostics of the 'recovered' series used to select the 'best' indicators.[2]

Most studies indicate that, as expected, real estate returns are strongly influenced by interest rates. Indeed, prior applications of TAR models in real estate (Lizieri et al. 1998, Brooks and Maitland-Smith 1999) both use real interest rates to determine thresholds. Lizieri et al. suggest that in the high interest rate environment, real estate exhibits greater volatility and sharply falling values than in low-interest-rate regimes, attributed to a leverage effect. The research thus tests whether behaviour varies in different interest rate environments.

Many models of real estate rents and capital values utilise an aggregate demand measure. A GDP measure will enable testing of whether property or appraiser behaviour differs in boom and recessionary periods.[3] As a further indicator of macro-economic conditions, service sector employment is examined, as a proxy for space demand (particularly in the office and retail sectors that dominate UK institutional real estate investment).

A financial asset indicator is also employed, based on a broad equity market index. This can be justified as an extension of the market model (Ling and Naranjo 1997, 2000, Wike and Gillen 2008); furthermore, given the growing attention on tail dependence (and, in particular, asymmetric tail dependence – see Knight, Lizieri and Satchell 2005 for a real estate example and Working Paper 1 from this IPF project for a review), upward and downward spikes in equity prices may be associated with capital market conditions that are adverse or positive for real estate, influencing both return processes and valuer behaviour.

A real estate market indicator is included, the initial yield (the ratio of rent payable to capital value). This is, in part, endogenous, in that the yield represents the spot cash return on investment, and changes in yield (in effect the capitalization rate) drive shifts in capital values. However, with the growing attention on credit cycles, asset bubbles and the role of real assets as collateral, movements of the yield away from long-run average values might indicate that prices have moved above or below their fundamental economic values, presaging a correction.

[2] Specifically, the research tested which indicators (and which values of those indicators) minimised the sum of squared errors as a measure of goodness of fit.

[3] The UK does not have an equivalent to the NBER recession indicator – but, in any case, regimes might be defined in terms of higher and lower growth rather than falls and increases in output.

5. THE CHOICE OF STATE VARIABLES

Given that part of the case made for investment in real estate lies in its supposed 'inflation hedging' properties (although evidence for this is mixed, particularly regarding unexpected inflation: see Hoesli, Lizieri and MacGregor 2008, and IPF 2011 for reviews), the research includes tests using RPIX as a broad measure of UK inflation.[4] Finally, given that real estate investment is increasingly global, and because changes in the exchange rate reflect expectations regarding national economic performance, the USD–GBP exchange rate is examined.[5]

5.1 Data Employed

The measure of private real estate returns is the log difference of the IPD UK Total Return Index for all property. Monthly data testing is utilised, initially the period from December 1986 to December 2008, thus including the onset of the market correction at the end of the period; the research then reanalyses the data to mid-2011 to provide robustness checks over the period following the global financial crisis. While the IPD monthly index does not completely track the IPD annual index, it represents institutional and professional investor holdings of real estate with a capital value of £32.5billion as at December 2008 and records of over 3,500 properties. The analysis, however, utilises quarterly returns. First, a number of the macro-economic regime indicators are only available quarterly; second, since monthly valuations frequently represent a simple desk-based update, and with greater information available on a quarterly basis, this may represent a more robust frequency compared to the more noisy monthly series.[6]

It is noted here that aggregating data from monthly to quarterly (or quarterly to annual) will often alter the dynamics of time series models. For example, consider three consecutive months' returns, where months one and two were in regime A and month three was in regime B. The quarterly return would represent a blend of effects from the two regimes. However, there is no time aggregation theory available for the regime-switching TAR model, still less for the newly developed TAR-TAR. This is an area for future research. For the present, only quarterly results are reported. This is consistent with the widest availability of data series for all the regime variables: it generates plausible empirical results; and it avoids the extreme serial correlation evident in the monthly appraisal-based real estate returns.

For potential regime indicators, as an interest rate variable the three-month UK LIBOR rate (as at the end of each quarter) is included, as set by the British Bankers Association and sourced from the Bank of England's statistics site. UK GDP growth is tested, using an output measure sourced from the Office for National Statistics, which also provided the employment measure, a seasonally adjusted measure of UK service employment. As an equity market index, the Financial Times All Share Total Return index (drawn from DataStream) is used. Initial yield data was sourced from IPD. As an inflation measure, the all-items Retail Price Index excluding mortgage interest (RPIX) is used, again from the Office for National Statistics. Finally, the exchange rate variable was the dollar sterling USD–GBP spot rate, drawn from Bank of England statistics. Descriptive statistics for these variables are shown in Table 5.

[4] RPI is used rather than CPI to provide comparability with prior studies of the relationship between real estate and inflation and since, for the vast majority of the period, inflation-linked liabilities were typically benchmarked to RPI.

[5] Bank lending variables are also considered as a measure of credit availability, financial and business service employment, Treasury Bill rates and household consumption data. Results from these variables are not presented here, for reasons of space. Generally, the variables had unsatisfactory statistical properties and/or were closely correlated with variables analysed in this paper.

[6] All properties in the IPD monthly index must be appraised every month – the 'stale appraisal' issue found in the NCREIF index does not apply to IPD, although quarterly and annual appraisals of properties not in the monthly index may influence results. Cho, Kawaguchi and Shilling (2003) find an insignificant coefficient on the fourth-quarter lagged return in their proposed revision to the standard unsmoothing model. The data show rapidly falling autocorrelation statistics, from 0.81 with a lag of one quarter to 0.42 after four quarters, suggesting more of an echo of the serial correlation than a clear information effect. The IPD monthly first-order serial correlation exceeds 0.9.

Table 5.1: Descriptive statistics main variables

Variables	Mean	Median	Max	Min	S.D.	Skewness	Kurtosis
IPD Returns r^t	2.15	2.53	8.03	–14.51	3.25	–1.98	10.67
LIBOR	7.20	6.04	15.25	2.83	3.18	1.20	3.44
Inflation	0.80	0.75	2.73	–0.57	0.63	0.85	4.22
Real interest	6.39	5.55	13.81	2.67	2.88	1.10	3.29
Initial yield	6.74	6.96	9.09	4.57	1.18	–0.06	2.16
Exchange rate	1.68	1.65	2.04	1.41	0.16	0.45	2.32
FT returns	2.02	3.53	18.84	–32.00	8.59	–1.08	5.31
GDP	0.60	0.65	2.20	–1.80	0.57	–1.15	7.01
Employment	29,240	29,030	31,661	26,762	1,386	0.24	1.85

The table shows descriptive statistics for the IPD returns and regime indicator variables. All returns are aggregated quarterly.

5.2 Summary

- Commercial real estate performance was measured using the IPD Monthly Index. To match with some of the aggregate macro-economic variables, this was aggregated to quarterly returns;
- The research initially analysed the data from 1986 to 2008, to take in the onset of the property market correction. It then reanalysed the data to mid-2011, to provide robustness checks and to assess the continuing impact of global financial instability;
- The choice of variables for analysis and for definition of regimes was determined by prior research on the external factors thought to drive commercial property returns;
- As an aggregate measure of demand in the economy, an output measure of GDP and changes in service employment were used to test whether return and valuer behaviour varied over the economic cycle;
- Returns from the FT All Share Index were used as a broad indicator of investment market performance and to investigate linkage between equity returns and the property market;
- Since prior research has shown that real estate values are sensitive to interest rates, the impact of interest rates was analysed, using three-month LIBOR as a reference value;
- As there is renewed interest in the inflation-hedging qualities of real estate, ONS's RPIX index of UK retail inflation was used;
- Given the growing importance of foreign investment in real estate, an exchange rate variable, the US$ rate against sterling, was included;
- Finally, as an 'internal' indicator of the property market, a yield or cap rate measure was included: after testing, the research utilised IPD's all-property initial yield figure.

6. EMPIRICAL RESULTS

In this section the results from the standard and regime-based analyses of UK IPD All Property total returns are presented. The research finds that return behaviour and valuation processes are affected by the interest rate, equity market and macro-economic variables.

