

**Investors Behaviour and Price Discovery:
A Tale from Smoothing Dynamics of Commercial Real Estate Returns**

Gianluca Marcato* and Vianey John Mushi†

[First draft: December 2014]

* School of Real Estate & Planning, Henley Business School, University of Reading, Reading RG6 6UD, United Kingdom, Tel: +44 (0)118 378 8178, Fax: +44 (0)118 378 8172, Email: g.marcato@henley.reading.ac.uk.

† [Corresponding Author] Department of Land Management and Valuation, Ardhi University, P.O. Box 35176, Dar es Salaam, Tanzania, Tel: +255-22-271272, Fax: +255 22 2775448, Email: viane@aru.ac.tz.

**Investors' Behaviour and Price Discovery:
A Tale from Smoothing Dynamics of Commercial Real Estate Returns**

[First draft: December 2014]

Abstract

Several sources of appraisal smoothing have been studied in the literature trying to explain the high level of cyclicity in asset pricing for alternative asset classes and particularly real estate and hedge funds. We focus on the role of mean shifts and time varying volatility to show that existing smoothing models overstate the magnitude of the smoothing parameter. Our analysis reveals that the mean of the generating mechanism evolves over time, and shows that when we embed inter-temporal shifts on the data generating process, the smoothing parameter is consistent with a much faster adjustment of frequently appraised properties than previously estimated. We argue that smoothing parameters based on empirically observed returns are biased upward and mask inter-correlated changes on the level of the process. Finally, we also observe that the impact of non synchronous appraisals is often understated, while the impact of seasonality of reappraisals is exaggerated if the instability on the generating mechanism is ignored.

1. Introduction

Existing literature reveals that appraisal based returns are less volatile and exhibit positive and significant serial correlations than would be suggested by the distributional characteristics of the underlying true series. Actually, it is argued that much as appraisals are cross sectionally distributed around the underlying true market values, their expectation do not corresponds to the true value of a property as of the same point in time (Geltner, 1991; Fisher et al., 1999 among others). Appraisals lag temporally true market values a phenomenon commonly referred to as appraisal smoothing. The incidence of smoothing can be examined econometrically by measuring the degree of serial correlation between adjacent returns derived in benchmark indices. That is, examining the speed of adjustment to the underlying new equilibrium value if new information enters a market as a random shock. Alternatively, it can be established by identifying the extent to which appraisals smooth out periodic fluctuations in price. A slower adjustment or volatility damping bias signifies that appraisals do not incorporate new information instantly but rather the impact of news would be spread overtime.

Attempts to describe a systematic process by which appraisals are smoothed have stimulated a lot of heated debate. There has developed a voluminous body of literature, both at theoretical and empirical level. A number of variables are thought to have a significantly effect on the price-setting rule and several techniques for dealing with the lagging effect have been considered. Notwithstanding these significant achievements, results emerging from the literature taking as a group are periodic specific, inconclusive and without doubt conflicting. At a very fundamental level, generating mechanism in the most reverse engineering filters tends to be very insular, confined to a time invariant mean and a transitory variance process as if appraisals are sampled from one distribution or the price formation process follows the same stochastic process overtime and across markets. Subsequently, the lagging effect tends to be overestimated. Clearly, characterization and formulation of the majority of the existing statistical models is not sufficiently general to be invoked in all situations that may arise, which in turn is bound to lead to variability within the approach (Lai and Wang, 1998; Brown and Matysiak, 2000 and Eldestein and Quan, 2006 among others).

The current study contributes to this debate by further exploring sources of serial correlations in appraisal bases series and examining the extent to which the smoothing parameter is explained by a number or magnitude of inter temporal shifts on investors' expectations and varying residual process in addition to aggregation, non synchronous effects of appraisals or seasonality of reappraisals. The novelty, of the current study is on modelling the propagation of the conditional

mean and the variance process of the error term using a model which explicitly incorporates a series of correlated changes on the mean of the process as well as uneven arrival of price sensitive information while accounting for the timing of appraisals. We then test the performance of the proposed model using the monthly IPD (UK) capital gain index. In short, we regard econometric models that we have proposed are very useful in explaining the speed of adjustment in appraisal based series as well underlying factors behind the aggregate returns.

The rest of this paper is organized as follows. Section 2 presents a comprehensive survey of issues germane on sources of smoothing at asset level and econometric considerations surrounding its modelling. Section 3 presents a smoothing model which explicitly accounts for a series of correlated changes on the mean of the process as well as uneven arrival of price sensitive information in addition to the timing of appraisals. The performance of the proposed model is tested using the overall monthly IPD (UK) capital gain index in section 5. Finally, section 6 concludes.

2. Literature Review

So far several key factors have been identified as the main drivers of serial correlation in real estate and hedge fund indices. The main one is represented by the partial adjustment in appraisals when price sensitive information enter the market as random shocks and old and new information are aggregated to update appraisals – e.g. Ibboston and Siegel (1984) and Blundell and Ward (1987) argue for problems within the existing custom and practice of the valuation process while Quan and Quigley (1991) rationalize this behaviour as optimal in the presence of market uncertainty. In line with Geltner (1991, 1993) – where appraisal lagging is due to the non to tyranny of past appraisals due to valuation timing or lack of confidence on new information –, we argue that such view is justified in an explicit forward looking appraisal process setting. Under such environment, current estimates will influence future appraisals as valuers are objectively committed in generating appraisals which minimize random valuation errors. In practice however, the valuation process tends not to be ahead of the market and thus, there will always be a lag between appraisal-based and market-based time series, especially when the market is changing very fast (Matysiak and Wang, 1995). Moreover, agency theory would also suggest that valuers may be partially adjusting appraisals to reduce the amplitude of swings in values as investors normally prefer more stable environments. This form of measurement error is also induced by anchoring and the recurrence of valuations made by the same valuer over time (Geltner, 1993 among others). Empirical evidence suggests a set of behavioural issues may influence the way appraisals are updated, resulting in smoothing in appraisal

based returns (Diaz and Wolverton, 1998; Geltner, et al, 2003). Indeed, while Clayton et al. (2001) reveal that the level anchoring increases when the same valuer is engaged on two consecutive appraisal assessments of the same property, Fu (2003) shows that anchoring increases even further if the effect of a lagging error is accounted for. On the other hand, McAllister et al. (2003) attribute anchoring to inflexible valuation methodologies, agency conflict, appraiser code of conducts and the complex interconnection between transaction prices and appraisal estimates. In addition, appraisers may contravene the rational updating rule when updating appraisals as a result of recency effects, confirmation bias, dilution effects (Gallimore, 1994 and 1996) – which are higher when negative rather than positive news are analysed Hanz and Diaz (2001) – and the agreed sale price being known at the time of the valuation (Gallimore and Wolverton, 2000). As unfamiliarity with the market environment appears to be a critical factor triggering the anchoring effect (Diaz and Hansz, 1997), prior transaction information influences “unfamiliar” valuers (Hansz, 2004).

Moreover, if the impact of smoothing is contingent upon the quality of market information as suggested in Quan and Quigley (1989, 1991) and Geltner (1991, 1993), the evidence is quite contrary to principles behind the partial adjustment process and lends a strong support to the idea that serial correlations in appraisal-based returns could be due to more than the optimal or behavioural response in the presence of market uncertainty. What is of greater interest to us, however, is whether intermittent shifts on the level of the data generating process in response to radical shifts in investors’ expectations as well as varying volatility could explain the presence of positive and significant serial correlations implied by previous statistical models.

Another stream of literature including Brown (1985) and Blundell and Ward (1987) rationalizes sluggishness in appraisals with the failure of price setting agents to derive trading strategies that could exploit returns predictability. However, markets are highly localised, they comprise heterogeneous and indivisible assets held as long term investments and their transaction costs impede a high frequency in portfolio rotation. Subsequently, it is very unlikely for returns’ dependence to be eliminated through active trading as the frequency at which properties are transacted is very low – nearly 20 years on average for commercial properties, or 6 to 7 years for institutional investors (Bond et al., 2004) – information is treated as confidential between parties of a transaction (Geltner, 1991, 1993), and transaction length and costs are significantly high³ (Brown and Matysiak, 2000, Bond et al., 2004, Clayton et al., 2001 and Fisher et al., 1999).