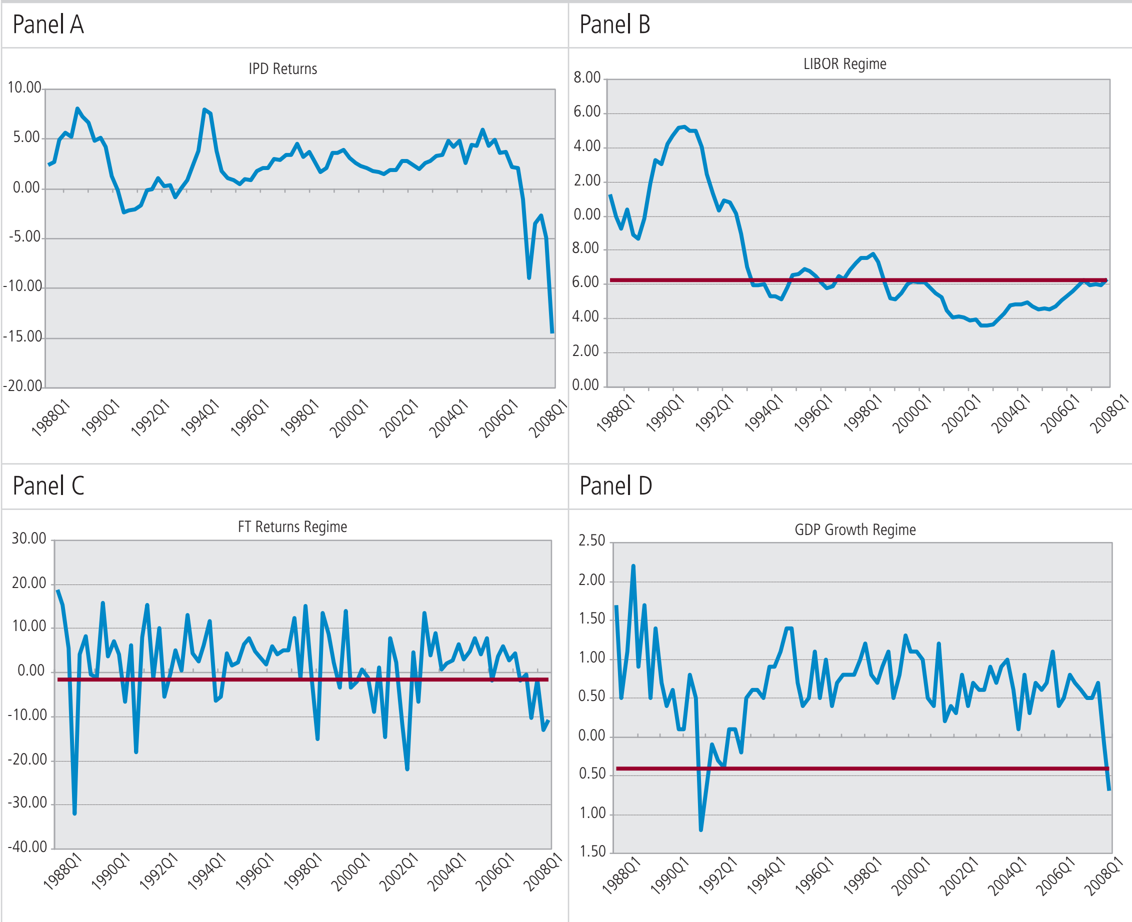
6.1 The AR and AR-TAR models

This section presents the analytic results from the analyses. First, the 1986–2008 quarterly results of the TAR models and the base case AR model are presented in Table 6.1. The estimated values for α and ϕ from the AR method are in line with the literature – the smoothing parameter is greater than half, while the lagged coefficient is relatively small in size, denoting small but non-zero autocorrelation in returns. For the TAR models, smoothing parameters vary between 0.1 (employment) and 0.9 (exchange rate) depending on the regime indicator. The smaller figure is the exception; most models show the expected high levels of smoothing. The best-performing TAR models, as measured by size of SSE, are the FT returns, LIBOR and GDP models (employment has a relatively low SSE, but is not analysed further given the insignificant smoothing parameter). In terms of SSE, the best-performing model is that defined by FT returns, with an SSE that is 42% lower than the base case AR model's error term. As explained below, the analyses focus on the FT and LIBOR variables as measures of the economic regimes.

Figure 6.1 shows quarterly time series plots, between 1986Q4 and 2008Q4, of log-returns on IPD total return index and the three best-performing exogenous variables: LIBOR, log-returns on FT index and quarterly GDP growth. The threshold value of each regime indicator is shown by the horizontal line. There have been two important crises in the UK real estate market, namely the 1990s crisis and the recent financial crisis (2007–2009). A good regime indicator should thus be able to pick these up. Figure 6.1 illustrates this point. While LIBOR managed to capture only the 1990s downturn, GDP growth also captures the correction associated with the global financial crisis. However, GDP seems to respond more slowly than the equity index – it takes some quarters before GDP switches to the 'bad' or low state. Equity returns, as measured by the FT, on the other hand, seem to be a good regime indicator. This variable not only captures the two important downturns in the real estate market, but also other smaller downturns. FT returns also respond much faster than GDP does, and the stock index is regarded as a leading indicator.

6. EMPIRICAL RESULTS

Figure 6.1:



IPD quarterly returns (Panel A) and the performance of the regime indicator variables for LIBOR (Panel B), Equity Market (Panel C) and GDP (Panel D). The solid horizontal line shows the threshold value dividing high and low regimes.

Table 6.1: Estimation results for AR-TAR (switching return)

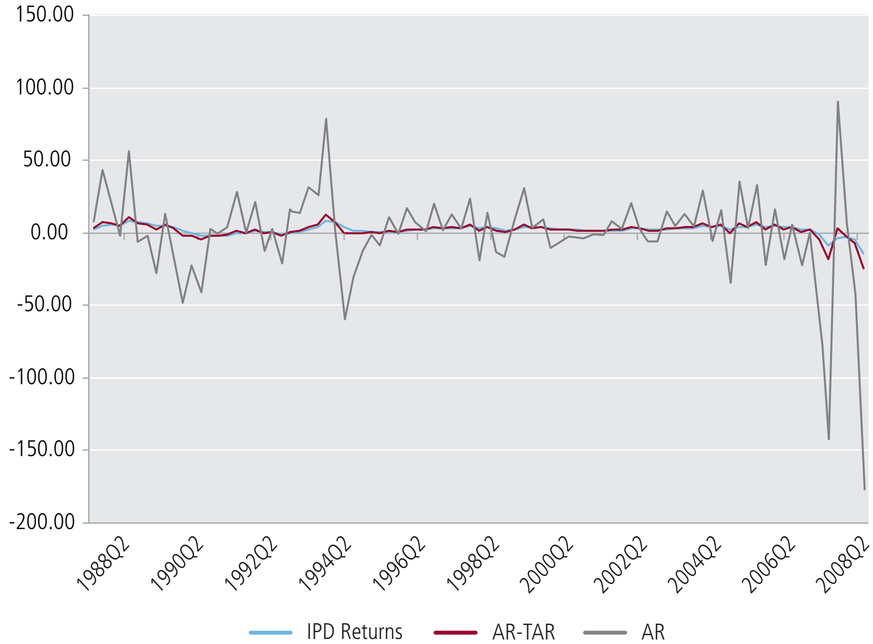
Model	α	γ_1	ϕ_1	γ_2	ϕ_2	c	π	[Min,Max]	SSE
TAR									
LIBOR	0.51**	–1.25*	1.27**	2.38**	0.18	6.25	0.56	[2.83,15.25]	233.45
	(0.07)	(0.48)	(0.10)	(0.65)	(0.11)				
Inflation rate	0.77**	0.25	–0.09	–0.22	0.95**	0.94	0.33	[–0.57,2.73]	259.44
	(0.09)	(1.67)	(0.15)	(1.08)	(0.23)				
Real interest	0.72**	–0.98	0.98**	3.01**	–0.17	5.12	0.57	[2.67,13.81]	242.68
	(0.14)	(0.75)	(0.12)	(1.13)	(0.09)				
FT returns	0.53**	2.22**	0.31**	–4.05**	1.77**	–1.54	0.76	[–32.00,18.84]	179.91
	(0.09)	(0.32)	(0.08)	(0.94)	(0.24)				
Exchange rate	0.93**	–40.54	1.70	1.33	0.02	1.95	0.05	[1.41,2.04]	240.19
	(0.02)	(235.98)	(7.65)	(2.20)	(0.10)				
Initial Yield	0.92**	1.60	0.02	–17.40**	1.76**	4.64	0.95	[4.57,9.09]	255.33
	(0.04)	(2.18)	(0.10)	(3.85)	(0.32)				
GDP Growth	0.81**	1.72	0.11	5.18	4.27*	–0.41	0.94	[–1.80,2.20]	208.52
	(0.12)	(0.99)	(0.08)	(6.66)	(1.86)				
Employment	0.08	–8.52	–0.32	0.41	0.83**	31,414	0.06	[26684,31661]	208.20
	(0.11)	(8.05)	(1.53)	(0.37)	(0.12)				
AR	0.94**	–1.35	0.12						309.53
	(0.04)	(2.82)	(0.15)						

Notes: (i) the parameters (α, ϕ_1, ϕ_2, γ_1, γ_2, c, π) denote the smoothing coefficient, the 'high state' coefficient, the 'low state' coefficient, the 'high state' intercept, the 'low state' intercept, the threshold value, and the probability of high state; (ii) [Min,Max] refers to the minimum and maximum values of the exogenous variables; (iii) Newey–West heteroscedasticity and autocorrelation consistent (HAC) standard deviations are reported in parentheses; (iv) * denotes significance at 5%, ** at 1%. To ensure sufficient observations, the search is restricted between 5th and 95th percentiles.

In the LIBOR regime, the 'high state' corresponds to interest rates in excess of 6.25%. In this state, returns are negative and ϕ is strongly positive, implying typically falling values. In the lower interest rate regime, the intercept is significantly positive and the autoregressive term insignificantly different from zero. Overall, this has a ready economic interpretation – with returns adversely affected by high interest rates – steady growth in more benign environments – a result consistent with prior research (eg Lizieri et al., 1998). The smoothing term is, however, relatively low compared to other models including the base case AR formulation. The GDP-based regime is somewhat harder to interpret: the only significant coefficient other than the smoothing parameter is the ϕ value for the low state, which is strongly positive and of large magnitude: since GDP is falling in the low state, this suggests sharp falls in value. However, the model is only in the low state 5% of the time. For the FT returns model, all coefficients are significant at the 0.01 level or beyond. When FT returns are above the threshold value, the intercept is positive and the ϕ term relatively small; in the low regime (when the equity market is falling), the intercept is strongly negative and ϕ is large, implying sharp falls. The world is in the low market state 24% of the time. In a number of models, the autoregressive coefficient, f, is explosive (has a value greater than plus or minus one). This is economically infeasible, were it to apply for long periods. However, the probability of remaining in the explosive state is sufficiently low that markets typically return to a more balanced environment relatively swiftly. The result does, though, point to the risk of 'tail events' where markets could fall catastrophically.

Figure 6.2 and Table 6.3 show fits of the AR and AR-TAR models and descriptive statistics for the FT return-based regime analyses, the best-fitting analysis. The AR process generates a highly volatile fitted, or 'recovered' return series with implausible spikes (which, allied to negative skew, generates a negative mean return) while the AR-TAR model tracks the smoothed IPD series more closely, albeit with considerably higher volatility.

Figure 6.2: Fitted AR versus AR-TAR



The original IPD returns, the fitted returns using a simple AR process and the fitted returns using the AR-TAR approach and the FT All Share equity index regime indicator. The AR series appears to be implausibly volatile.

Table 6.2: Descriptive statistics for IPD (smoothed), AR-TAR (FT) and AR series

	IPD Returns	AR-TAR	AR
Mean	2.15	1.92	–1.15
Median	2.53	2.22	1.86
Maximum	8.03	12.59	89.19
Minimum	–14.51	–25.36	–177.01
Std. Dev.	3.25	4.81	34.11
Skewness	–1.98	–2.79	–2.12
Kurtosis	10.67	16.44	13.16
Observations	88	87	87

Descriptives of the raw (smoothed) data series, the recovered series using the AR-TAR approach and, for comparison, figures from using the simple AR approach. All data quarterly, 1987 Q1 to 2008 Q4.

6.2 The TAR-TAR Model

Turning now to the possibility that both the underlying return process and the smoothing process are regime-based, the research examines the TAR-TAR co-switching model. The analysis is resticted to the exogenous variables that proved most successful in the previous models: FT returns and LIBOR. Table 6.3 presents results for four possible models: one with both regimes defined by interest rates, one with both regimes defined by equity returns and two models that mix FT returns and LIBOR as the determinants of the regimes. All four models show lower SSEs than the base case AR model, with the model where both regimes are defined by FT returns (hereinafter FT-FT) exhibiting the lowest SSE, a full 41% below the base case result. The next best performing model has the smoothing regime defined by equity returns but the returns regime defined by LIBOR.

Examining, first, the FT-LIBOR model, smoothing appears to be more extreme in the low equity return regime – which only occurs when FT returns are falling very rapidly (the threshold value is –13%). For higher equity returns, smoothing, while still strongly significant, is below the level of the base case AR model and, hence, below conventional estimates. The low FT, high smoothing regime only occurs 8% of the time. The return regimes are determined by LIBOR; when interest rates are below the 6% threshold, ϕ is not significantly different from zero, with returns largely determined by the intercept, implying steady growth. In the higher-interest-rate environment, which one might expect to be associated with weaker real estate returns, the intercept is insignificant while the autoregressive term is significant at the 0.05 level.[7] A combination of high smoothing (falling FT values) and high interest rates (significant auto regression) suggests sharply falling returns in successive periods. However, perhaps fortunately, this combination of regimes is rare, occurring just 2% of the time.

The FT-FT model identifies more extreme regimes, with both threshold values indicating falling equity values. The smoothing regime is defined by sharply falling FT prices: below the threshold, the smoothing parameter is far higher, at 0.96, than above. The return process regime threshold is just negative at –1.2% (occurring 26% of the time). When equity returns are falling, the real estate intercept is strongly negative and there is significant and explosive auto-regression, suggesting sharply falling real estate returns. Above the threshold, the intercept is positive and ϕ insignificant, suggesting steady growth. Around three-quarters of the time, the market is in the steady growth, lower smoothing state; the stronger-smoothing, falling-return environment is rare, occurring just 7% of the time, identifying extreme states in the market.

[7] This has resonances with the results on asymmetric dependence, reported in subsequent papers.

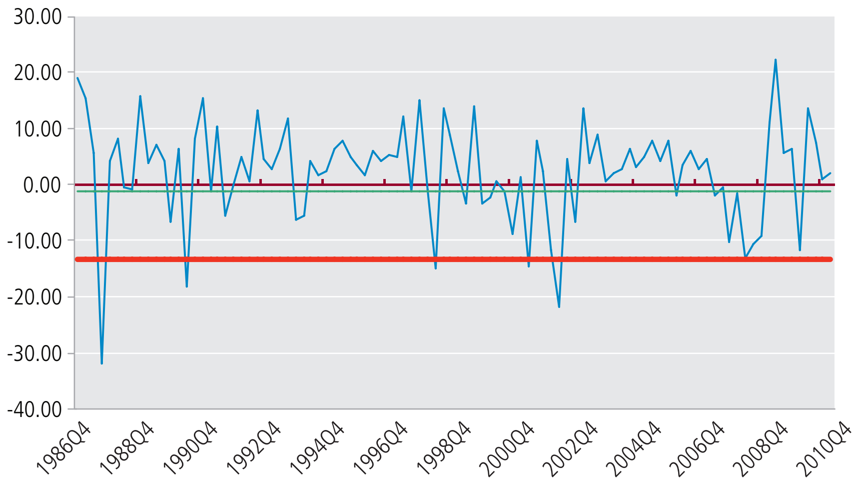
Table 6.3: Estimation results for AR-TAR (switching return)

Model	α_1	α_2	γ_1	ϕ_1	γ_2	ϕ_2	c_1	c_2	π_{ll}	π_{lh}	π_{hl}	π_{hh}	[Min,Max]	SSE
TAR														
LIBOR-LIBOR	1.42**	0.73**	−0.37	0.79**	3.05**	−0.04	6.21	11.31	0.55	0.00	0.33	0.12	[2.83,15.25]	250.27
	(0.28)	(0.07)	(1.33)	(0.14)	(0.68)	(0.15)								
FT-FT	0.72**	0.96**	3.36**	0.01	−7.13*	1.40**	−13.33	−1.20	0.07	0.00	0.19	0.74	[−32.00,18.84]	183.16
	(0.07)	(0.04)	(0.70)	(0.09)	(2.61)	(0.41)								
LIBOR-FT	1.40**	0.56**	1.63**	0.35**	5.28**	−0.85*	6.21	−1.79	0.15	0.40	0.09	0.36	as above	335.93
	(0.24)	(0.09)	(0.61)	(0.12)	(1.61)	(0.42)								
FT-LIBOR	0.79**	2.22**	0.24	0.59*	3.34**	−0.18	−13.34	5.95	0.02	0.06	0.41	0.51	as above	211.80
	(0.10)	(0.80)	(1.49)	(0.29)	(1.03)	(0.13)								
AR	0.94**		−1.35	0.12										309.53
	(0.04)		(2.82)	(0.15)										

Notes: (i) the parameters ($\alpha_1, \alpha, \phi, \phi_2, \gamma_1, \gamma_2, c_1, c_2$) denote the 'high state' smoothing coefficient, the 'low state' smoothing coefficient, the 'high state' coefficient, the 'low state' coefficient, the 'high state' intercept, the 'low state' intercept, the threshold value of the smoothing equation, and the threshold value of the returns process; (ii) the probabilities ($\pi_{ll}, \pi_{lh}, \pi_{hl}, \pi_{hh}$) denote the state probability of both the smoothing equation and the returns process being in the low state, the probability of the smoothing equation being in the low state and the returns process in the high state, the probability of the smoothing equation being in the high state and the returns process in the low state, and the probability of both the smoothing equation and the returns process being in the high state; (iii) [Min,Max] refers to the minimum and maximum values of the exogenous variables; (iv) the Newey–West heteroscedasticity and autocorrelation consistent (HAC) standard deviations are reported in parentheses; (v) * denotes significance at 5%, ** at 1%.