³ Marcatto and Key (2005) indicate cost for transacting real estate assets is nearly 7.5% of a property value

This initial discussion leads us to the first main argument of the current paper: if decisions are taken every T -periods but data are observed only every $J \cdot T$ (with $J > 1$), the extent of appraisal obsolescence will depend upon the length of and the amount and direction of market movements during the lag period. In other words, smoothing in appraisals could reflect a complex time varying function of market-derived information.

Another stream of literature appears to suggest that appraisals depart from fundamental value due to slow or absence of information transfer from other markets which share a common set of variables governing the pricing process. Specifically, smoothing is attributed to factors which are responsible for sluggishness in the information diffusion process. These range from the fact that the values of commercial property are smoothed appraisals or accounting-based, rather than transaction-based, and hence do not update the information set as quickly transaction-based ones (McGregor and Nanthakumaran, 1992; Myer and Webb, 1994; Barkham and Geltner, 1994 and 1995; Eichholtz and Hartzell, 1996; Chau et al., 2001). This feature introduces the cyclicity of real estate returns, which has been recognised to be asymmetric and resulting in structural shifts, but with no formal mechanism which explicitly and simultaneously incorporates intermittent shifts on the level of the process and varying volatility when quantifying smoothing effect (which represents the focus of this paper).

The overall methodological approach also influences the adjustment mechanism obtained to modify original return time series. So far in the literature a series of techniques have been suggested. Reverse engineering filters, mostly used in the literature constitute the main approach. In particular, Blundell and Ward (1987) were the first to present a model for extracting true market price from appraisal based series by running a first order autoregressive process. Quan and Quigley (1989) propose a price determination model in a market characterized with incomplete information, varying expectation as well as high and heterogeneous search costs. In a follow up study, Quan and Quigley (1991) present a statistical model for extracting true market value from appraisals series in the presence of noisy signals. Along the same line, while Childs et al (2002a,b) rationalized the Quan and Quigley (1991) response function in continuous framework while supposing returns are mean reverting and the noise process is time varying, Brown and Matysiak (1998) re-estimate the Quan and Quigley (1991) model using the Kalman filter algorithm in order to calibrate the time varying smoothing parameters and Chaplain (1997) employs the procedure to calibrate time varying smoothing parameters for extracting true rental value and initial yields rates series from smoothed data by using a threshold regime switching process

Some studies are of particular importance for this paper. Under explicit assumptions of how behavioural issues are likely to incorrectly influence the way appraisals are updated, Geltner (1989, 1991) derive a process for calibrating the true systematic risk, total risk and heterogeneity from smoothed appraisal-based series. The proposed procedure reveals that appraisals are better approximated by a response function with exponentially declining transfer weights; and that, while volatility of unobserved true returns corresponds to the weight assigned on new market information, the variance of empirically observed returns is due to exogenous market condition. Along the same line, Fisher et al (1994) argue that the mis-representation of the underlying true volatility in the Geltner (1991) analytical procedure may be circumvented by imposing an explicit condition requiring it to be half of the stock market' volatility. Cho et al (2003) re-estimated the Fisher et al (1994) model by using generalized difference returns in order to address the problem of biased estimates as the sample size increases. In a related development, Geltner (1993) presents a model that approximate the lagging tendency in appraisals without assuming market efficiency and i.i.d. returns and Fisher and Geltner (2000) generalize this model by estimating the smoothing parameter based on the observed appraised values and transaction prices.

Nevertheless, the performance of reverse engineering techniques is tested assuming the most probable exogenous process governing the behaviour of unobserved true values and valuation updating processes, while imposing ad-hoc assumptions. Moreover, the primacy of first order autoregressive reverse engineering transfer functions are no longer accepted as they are considered reduced forms of error correction methods, or not reflecting an ARMA representation where the error term is fractionally integrated rather than exponentially decaying in the presence of appraisal smoothing and non-synchronous appraisal effects (Bond and Hwang, 2007). Furthermore, a number of studies discount most of theoretical arguments based on exponential reverse engineering techniques. Their disquiet rests on the argument that these filters are derived under implicit, if not explicit, assumptions by which appraisers' behaviour impacts at asset level and therefore are not optimal for modelling the dynamics of aggregate returns. In particular, it is argued that serial correlations in an index could also arise from other processes such as seasonality of valuations, stale appraisals or aggregation effects in addition to appraisal smoothing effects (Bond et al., 2012).