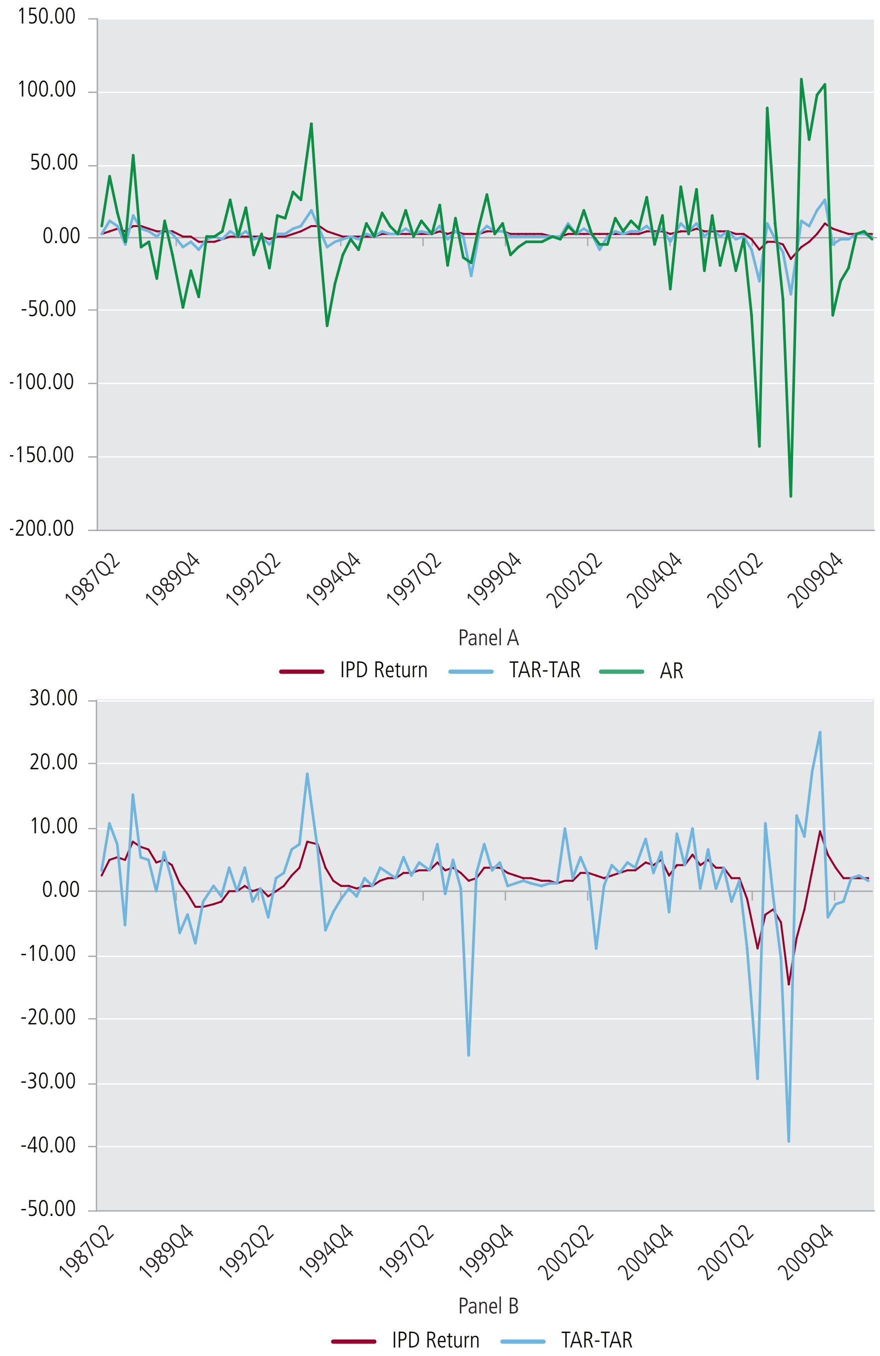
Figure 6.3 shows the return process and appraisal smoothing regimes using the FT Return indicator. When FT returns fall below −1.2%, then the return process shifts from the normal regime – where real estate returns have a positive mean and exhibit little persistence – to the bad or 'crisis' regime – where returns have a negative mean and are highly explosive. However, it is not until FT returns fall below −13.33% that appraiser smoothing behaviour shifts to a new regime. Figure 6.4 shows the fitted results, comparing IPD returns with the recovered series using the TAR-TAR and the AR models. Panel A compares the index returns with both the TAR-TAR and AR results. The extreme returns generated by the AR model obscure the relationship between the index returns and the TAR returns, shown more clearly in Panel B (note the differences in the vertical scales).

Figure 6.3: TAR-TAR in FT returns



FT returns and the two regime thresholds. The upper horizontal line (at –1.2%) is the return process threshold, while the lower horizontal line (at –13.3%) is the appraisal smoothing threshold. In each case, the line divides high and low regimes.

Figure 6.4: Fitted TAR Returns versus AR and reported data



The graphs plot the original (smoothed) IPD returns against the recovered returns from the TAR-TAR and the simple AR process. Panel A shows both the AR and TAR-TAR approaches, with the AR series showing extreme volatility. Panel B compares the IPD raw returns with the TAR-TAR alone: note the difference of scales between Panel A and Panel B.

Table 6.5 shows descriptive statistics for the original appraisal-based index and the returns from the AR and TAR-TAR process. The AR process seems unsatisfactory, generating a negative mean return as a result of the extreme negative values at the end of the period (the median is positive) and with an infeasibly large standard deviation. The results from the TAR-TAR model seem intuitively more sound, with the standard deviation 2.4 times higher than the appraisal-based return and with a sharp reduction in the serial correlation. The final column of the table provides descriptive statistics for a 'conventional' style unsmoothing model as per Equation 2, with alpha set equal to 0.8. The results are similar to the TAR-TAR model (the two series have a 0.92 correlation) but with a higher standard deviation across the whole series. The conventional AR model suggests a fall of 60% in capital values in the second half of 2008, compared to a 45% for the TAR-TAR model and a reported fall of less than 20%.[8]

Table 6.5: Descriptive statistics, indexed, TAR-TAR and AR models

	IPD Returns	TAR-TAR	AR	$\alpha = 0.8$
Mean	2.15	1.25	–1.15	1.36
Median	2.53	2.22	1.86	2.62
Maximum	8.03	12.59	18.52	24.42
Minimum	–14.51	–25.36	–39.21	–53.00
Std. Dev.	3.25	7.95	34.11	9.82
Skewness	–1.98	–2.79	–2.47	–2.72
Kurtosis	10.67	12.66	13.16	13.73
Serial Correlation	0.813	0.199	0.098	0.222
Observations	88	87	87	87

Descriptives of the raw (smoothed) data series, the recovered series using the TAR-TAR approach, the simple AR approach and, for comparison, the 'naïve' unsmoothing approach using an alpha value of 0.8. All data are quarterly, 1987 Q1 to 2008 Q4.

Figures 6.3 and 6.4 show the results estimated over the 1986–2008 period projected forward to mid-2011 using an extended data set. The relationship between the valuation-based returns and the TAR-TAR returns remains stable over the added period. The research also re-ran the results for the 2009–2011 period using GDP, LIBOR and FT returns as regime indicators. The provisional GDP figures for recent years give some cause for concern as there have been numerous revisions to figures. The results using FT and LIBOR variables are broadly comparable to those found for the 1986–2008 analysis period. In the extended period, interest rates appear more significant that the equity market as a driver of underlying real estate returns: the best-performing model is a TAR-TAR with FT returns determining smoothing but interest rates determining the return process, while a model based entirely on LIBOR performs well relative to one based solely on equity returns. The dramatic fall in LIBOR in the aftermath of the global financial crisis clearly influences this result.

Examining the regime indicators, there is considerable stability across the models. For the FT-FT model, the threshold values for both smoothing and returns regimes fall a few basis points to –13% and –0.8%; in the FT- LIBOR model, the LIBOR returns process threshold remains just below 6%, while in the LIBOR-LIBOR model the smoothing threshold is around 6% and the returns threshold moves slightly lower from 11.3% to 10.3%. The signs and size of the smoothing and AR coefficients within the models are also broadly unchanged, although the FT-FT model suggests extreme smoothing in the low-FT regime with rapidly falling equity prices – a result that would be consistent with a rapid fall in reported property values lagging a sharp downward correction in the equity market. This rapid downward shift following an external market shift would also fit with informal evidence that valuers were more prepared to shift prices downward in the absence of transactional evidence in the 2008 correction than they had been in 1990. This also results in a less explosive return process in the low equity market state than was observed in the 1986–2008

[8] Tests of significance for TAR models are complex. Results of a series of tests are presented in Appendix B.

analysis (as a consequence of the sharp downward adjustment in 2007–2008, there was a more rapid, if ultimately anaemic, recovery from mid-2009. By contrast, IPD monthly capital values fell every single month from October 1989 until May 1993).

6.3 Summary

- As is standard, the high autocorrelation and low relative risk of the raw IPD total return index gives credence to suggestions that the series is smoothed due to valuer behaviour;
- The basic autoregressive and AR-TAR models provide strong evidence of smoothing behaviour, with almost all variables generating high values of alpha, the smoothing parameter;
- For the AR-TAR models, the best-fitting variables are GDP, LIBOR and FT returns, with the equity market returns providing the best fit for the 1986–2008 period. GDP is a sluggish indicator, while the FT regimes seem best able to capture periods of poor real estate performance;
- In terms of return processes, the LIBOR regime model suggests, consistent with prior research, that when interest rates rise above a threshold value, property returns become negative with strong downward momentum;
- With FT returns defining return regimes, it appears that property returns are positive and stable when equity markets are positive. However, falling equity prices are linked to sharply falling property returns with downward momentum. Fortunately these low regimes tend to be short-lived;
- The co-switching or TAR-TAR models provide evidence that valuer behaviour is also time-varying, with smoothing more evident in the poorly performing down-market states;
- FT returns provide the best indicator of valuer behaviour, with very high levels of smoothing occurring when the equity market is in a ‘bad’ regime of sharply falling prices. This coincides with falling underlying returns.
- The results are robust to the inclusion of data covering the post-market correction period from 2009 to mid-2011. The models provide similar results. However, it appears that inclusion of the period after the global financial crisis suggests that the commercial property market has become more sensitive to interest rates;
- Examining the smoothing coefficients in the models using FT as a regime indicator gives some support for the suggestion that valuers marked capital values down more sharply in the 2007–2008 correction than in the 1990 downturn and were prepared to use evidence external to the market.

7. CONCLUSIONS AND IMPLICATIONS

Investors exposed to private commercial real estate must confront measurement issues from the valuation-based nature of the indices of real estate market performance. There have been numerous attempts to find ways of recovering the 'true' underlying return performance from the smoothed, appraisal-based returns. A new unsmoothing technique for returns on an appraisal-based valuation index examines both the underlying return-generating process and appraiser behaviour, a procedure using threshold autoregressive (TAR) models. Critically, this allows testing for return-generating processes and smoothing which may vary across time due to the existence of distinct regimes. The regime-switching TAR methodology allows 'normal regime' variance to be distinguished from variance in rarer, more extreme regimes and provides new information on the sensitivity of real estate to macro-economic and capital market shocks. These models are tested using UK commercial property data, with a range of macro-economic and financial market variables as potential regime indicators, variables identified as significant in the determination of real estate returns.

Clear evidence of regime effects and time-varying behaviour in the commercial real estate returns are found. The most promising results come from the use of FT equity returns, interest rates (measured by LIBOR) and, to a lesser extent, GDP as regime indicators. Models are examined where parameter is assumed constant but the underlying return process varied by regime (an AR-TAR model); where the smoothing parameter changed but the returns process was time invariant (a TAR-AR model, not reported here) and the least restrictive set of models where both smoothing parameter and returns process can switch (the TAR-TAR model). The best models outperform the base case single smoothing parameter AR process model, with sum of squared errors over 40% lower than the base case.

Of the TAR-TAR models, the best performing had both smoothing and returns process regimes determined by FT returns. The test results agree with this. When equity markets are falling, underlying real estate returns appear to behave differently than when they are rising: the intercept term is strongly negative and the autoregressive parameter exceeds one, implying sharply falling property prices. Furthermore, when equity prices are falling particularly sharply, appraisal smoothing behaviour increases. Given that the model suggests that real estate returns are likely to be negative in this market environment, this may well be an information effect as transaction volumes fall. It also suggests that real estate performs worse when equity markets are in crisis, which is significant for understanding of the nature of diversification benefits that real estate brings. This high-smoothing, explosive regime is, perhaps fortunately, short-lived. The results shed light on the interaction between returns processes and appraisal behaviour in different market regimes.

The results are robust to the inclusion of data for the period following the global financial crisis. Including data up to June 2011 provides some indication that commercial real estate has become more sensitive to interest rates: perhaps unsurprising given the disruption to LIBOR in the illiquidity crisis and in the aftermath of the financial crisis as central banks and governments attempted to deal with the consequences. Both LIBOR- and FT-based analyses provide evidence of time-varying return behaviour and differences in the extent of smoothing over the market cycle. There is also tentative evidence from the models over the extended period that valuers were more prepared to use external evidence in their valuations are marked prices down more sharply in 2007 and 2008 than they had in earlier market corrections. In the 'bad' regimes (for example, when equity market returns are falling rapidly) there is evidence of very strong downward momentum in both the underlying returns and in the valuation process, producing a very sharp correction from peak values.

7. CONCLUSIONS AND IMPLICATIONS

The results here have relevance for investors. While the unconditional variance from the TAR models will not differ greatly from that of the conventional smoothing model, the latter masks time-varying behaviour, both in the underlying market and in the valuation processes that drive the performance measurement indices. The TAR models allow estimation of conditional variances which are both more informative and have implications for conditional asset allocation models – for example, suggesting that active asset allocation strategies need to vary depending on (beliefs about) market trajectory around regime thresholds. In private real estate markets, illiquidity and high transaction costs tend to frustrate active management and portfolio rebalancing – in which case, investors need to be aware of the risk switching that may occur.

Furthermore, the models shed more light on the nature of real estate risk; single-parameter smoothing models and unconditional variance measures do not fully reflect the impact of return processes and appraiser behaviour in the extreme regimes which, while they might be short-lived, can have profound effects on asset values. This has strong implications for risk management strategies, particularly for any investors facing abrupt liability or redemption calls. Risk measures that assume normal, symmetrical returns will understate the probability of high negative returns. The evidence of negative skewness and excess kurtosis in property returns already provides an indication of this risk: the findings here emphasise the interplay between the underlying return processes and the behaviour of valuers that can mask these effects. Further, there appears to be a link between these extreme real estate events and returns in other asset markets.

The significance of the FT returns as a regime indicator both for smoothing and for return process, and the extreme behaviour in the falling-value high-smoothing regime points to possible tail dependence between real estate and equity returns distributions, providing an interesting link to the emerging literature on tail dependence and asymmetric dependence in financial asset markets and complementing research on asymmetric behaviour in real estate price formation. This, too, has important implications for mixed-asset portfolio diversification strategies and suggests that more research is required on the time-varying relationship between private real estate returns and financial asset markets. In similar vein, the significance of LIBOR as a regime indicator once again points to the downside risk implicit in investment strategies based on high leverage.

The remaining working papers will examine these issues further. Working Paper 3 examines the time-varying behaviour of real estate returns in relation to financial assets – it will compare both public and private real estate returns (the performance of listed property companies and REITs and of directly held real estate) to equity, small cap stock and bond market performance. Working Paper 4 focuses more directly on the tail dependency issue noted above. Is there a higher probability than would be expected given conventional portfolio theory assumptions that strongly negative real estate returns are associated with strongly negative equity market returns? If that were the case, then it would mean that the diversification benefits of real estate are less effective when they are most needed.

7. CONCLUSIONS AND IMPLICATIONS

7.1 Summary: Key Findings

- The valuation basis of most commercial real estate indices has implications for analysis of property returns. Investors must try to disentangle valuation effects from movement in fundamental underlying values and attempt to estimate the true risk of real estate as an asset;
- Conventional desmoothing techniques make strong assumptions about underlying return processes and tend to assume that smoothing effects apply under all market conditions;
- Research in many asset markets suggest that return processes vary over time. One way of capturing this is to identify particular regimes – economic states – across which the factors driving returns operate in different ways;
- The extension offered in this paper is the insight that valuer behaviour might also vary across economic regimes. As a result, standard desmoothing techniques may not fully capture underlying market dynamics;
- Empirical results for UK commercial property markets strongly suggest that both return processes and valuation behaviour are time-varying. Return regimes are defined by equity market returns, by interest rates and (in a less satisfactory way) by macro-economic growth. In 'good' market environments (positive equity returns or lower interest rates) returns are positive and steady; in 'bad' environments (falling share prices or high interest rates), returns fall sharply and there are strong downward momentum effects;
- Valuation smoothing also appears to be regime-based. Smoothing is strongest in 'bad' economic states, notably where there are sharply falling equity prices and less marked in more benign market conditions;
- These results were estimated for quarterly data from 1986–2008, but appear robust when the data set is extended into 2011. However, there is some tentative evidence that valuers may have reacted more sharply to external market signals in the 2007–2008 correction than in previous downturns;
- The findings have implications for risk management and portfolio strategy. First, they suggest that the dynamic relationships between real estate returns and those of other asset classes are complex and must be considered carefully. For example, it would be misleading to assume a single relationship between equity market performance and property returns that was constant across all market conditions.
- Second, the results suggest that return distributions are asymmetric and, critically, that the relationship between equity markets and property markets is asymmetric and time-varying. By implication, this means that diversification benefits will change over time. In particular, if real estate return behaviour is adversely affected by problems in equity markets – as the results suggest – then diversification may not occur when it is most needed.
- Third, the results again highlight the importance of the relationship between real estate risk and interest rates – if interest rates rise over a threshold value, there are marked negative implications for real estate returns – and for highly geared real estate investment vehicles and bank lending to property.

REFERENCES

Alba, J. D. and Park, D. (2005). An empirical investigation of Purchasing Power Parity (PPP) for Turkey, Journal of Policy Modeling 27, 989–1000.