At a very fundamental level, irrespective of the technique employed, attempts to validate the proposed statistical models have produced diverse results. In particular, existing transformation filters seem to suggest that the speed of adjustment is infinitely slow, ranging from 0.5 to 0.9. Actually, an important message in Appendix 1 is that it takes approximately 4 to 8 quarters for deviations between appraisal-based series and the underlying true values to be fully eliminated.

Although the evidence prompts a strong desire to infer that appraisal process induces serial correlations in successive returns, empirical evidence is very thin (Giaccotto and Clapp, 1992). This argument is echoed in Brown and Matysiak (1998, 2000), Clayton et al. (2001) and very recently by Bond et al. (2012), where the authors show that the level of serial correlations of a random sample of frequently valued commercial properties is nearly 0.15, and on average smaller than the magnitude of smoothing implied by statistical procedures. Along the same line, De Wit (1993) reveals that appraisals prepared by independent consultants do not suffer from smoothing effects.

Motivated by these concerns, the current study maintains that the magnitude of smoothing implied by previous models can be due to more than the optimal behavioural response, but the observed effect may have resulted from a different process and therefore biased. The bias could reflect misrepresentation of the stochastic process governing the behaviour of unobserved true asset value due, at least in part, to methodological limitations, lack of a common consensus about the basic framework for dealing with wider issues about pricing in private real estate markets, structural shifts in the underlying process, as well as varying volatility. In other words, the smoothing parameter is likely to be far from its equilibrium when the level of the underlying process is correlated over time, or the variance process is time varying, or if both. The potential effect of a sequence of correlated changes on the level is to induce spurious serial correlations on the data generating process even if appraisals follow a random walk process. Thus, if these effects are not properly identified and managed, it is very difficult to identify a correct estimate of the smoothing parameter that reflects appraisers' behaviour. These two effects need to be considered simultaneously as they dynamically act and react to each other in such a way to induce smoothing effect in observed series.

This being the case, we argue that a non linear specification with occasional shifts in both mean and variance could represent a further mechanism generating smoothing. Actually, we base our assumptions on more general finance literature, which demonstrates how stochastic shifts on the underlying pricing mechanisms render the partial sum of variances to decay (slowly) at hyperbolic rate and thus impounds persistence in observed/realized returns even if the underlying returns (data) generating process were stationary, uncorrelated and unpredictable, and the level of bias increases in number and break size (Nelson and Plosser, 1992; Diebold and Inoue, 2001 and Perron, 1989). Thus, the current study presents a smoothing appraisal model which explicitly and simultaneously accounts for sporadic shifts in investors' expectations and uneven arrival of price sensitive information in addition to the timing of appraisals. Our focus is to determine the extent to which smoothing is explained by inter-temporal shifts on the level, or varying residual or both. Finally, we quantify smoothing by using the aggregate index after controlling for stochastic shifts on the

propagating mechanism. The next section presents the model, section 4 describes the data used in the empirical estimation and the remaining two sections discuss results and conclude the paper.

3. Theoretical Model

The distinction between stationary and time varying data generating process is not minor. The unsmoothing model in which both the mean and error terms remain constant overtime neither will be able to approximate the generating process which explains the propagation mechanism of Figure 1, nor generate informed smoothing parameters. To examine this econometric problem, let us assume that the profile of Figure 1 could essentially be approximated by equation (2) where, the indicator function $I_{(\cdot)}$ is equal to 1 with probability p , signifying that changes in the mean, in the dynamics or the covariance matrix of a vector of empirically observed commercial aggregate returns have taken place relative to the previous process. On the other hand, the indicator function is zero with probability $(1-p)$, which essentially implies that, no changes in the mean, in the dynamics or the covariance matrix of a vector of empirically observed commercial aggregate returns have taken place. Further, let us assume that there are k different means (i.e. \mathbb{U}_i) in Equation (2), signifying that there are $k-1$ break points of length T_p proportional to the overall sample size – T , and that returns distribution in each sub sample is homogenous after a shock to the process.

$$\mathbb{R}_1^1 \dots \mathbb{R}_t^1 I_{\{t > (Tp1)\}}, \mathbb{R}_{[Tp1]+1}^2 \dots \dots \mathbb{R}_t^2 I_{\{t > (T(p1+p2))\}} \dots \dots \mathbb{R}_{[T(1-pk)]}^k \dots \mathbb{R}_T^k \quad (2)$$

$$\text{where: } I_{\{t > (t,T)\}} = \begin{cases} 0, & \text{With probability } 1 - p \\ 1, & \text{With probability } p \end{cases}$$

Expression (2) implies the following moments. The unconditional mean of portfolio returns with structural shifts can be estimated using expectation process which converges in probability as follows:

$$\bar{\mathbb{R}}_t \equiv \mathbf{E} [\mathbb{R}_t] \xrightarrow{p} \sum_{i=1}^k P_i \mathbb{U}_i \quad (3)$$

Define $\mathbf{Var} [\mathbb{R}_t]$ and $\Theta_m(n)$ as variance and covariance estimators given market information at time t respectively. Notice that because of covariance stationarity in each sub sample, the sample covariance function is expressed as: $\hat{\sigma}_k(T) = \frac{\sum_{j=1}^T (r_t - \bar{r}_t)(r_{t+j} - \bar{r}_t)}{T}$ where \bar{r}_t^a indicates the overall appraisal based average returns at time t . This implies that: $\hat{\sigma}_k(T) = \frac{\sum_{j=1}^T (r_t)(r_{t+j}) - (\bar{r}_t)^2}{T} +$

$\frac{\bar{r}_i(\sum_{j=1}^T r_{i,t} + \sum_{j=1}^T r_{i,t})}{T}$. This being the case, it can be shown that the limit of $\frac{\bar{r}_i(\sum_{j=1}^T r_{i,t} + \sum_{j=1}^T r_{i,t})}{T}$ as the sample size increases to infinity approaches zero in probability. Similarly, the overall mean of appraisal based aggregate returns, \bar{r}_t , tends to the sum of all expected mean in various sub series. Further, it can be demonstrated that $\frac{\sum_{j=1}^T (r_{i,t})(r_{i,t})}{T} \xrightarrow{p} \sum_{i=1}^k P_i (\hat{\sigma}(i) - (U_i)^2)$ where $\hat{\sigma}(i)$ is the variance of the i^{th} subsample. To this end, it follows that the variance of the appraisal based returns with intermittent shifts on the level of the data generating process is approximated by (4) where P_i indicates the probability of breaks.

$$\mathbf{Var} [r_{i,t}] = \sigma_{r_{i,t}}^2 - \left(\sum_{i=1}^k P_i U_i \right)^2 \quad (4)$$

Following Granger and Hyung (1999), the sample covariance function at a fixed lag m is expressed as: $\Theta_m(n) \equiv \text{Cov}_m(n) [r_{m,t}] = \sum_{i=1}^k P_i \Theta_m^{(i)} + \sum_{i=1}^k \sum_{j=1}^k P_i P_j (U_i - U_j)^2$. Thus, the autocorrelation function at a fixed lag m is:

$$\rho_m \equiv \text{Cor} [r_{m,t}] = \frac{\sum_{i=1}^k P_i \Theta_m^{(i)} + \sum_{i=1}^k \sum_{j=1}^k P_i P_j (U_i - U_j)^2}{\sigma_{r_{i,t}}^2 - \left(\sum_{i=1}^k P_i U_i \right)^2}; \quad i \neq j \quad (5)$$

The numerator in equation (5) indicates there are two sources of serial correlation, namely serial correlation due to appraisal smoothing $\sum_{i=1}^k P_i \Theta_m^{(i)}$ and serial correlation as a result of intermittent shifts on the level of generating process - $\sum_{i=1}^k \sum_{j=1}^k P_i P_j (U_i - U_j)^2$. Both components are non-negative because of positive correlations in the data. It immediately follows that if the level of the underlying pricing mechanism shifts overtime, one would expect there to be spurious persistence in the observed value, resulting in upward exaggerated serial correlations. The magnitude of bias is a function of expected number of breaks $\sum_{i=1}^k P_i U_i$ as well as break size - $(U_i - U_j)^2$. This being the case, the smoothing parameter calibrated based on time invariant data generating will be a mixture of appraiser behaviour as well sporadic shifts on the level process. The failure to adjust for intermittent shifts on the level of the process when modelling the incidence of smoothing in appraisal based series, one is bound to overstate the nature and significance of the smoothing parameter, resulting in misleading inference. On the other hand, if the probability of a break is zero, then the sample autocorrelation function parallels the autocorrelations function of a random walk

process. The evidence parallels findings in the micro and finance literature, see for example, Granger and Hyung (2004) and Getmansky et al. (2004) who demonstrate that when in the presence of structural breaks, returns persistence is largely driven by the magnitude of shifts between regimes and not otherwise.