Andel, J. (1976). Autoregressive series with random parameters, Math Operationsforsch Statist 7, 735–741.

Baum, A. (2009). Commercial Real Estate Investment, EG Books, London.

Blundell, G. and Ward, C. (1987). Property portfolio allocation: A multi factor model, Land Development Studies 4, 145–156.

Bond, S., Hwang, S., Lin, Z. and Vandell, K. (2007a). Marketing period risk in a portfolio context: Theory and empirical estimates from the UK commercial real estate market, Journal of Real Estate Finance and Economics, 34, 447–461.

Bond, S., Hwang, S., Mitchell, P. and Satchell, S. (2007b). Asset Allocation in a Modern World, Technical Report, Investment Property Forum, London.

Booth, P. and Marcato, G. (2004). The measurement and modelling of commercial real estate performance, British Actuarial Journal 10, 5–61.

Brooks, C. and Maitland-Smith, J. K. (1999). Threshold autoregressive and Markov switching models: An application to commercial real estate, Journal of Property Research 16, 1–19.

Brown, G. and Matysiak, G. (1997). Valuation smoothing without temporal aggregation, Journal of Property Research, 15, 189–210.

Chan, K. S. (1990). Deterministic stability, stochastic stability, and ergodicity, in H. Tong, Non-linear Time Series: A Dynamical Systems Approach, Oxford University Press, Oxford.

Chaplin, R. (1997). Unsmoothing valuation-based indices using multiple regimes, Journal of Property Research 14, 189–210.

Cho, H., Kawaguchi, Y. and Shilling, J. (2003). Unsmoothing commercial property returns: A revision to Fisher–Geltner–Webb's unsmoothing methodology, Journal of Real Estate Finance and Economics 27, 393–405.

Davies, R. B. (1977). Hypothesis testing when a nuisance parameter is present only under the alternative, Biometrika, 64, 247–254.

Davies, R. B. 1987. Hypothesis testing when a nuisance parameter is present only under the alternative, Biometrika, 74, 33–43.

Diaz, J. (1997). An investigation into the impact of previous expert value estimates on appraisal judgement, Journal of Real Estate Research, 13(1), 57–66.

Diaz, J. and Hansz, J. (2007). Understanding the behavioural paradigm in property research, Pacific Rim Property Research Journal, 13(1), 16–32.

REFERENCES

Diaz, J. and Wolverton, M. (1998). A longitudinal examination of the appraisal smoothing hypothesis, Real Estate Economics, 26(2), 141–148.

Feigin, P. D. and Tweedie, R. L. (1985). Random coefficient autoregressive processes: a Markov chain analysis of stationarity and finiteness of moments, Journal of Time Series Analysis 6, 1–14.

Fisher, J., Gatzlaff, D., Geltner, D. and Haurin, D. (2003). Controlling for the impact of variable liquidity in commercial real estate price indices, Real Estate Economics 31, 269–303.

Fisher, J., Geltner, D. and Webb, R. (1994). Value indices of commercial real estate: A comparison of index construction methods, Journal of Real Estate Finance and Economics 9, 137–164.

Franses, P. H. and van Dijk, D. (2000). Non-linear Time Series Models in Empirical Finance, Cambridge University Press, Cambridge.

Gallimore, P. (1994). Aspects of Information processing in valuation judgement and choice, Journal of Property Research, 11(1), 97–110.

Gallimore, P. (1996). Confirmation bias in the valuation process: A test for corroborating evidence, Journal of Property Research, 13(4), 261–273.

Geltner, D. (1991). Smoothing in appraisal-based returns, Journal of Real Estate Finance and Economics 4, 327–345.

Geltner, D. (1993). Estimating market values from appraised values without assuming an efficient market, Journal of Real Estate Research 8, 325–345.

Geltner, D., MacGregor, B. and Schwann, G. (2003). Appraisal smoothing and price discovery in real estate markets, Urban Studies 40, 1047–1064.

Hansen, B. (1996). Inference when a nuisance parameter is not identified under the null hypothesis, Econometrica, 64, 413–430.

Hansen, B. (1997). Inference in TAR models, Studies in Nonlinear Dynamics and Econometrics, 2, 1–14.

Hansen, B. (2000). Sample splitting and threshold estimation, Econometrica, 68, 575–603.

Hazewinkel, M. (ed.) (2002). Encyclopaedia of Mathematics, Supplement III, Kluwer, Dordrecht.

Hoesli, M., Lizieri, C., and MacGregor, B. (2008). The inflation hedging characteristics of US and UK investments: A multi-factor error correction approach, Journal of Real Estate Finance and Economics, 32, 483–506.

Hudson-Wilson, S., Fabozzi, F. and Gordon, J. (2003). Why real estate, Journal of Portfolio Management Real Estate Issue, 12–24.

IPD/RICS (2010). Valuation and Sale Price Report UK 2010, London, Royal Institution of Chartered Surveyors.

REFERENCES

Kendall, D. G. (1959). **Unitary dialations of Markov transition probabilities and the corresponding integral representations for transitions probability matrices,** in Grenandir, U. (ed.). Probability and Statistics, Almqvist and Wiksell, Stockholm.

Knight, J., Lizieri, C. and Satchell, S. (2005). **Diversification when it hurts? The joint distribution of real estate and equity markets**, Journal of Property Research, 22, 309–323.

Knight, J. and Satchell, S. forthcoming. **Some new results for Threshold AR(1) models,** Journal of Time Series Econometrics, forthcoming.

Li, W. K. and Lam, K. (1995). **Modelling asymmetry in stock returns by a threshold autoregressive conditional heteroscedastic model**, The Statistician, 44, 333–341.

Ling, D. C. and Naranjo, A. (1997). **Economic risk factors and commercial real estate returns**, Journal of Real Estate Finance and Economics, 14, 283–307.

Ling, D. C. and Naranjo, A. (2000). **Commercial Real Estate Return Performance: A Cross-country Analysis**, Warrington College Working Paper, University of Florida.

Lizieri, C., Satchell, S., Worzala, E. and Dacco, R. (1998). **Real interest regimes and real estate performance: A comparison of U.K. and U.S. markets**, Journal of Real Estate Research 16, 339–355.

Marcato, G. and Key, T. (2007a). **Index Smoothing and the Volatility of Commercial Property**, Technical Report, Investment Property Forum, London.

Marcato, G. and Key, T. (2007b). **Smoothing and implication for asset allocation choices**, Journal of Portfolio Management 32, 85–99.

McCabe, B. and Tremayne, A. (1993). **Elements of Modern Asymptotic Theory with Statistical Applications**, Manchester University Press, Manchester.

Nicholls, C. F. and Quinn, B. G. (1981). **Multiple autoregressive models with random coefficients**, Journal of Multivariate Analysis 11, 185–198.

Pham, T. D. and Tran, L. T. (1985). **Some mixing properties of time series models**, Stochastic Processes and their Applications, 19, 297–303.

Quan, D. C. and Quigley, J. (1991). **Price formation and the appraisal function in real estate**, Journal of Real Estate Finance and Economics, 4, 127–146.

Quinn, B. G. (1982). **A note on the existence of strictly stationary solutions to bilinear equations**, Journal of Time Series Analysis 3, 249–252.

Tong, H. (1978). **On a threshold model**, in C. H. Chen (ed.), Pattern Recognition and Signal Processing, Sijthoff and Noordhoff, Amsterdam.

REFERENCES

Tong, H. (1990). Non-linear Time Series: A Dynamical Systems Approach, Oxford University Press, Oxford.

Wike, E. and Gillen, K. (2008). Loan Performance HPI forecasts, Presentation, First American Core Logic.

Worzala, E. and Sirmans, C. (2003). Investing in international real estate stocks: a review of the literature, Urban Studies, 40, 1115–1149.

Young, M. (2007). Revisiting non-normal real estate return distributions by property type, in the U.S. Journal of Real Estate Finance and Economics, 36, 233–248.

APPENDIX A: THE MATHEMATICS OF THE RETURN PROCESS AND THRESHOLD AUTOREGRESSIVE MODELS

A1 The Measurement Equation

In this appendix, the research sets out the underlying models behind the standard smoothing approach, reintroduces the idea of an underlying return generating process that interacts with the smoothing process and then introduces the threshold autoregressive models used in the estimation process described in the main text. Consider a simple smoothing model, typical of those employed in the property literature:

Equation A1:

$$r_t^* = \alpha r_{t-1}^* + (1-\alpha) r_t$$

where r_t^* denotes the reported valuation-based return at t, r_t the 'true' underlying return, and α the smoothing parameter – which is a weight given to information about the prior valuation, $\alpha \in (0,1)$. From Equation A1, given the value for the smoothing parameter, the unsmoothed returns can be computed by

Equation A2:

$$r_t = \frac{1}{1-\alpha}\left(r_t^* - \alpha r_{t-1}^*\right)$$

Equation A3:

$$\mathrm{var}(r_t) = \frac{\mathrm{var}(r_t^*)\left[1 - 2\alpha p + \alpha^2\right]}{(1-\alpha)^2}$$

Equation A4:

$$\left.\frac{\partial\, \mathrm{var}(r_t)}{\partial \alpha}\right|_{\alpha\in(0,\,1)} = \frac{2\mathrm{var}(r_t^*)}{(1-\alpha)^2} > 0$$

This result shows that the implied variance is increasing in α, when the parameter lies between zero and one.