A smoothing appraisal model under stochastic shifts on the level

A solution to the above problem is to employ a data generating process with sporadic level shifts rather than time invariant process if the smoothing parameter were to be correctly estimated. Essentially, there are different ways in which one could approach this problem. Firstly one can deal with changes in the mean by employing subsamples which are assumed to be homogenous. Modelling the incidence of smoothing based on sub periods is indeed the easiest way to go around. Nevertheless, the option might not always be possible if sporadic shift on investors' sentiment occur at the end of the spectrum or when there are several of them. Another problem is that changes in investors' sentiment may not exhibit sporadic shift at a specific point of time but rather takes a duration till its fully impact is realized. Under such circumstances, allowing distribution properties to vary across subsamples but assuming constancy within a subsample will not be helpful largely because changes in the mean of the generating process exhibiting slowly evolving features is more consistent with a time varying coefficients specification. It is also possible that changes in generating mechanism are connected to expansions and contractions in the market. On the other hand, Lizieri and Satchell (1996) apply the Self Exciting Threshold Autoregressive (SETAR) approach, Lizieri et al. (1998) invoke the regime switching - TAR process, Chaplain (1997) implemented the time varying multiple regime switching process, Liow and Webb (2008) estimated the logistic regime switching process. Nevertheless, smoothing parameters tend to be highly sensitive to regime switch variables, number of regimes specified, sample size in a given state as well as the ratio of market to transaction noise in each state. As well, the literature in the macro and finance indicates that when regimes are determined based on instinctive guess of reality or for convenience purposes, misspecifications for the true market changes point could result simply because changes could be slowly assimilated or implicitly correlated (Hansen, 1992). More significantly, the variations of the smoothing parameter takes place around a stable long run expected value as if the mean of the data generating mechanism follows a random walk process and are time invariant. In addition, Brown and Matysiak (2000) employ a stick appraisal mechanism, Fu (2003) and Clayton, Geltner and Hamilton (2001) estimated the dynamic state space model and structural model of appraisal behaviour respectively. However, generating mechanisms in these studies are very insular as they are not flexible enough to incorporate a number of time series behaviour of commercial real estate returns such as appraisals

smoothing, nonsynchronous appraisals effects, seasonality of reappraisals, the effect of cross sectional aggregation, varying volatility, volatility clustering, persistent noise process and structural shifts on the data generating process.

Our approach focuses on generating an index which holds constant the level of the data generating process over the measurement period. This involves stripping off all non linearity in the data generating mechanism by demeaning empirically observed returns with expected value of the level shifts as well as accounting for uneven arrival of price sensitive information in addition to the timing of appraisals. The model we propose is a modification of the Bond and Hwang (2007) model reproduced in this study as expression (6) where; \mathbf{r}_{mt} represents a vector of cross-sectionally realized aggregate returns constructed on individual asset prices, \mathbb{U}_m reflects cross sectional average returns (i.e. cross sectional expectation) and thus $(\mathbf{r}_{mt} - \mathbb{U}_m)$ indicates mean adjusted portfolio returns. $\Phi_\xi(\mathcal{L}) = (1 - \beta_1\mathcal{L} - \beta_2\mathcal{L}^2 - \beta_3\mathcal{L}^3 - \dots - \beta_p\mathcal{L}^p$ and $\theta(\mathcal{L})\varepsilon_t^* = (1 + \phi_1\mathcal{L} + \phi_2\mathcal{L}^2 + \phi_3\mathcal{L}^3 + \dots + \phi_q\mathcal{L}^q$ are polynomials in the lag operators \mathcal{L} with stable roots. In this case, the autoregressive parameter Φ_ξ measures the degree of persistence of unobserved common factors, the moving average parameter $\theta\varepsilon_{t-1}^*$ captures the impact of non synchronous appraisals (i.e. $E_C(\theta_i)$ and $\varepsilon_t^* = E_C(\varepsilon_{it}^*)$). In addition, the fractional differencing parameter $(\mathbf{1} - \mathcal{L})^\delta$ is defined above, where δ is analogous to the first order autoregressive parameter computed using first order autoregressive or exponential filters, that is, $\delta = E_C(\phi_{st})$ and measures the average level of smoothing at individual level.