Artificially high values of alpha would inflate the variance, while values that were too low would understate volatility in the underlying return series. This may be important where researchers 'assume' a value of alpha to unsmooth an appraisal based series or where mis-estimation of alpha occurs.

It is clear that, at this point, the variance implied by the smoothing equation has no direct relationship with the assumed 'true' returns. When the smoothing coefficient is known, it does not matter what assumption is made regarding the true return-generating process. The true return-generating process comes into the picture only when an attempt is made to estimate α.

A2 The State Equation

The conventional approach to asset returns assumes that the true (unobservable) returns follow a stationary AR(1) process:

Equation A5:

$$r_t = \gamma + \phi r_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \text{iid}\,(0, \sigma_\varepsilon^2)$$

where $|\phi| < 1$ by assumption.[9]

Using Equations A1 and A5, and given the value for γ and ϕ, the weight α can be estimated consistently by a recursive procedure from an implied AR(2) model of the observed returns

Equation A6:

$$r_t^* = \gamma(1 - \alpha) + (\alpha + \phi)r_{t-1}^* - \alpha\phi r_{t-2}^* + v_t$$

where $v_t = (1 - \alpha)\,\varepsilon_t$. This residual term assumes γ and ϕ, as given, and varies with α alone, ie $v_t = v_t\,(\alpha; \gamma, \phi)$. The least squares method gives

Equation A7:

$$\hat{\alpha} = \arg\min \sum_T v_t^2\,(\alpha; \gamma, \phi)$$

The unsmoothed returns will then be given by

Equation A8:

$$r_t = \frac{1}{1 - \hat{\alpha}} \left(r_t^* - \hat{\alpha} r_{t-1}^*\right)$$

A new pair of γ and ϕ is a least squares estimate of Equation A5,

Equation A9:

$$(\hat{\gamma}, \hat{\phi}) = \arg\min \sum_T \varepsilon_t^2\,(\gamma, \phi; \alpha)$$

[9] Some of the earlier studies (eg Quan and Quigley 1991) suppress the intercept term, arguing that the model is applied to demeaned series. Such a practice will, however, result in an identification problem (proof available from the authors).

where at the moment the residual $\varepsilon = \varepsilon\ (\gamma,\ \phi;\ \alpha)$ varies with γ and ϕ. The recursion continues until $(\hat{\gamma},\ \hat{\phi})$ converges – that is, when each differs from the previous value by a small amount, eg 0.01 (Cho, Kawaguchi and Shilling 2003). The same estimation procedure still applies to extensions of the simple smoothing model, for example, to the inclusion of more lagged values of valuation based returns in the measurement equation, or to the generalization of the true returns to an ARMA process.

Now consider the variance of the reconstructed estimate of underlying returns. By construction:

Equation A10:

$$\text{Est. var}\ (r_t) = \frac{\sigma_\varepsilon^2}{1 - \hat{\phi}^2}$$

This has been argued to be too small a value to reflect actual risks in the underlying asset. As will be shown shortly, assuming the true returns follow a TAR process provides 'built-in' volatility, while the usual iterative estimation procedure is still applicable.

A3 TAR Models

The research now sets out how a regime-switching approach can be incorporated into smoothing models. First, it reviews the TAR model and its properties. Then it demonstrates how to implement the regime-based unsmoothing methodology.

A3.1 TAR Processes and Properties

Suppose, now, that the true returns follow a threshold autoregressive process, where the intercepts are suppressed to avoid excessive algebra:

Equation A11:

$$r_t = \begin{cases} \phi r_{t-1} + \varepsilon_t, & z_{t-1} > c, \\ \phi_2 r_{t-1} + \varepsilon_t, & z_{t-1} \leq c. \end{cases}$$

The model can be written succinctly as

Equation A12:

$$r_t = (\phi_1 I_{t-1} + \phi_2\,(1 - I_{t-1}))r_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \text{iid}\ (0, \sigma_\varepsilon^2)$$

Here z_t is an observable (weakly) exogenous regime indicator (is discussed the nature of the indicator variable below), with the corresponding indicator function $I_t = 1(z_t > c)$. ϕ_1 will be referred to as the 'high state' coefficient, and ϕ_2 as the 'low state' coefficient. This non-linear model, initially proposed by Tong (1978), splits the time series of interest into subsets, or 'regimes' defined with respect to the value of some regime indicator.[10] The variable z_t can be one of a range of variables known at time t.

Given *c*, the coefficients ϕ_1 and ϕ_2 can be estimated by applying OLS to Equation A12. Otherwise, the threshold value can be estimated empirically as

Equation A13:

$$\hat{c} = \arg\min_{c \in C} \hat{\sigma}(c)$$

where C represents the set of all allowable threshold values, and $\sigma(c)$ the standard error of regressions given the threshold value. A popular choice of C that ensures consistency requires that each regime contains at least 15% of the number of observations (Franses and van Dijk 2000). Other goodness of fit measures, eg the Akaike Information Criterion or Bayesian Information Criterion, may be used instead.

In the above specification, the variance of r_t can be computed using the Law of Iterated Expectation.

Equation A14:

$$\text{var}(r_t) = \frac{\sigma_\varepsilon^2}{1 - (\pi\phi_1^2 + (1 - \pi)\phi_2^2)}$$

where π denotes the steady-state probability of the first regime. Comparing this to the variance implied by the AR process in A10, it is not possible to tell whether or not the TAR approach will imply greater underlying volatility, as the relative magnitude of the two variances is not immediately clear. However, if the single-regime process is assumed, but the true returns do exhibit regime-switching behaviour, then the implied AR variance will be consistently lower than the true variance.

A3.2 Implementing the Unsmoothing Technique

Now the research will present the implementation of the unsmoothing methodology, which is analogous to that of the conventional technique (see eg Cho, Kawaguchi and Shilling 2003). The main difference between the two techniques is that while the conventional one is linear, this model is non-linear.

[10] Further discussion of TAR, as well as other regime-switching models, can be found in Tong (1990). Franses and van Dijk (2000) provide an excellent textbook treatment on the subject.

APPENDIX A: THE MATHEMATICS OF THE RETURN PROCESS AND THRESHOLD AUTOREGRESSIVE MODELS

Equations A1 and A12 imply the following process in the observed returns:

Equation A15:

$$\left(1 - \left(\phi_1 I_{t-1} + \phi_2 (1 - I_{t-1})\right) L\right)(1 - \alpha L) r_t^* = v_t$$

where L denotes a lag operator defined by $Lx_t = x_{t-1}$, and again $v_t = (1 - \alpha)\varepsilon_t$. The recursion is initialised by the values of $(\phi_1^0, \phi_2^0, c^0)$. The smoothing coefficient α in Equation A15, given particular values of the three TAR parameters, by ordinary least squares (OLS). By using the estimated smoothing coefficient and the measurement Equation A2, the unsmoothed returns can be computed. These reconstructed estimates of the underlying returns will then be modelled as a TAR process. A new set of (ϕ_1, ϕ_2, c) is estimated, as described in Section 4.1, with the estimated threshold value being that which minimises the standard error of regression.[11] The new set of $(\phi_1^1, \phi_2^1, c^1)$ will then be used in the next round of estimation, and the recursion stops when (ϕ_1, ϕ_2) converge in value. This will be called an AR-TAR process.

A3.3 Generalisation

The formulation described above assumes that there exist different return regimes but a single smoothing process and, hence, a single value of α. However, there may also exist 'smoothing regimes' where appraiser behaviour differs. For example, there may be periods characterized by thin trading (typically these will be periods when prices are falling, as owners with discretion may choose not to crystallise losses and retain their properties): in the absence of dense transaction evidence, appraisers may be more prone to smooth than in market environments with rich comparable evidence. While such smoothing regimes may coincide with the return process regimes, there is no reason why they **must** coincide. Accordingly, smoothing regimes are separately defined via a TAR process, producing a double-TAR, or TAR-TAR process. Generalising, the research defines:

Equation A16:

The Smoothing Equation: $r_t^* = \alpha_t r_{t-1}^* + (1 - \alpha_t) r_t$

Equation A17:

The Returns Process: $r_t = \gamma_t + \phi_t r_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \text{iid}\,(0, \sigma_\varepsilon^2)$

Here r_t^* denotes the observed 'smoothed' returns, r_t the actual returns, ε_t the residual in the returns process, α_t the smoothing coefficient, γ_t the intercept term, and ϕ_t the persistence coefficient. The parameters are allowed to be to be regime-switching – hence the time subscript – according to certain exogenous variables z_1 and z_2 as follows.

[11] In estimating the threshold value c, the research uses a grid search in its estimation since the search domain is of low dimensionality.