$$\Phi_\xi(\mathbf{1} - \mathcal{L})(\mathbf{1} - \mathcal{L})^\delta(\mathbf{r}_{mt} - \mathbb{U}_m) = \theta\varepsilon_{t-1}^* + \varepsilon_t^* \quad (6)$$

$$\text{where: } (\mathbf{1} - \mathcal{L})^\delta = \frac{\Gamma(r-\delta)\mathcal{L}^r}{\Gamma(r+1)\Gamma(-\delta)}$$

$$0 \leq \delta \leq 1$$

Bond and Hwang (2007) proposed expression (6) for examining the average level of smoothing at property level in the presence of appraisal smoothing, non-synchronous appraisals and temporal aggregation effects under assumptions that real estate markets are less informative. Nevertheless, the asymptotic distribution theory governing (6) concerns behaviour of statistics constructed from a stationary process and thus, the only point in time under which it will generate consistent estimates is returns have the same expected value overtime and covariance between any pair of returns is a

function only of temporal separation, or if the noise component follows a random walk process. In situation where valuation process or appraisers' behaviour differs significantly overtime, expression (6) tends to be very insular as variations in the mean or noise components could make the distribution of the underlying process not only to vary relative to the prior expectation but also changes could be correlated, resulting in inconsistent estimates. Thus, the modification we propose transforms the propagation mechanism of (6) by allowing the mean and the noise components to update and evolve overtime.

Addressing the first problem leads us to equation (7) where; $I_{(\cdot)}$ is an indicator function; Ω_{τ} is the τ^{th} step on the returns generating process relative to the previous discontinuity, T is a sample size and τT is a break point, \wp_t and $\Delta\Psi_t$ reflects illiquidity premium and changes in the other component of the expected returns at time t respectively.

$$\mathbb{U}_{m,t} = \mathbb{U}_{m,t-1} + \Omega_{\tau} I_{\{t > (\tau T)\}} \quad (7)$$

$$\text{where: } I_{\{t > (\tau T)\}} = \begin{cases} 0 & \text{with probability } 1 - p \\ 1 & \text{with probability } p \end{cases}$$

Equation (7) indicates that when an indicator function is zero, the current level of the underlying pricing process is the same to that of the last period. Conversely, (7) permits equilibrium returns component to evolve over time intermittently to a new level whenever the indicator function is one. In this perspective, it enables us to identify and determine the nature and magnitude of random variations on investors' expectation in the underlying returns generating process. However, the data requirement for this formulation is information from both changes on illiquidity premiums as well as the combined effects of changes in illiquidity premiums and other value affecting factors in addition to the observed returns of property. However, information on changes on illiquidity premiums as well as the combined effects of changes in illiquidity premium and other value affecting factors are both unobserved. For this purpose, a reasonable assumption can be made in view of when the level of the data generating process of expected returns component has significantly changed. Thus, we can describe this econometric approach as observed if illiquidity premium component of expected returns is significant, and if investors comprehensively track changes on the liquidity over time in a manner which is not offset by simultaneous changes in the other components of the expected returns. That is, a significant shift on the level of the process is observed if illiquidity premium (\wp_t) exceeds simultaneous changes in other components ($\Delta\Psi_t$) of the process. Combining (6) and (7) and a simple rearrangement yields a smoothing appraisal model under stochastic shifts on the level

of the data generating process in the presence of appraisal smoothing and non-synchronous appraisal effects as:

$$\emptyset_{\xi}(\mathbf{1} - \mathcal{L})(\mathbf{1} - \mathcal{L})^{\delta}(\mathbb{r}_{m,t} - \langle \mathbb{U}_0 + \sum_{\tau=1}^T \Omega_{\tau} I_{\{t > (t, T)\}} \rangle) = \theta \varepsilon_{t-1}^* + \varepsilon_t^* \quad (8)$$

$$\text{where: } I_{\{t > (t, T)\}} = \begin{cases} 0 & \text{Unobserved} \\ 1 & \text{Observed if } \wp_t > \Delta\Psi_t \end{cases}$$