Equation A18:

$$\alpha_t = \begin{cases} \alpha_1, & z_{1t-1} > c_1 \\ \alpha_2, & z_{1t-1} \leq c_2 \end{cases}$$

Equation A19:

$$(\gamma_{t,} \phi_t) = \begin{cases} \gamma_1, \phi_1), & z_{2t-1} > c_1 \\ \gamma_2, \phi_2), & z_{2t-1} \leq c_2 \end{cases}$$

As before, the specification concerns the lagged value of the exogenous variables, and hence the current regimes are observable. Parameters are estimated iteratively using a grid search technique to identify the lowest SSEs as in the AR-TAR formulation in Equation A15.

APPENDIX B: TESTING THE SIGNIFICANCE OF THE MODELS

The inferential procedure in the TAR-TAR models, similar to that in the more common TAR, suffers from the nuisance parameter problem, also known as Davies' problem (1977, 1987), ie one or more of the threshold parameters are not identified under the null hypothesis of absent regimes. Tests of this kind have been developed and popularised by Hansen (1996, 1997, 2000).

The essential requirement of the Hansen procedure is that the data be strictly stationary and geometrically ergodic.[12] Using a result of Chan (1990), Hansen shows that geometric ergodicity can be replaced by a weaker condition of absolute regularity, to be discussed briefly. Under some assumptions about the data, the Hansen procedure is applicable to the purpose of the research. It will thus assume that the data (r^*_t, x'_t, z'_t) where

$$x'_t = (I_{t-1}, I_{t-1}r^*_{t-1}, I_{t-1}r^*_{t-2}, (1 - I_{t-1}), (1 - I_{t-1})r^*_{t-1}, (1 - I_{t-1})r^*_{t-2})'$$

and $z_t = (z_{1t}, z_{2t})'$ are strictly stationary and absolutely regular with mixing coefficients $\beta(m) = O(m_{-A})$ for some $A > \kappa/(\kappa-1)$ and $\lambda > \kappa > 1$ and that z_t has density function $f(z)$ such that $\sup_{x \in R^2} f(x) = \overline{f} < \infty$.[13] Pham and Tran (1985) have shown that ARMA processes with iid innovations are absolutely regular when the innovations have a bounded, continuous density.

In Section 4 (pp.420–422) of Hansen (1996), he discusses applications of his procedures to threshold models of the form:

Equation B1:

$$y_t = x_t'\beta_1 = \{z_t \leq c\}\, x_t'\beta_2 + \varepsilon_t$$

where $\{\bullet\}$ denotes the indicator function, and z_t may be an element of x_t, for instance, $z_t = z\{y_{t-1}, y_{t-1}, \ldots; y_{t-d})$ as in Hansen (1997). Although the research case is not exactly a special case of this result, the basic procedure should still go through in testing. Given the above conditions, this allows the use of bootstrap procedures to compute critical values for test statistics with non-standard distributions. It is legitimate to test the non-linear TAR-TAR model (which 'nests' AR-TAR and TAR-AR) against the linear AR(2) model. The cases for TAR-TAR against the single-indicator AR-TAR or TAR-AR remain unproved. There is, however, no problem testing AR-TAR against AR or TAR-AR against AR.

Hansen suggests using the pointwise F-statistic, and the research shall follow him in using:

Equation B2:

$$F_T = T\left(\frac{\sigma^2 - \hat{\sigma}^2(c)}{\hat{\sigma}^2(c)}\right)$$

[12] The concept of geometric ergodicity is introduced by Kendall (1959), referring to the situation in which the n-step transition probability of a Markov process converges to some limiting probability, and also at a geometric rate of convergence.

[13] Absolute regularity of a stochastic process $\{y_t\}_{t=1}^{\infty}$ is described by its β β-mixing coefficient defined as $\beta(m) = \sup_t \beta(\sigma\{y_u : u \leq t\}, \sigma\{y_u : u \geq t + m\})$ where $\sigma\{\}$ denotes a sigma-algebra, and $\beta(A,B) = ½\sup \sum_{i=1}^{I} \sum_{j=1}^{J} \left| P(A_j \cap B_j) - P(A_j)P(B_j) \right|$ over some finite partitions $\{A_1, A_2, \ldots, A_I\}$ and $\{B_1, B_2, \ldots, B_J\}$ (Hazewindel 2002).

where c denotes the threshold parameter, $\sigma^2(c)$ the regression variance of the TAR model, and σ^2 the regression variance of the non-regime AR model, and T the number of observations. In addition, because the threshold parameter is chosen such that the variance is minimised, it is true that

Equation B3:

$$F_T = \sup_{c \in C} T\left(\frac{\sigma^2 - \hat{\sigma}^2(c)}{\hat{\sigma}^2(c)}\right)$$

The distribution of F_T, however, is non-standard, and Hansen suggests the following bootstrap procedure to determine the critical values. Let $u_t^* \sim iidN(0,1)$, and set the dependent variable $y_t^* = u_t^*$. Estimate the TAR-TAR model of y_t^* on x_t, as described in Section 4.3, and obtain the regression variance $\sigma^2(c_1,c_2)$. The intuition behind these procedures is that the threshold estimator is of higher order than conventional regression estimators so that the latter can be ignored in terms of simulating the asymptotic distribution; thus, when simulated, they can be set equal to zero. Next, the linear AR(2) model of y_t^* on $(1, r_{t-1}^*, r_{t-2}^*)'$ is estimated, and the regression variance σ^2. The F-statistic is calculated:

Equation B4:

$$F_T^* = T\left(\frac{\sigma^2 - \hat{\sigma}^2(c_1, c_2)}{\hat{\sigma}^2(c_1, c_2)}\right)$$

The distribution of F_T^* should converge to that of F_T, so that repeated draws from F_T^* may be used to approximate the asymptotic null distribution. The asymptotic p-value is formed by counting the percentage of bootstrap samples of which $F_T^* > F_T$.

Initially, the number of iterations is set to 500. One difficulty encountered in the bootstrap procedure was negative F_T^* which, on average, account for about 40% of the sample. This is not unexpected: given the non-linearity of the problem, the recursive technique will not always ensure the global minimum in a sense that sometimes $\sigma^2 < \hat{\sigma}^2(c_1,c_2)$, and hence $F_T^* < 0$. Incorporating these negative values in the calculation of critical values would only lower them – thereby making it easier to reject the null of AR while increasing the probability of Type I error – and would be incorrect anyway as there would be prima facie evidence of convergence failure. The number of iterations was increased, therefore, such that the number of positive F_T^* equal 500, and this rule has been abided by in all exercises. Table B1 reports the test results for the AR-TAR and TAR-TAR models.

APPENDIX B: TESTING THE SIGNIFICANCE OF THE MODELS

Only the models that use FT returns or GDP growth as a regime indicator indicate some statistical significance. This finding confirms the belief about the quality of these two variables as the real estate market indicator. Nevertheless, these results tend to be weaker than what the research had hoped for in that they are usually significant at 10% level. However, this could be expected of these types of tests, which generally have low power. Overall, the test results provide some support for the existence of regimes, and also the use of the regime-switching unsmoothing technique over the AR method. That the results are not decisive is probably attributable to the embedded uncertainty around the threshold value(s). Consequently, another set of tests was conducted by treating the estimated threshold as if it was true, and known to the researchers. The new results, shown in Table B2, are in line with, but much stronger than, those reported in Table B1, with FT returns, once again, proving to be the most significant regime indicator.

Table B1: Test results

AR-TAR		TAR-TAR	
Indicator	p-value	Indicator	p-value
LIBOR	0.174	LIBOR-LIBOR	0.281
Inflation rate	0.214	FT-FT	0.087*
Real interest	0.202	LIBOR-FT	N/A
FT returns	0.023**	FT-LIBOR	0.138
Exchange rate	0.221		
Initial yield	0.312		
GDP growth	0.067*		
Employment	0.118		

Notes: the figures in the table denote the p-values testing from the bootstrapping exercise: * denotes significance at 10%, and ** at 5%; (ii) N/A denotes Not Applicable, due to the negative F-statistic of that model (recall Table 4).

Table B2: Test results with known threshold values

AR-TAR		TAR-TAR	
Indicator	p-value	Indicator	p-value
LIBOR	0.034*	LIBOR-LIBOR	0.172
Inflation rate	0.057	FT-FT	0.004**
Real interest	0.046*	LIBOR-FT	NA
FT returns	0.001**	FT-LIBOR	0.008**
Exchange rate	0.104		
Initial yield	0.132		
GDP growth	0.018*		
Employment	0.047*		

Notes: the figures in the table denote the p-values testing from the bootstrapping exercise with threshold values assumed to be known: * denotes significance at 10%, and ** at 5%; (ii) N/A denotes Not Applicable, due to the negative F-statistic of that model (recall Table 4).

NOTES

Printed on recycled paper

Investment Property Forum
New Broad Street House
35 New Broad Street
London EC2M 1NH

Telephone: 020 7194 7920
Fax: 020 7194 7921
Email: ipfoffice@ipf.org.uk
Web: www.ipf.org.uk