The basic idea of equation (8) may be explained as follows. Equilibrium returns are allowed to vary overtime. The inclusion of the level shifts on the underlying returns generating process reflects investors' behaviour to revise their perception of the market's expectation of the future cash flows and discount rate in the valuation process. Consequently, a sequence of correlated changes on the level of the process may be introduced in the property returns series by appraisal process which in turn affects the apparent risk and returns properties of commercial property market. The significance of parameters \emptyset_{ξ} , θ and δ is extensively discussed in the Bond and Hwang (2007) paper, where some credible economic theories in the context of this analysis and regarding the appraisal behavioural determinants of δ is developed. It is convenient to recast the smoothing implications implied by (8) above. In short, it is the order of integration δ which determines the nature and magnitude of appraisal smoothing at individual property level. Actually, δ is usually a non integer number that takes value as defined by $\delta \in [0 < d_i < 1/2]$ for smoothed stationary process and $\delta \in (0.5, \infty)$ in the case of non stationary process. When $\delta > 0$ signifies the process is characterized with very strong autocorrelation structure that decays slowly toward zero and remains significant for very large lags - temporal appraisal lag bias. In other words, current estimates will be influenced by previous information, resulting in smoothed process. This phenomenon has the effect of greatly reducing the extent of volatility that is in the appraisal based series; corrupting serial and cross correlations between real estate assets and other investment vehicles such as bonds and stock. To the contrary, If $\delta \in [-1/2 < d_i < 0]$, we would expect appraisal based series to display anti-persistent behaviour – that is, a rapid decline of the autocorrelation function, and thus no evidence of appraisal smoothing. In addition, if $\delta = 0$ illustrates commercial property market is well functioning and very fast in processing signals relevant to the pricing of real estate assets.

Expression (8) presents a vital process that we can utilize to improve our understanding on the nature and magnitude of persistence in commercial real estate market. Indeed, (8) implies that if lagging tendency of appraisal based series relative to the underlying true returns is a natural or true

behaviour of the commercial real estate market, such a tendency will be captured by appraisal based returns series filtered for a sequence of correlated changes on the level of returns generating process. As mentioned above, a failure to allow for intermittent shifts on the level of the process induces a very strong and spurious autocorrelation structure irrespective of whether appraisals smoothing effect exists or not. The magnitude of bias in the smoothing parameter is governed by expected number of breaks as well as the magnitude of level shifts as measured by the difference of the τ^{th} step on the returns generating process relative to the previous level⁴

Modelling the time varying noise process

However, expression (8) is not an appropriate “model” to approximate aggregate behaviour of investors in the commercial real estate market as the error term (i.e. ε_t^*) is subjected to a set of linear restrictions as if information arrives at a constant rate. Yet, it is well known the cross-sectionally dispersed pricing errors component vary overtime and reflects a vector of random and unexpected set of events that affect perceptions of investors or their pricing agents on future property values as well as their differing transaction costs. Thus, in the commercial property market, the homeskedasticity assumption is very restrictive and stronger than necessary, largely because the rate of information flow is firstly impounded into the valuation process gradually and consequently, resulting in understating the sensitivity of prices in the incoming market signals –understates volatility. Overtime however, conditional on observable market events, property prices tend to experience post events drifts in the same direction as the initial event impact and consequently impound more variations on property prices than before.

Thus, for analytical purposes, assumptions governing propagation of innovations (ε_t^*) in (8) are modified to allow for the variance process evolve overtime. The model specification proposed is geared to examine to what extent the intensity of the smoothing parameter is biased as a result of misspecification of the residual process. The modification involves replacing σ^2 using a procedure pioneered by Davidson (2004) such that $\varepsilon_t \sim \text{IID}(0, \mathbf{h}_t)$ and \mathbf{h}_t propagates as a Hyperbolic-GARCH – HYGARCH (p, δ, q) – process⁵. The HYGARCH model is a class of models where

⁴ In similar vein, Bos et al. (1999); Granger and Hyung (1999) and Getmansky et al. (2004), Hsu (2005) among others demonstrate that the extent of returns dependence bumps up as the scale of the level shift or expected number of breaks increases.

⁵ The HYGARCH(p, δ, q) process was pioneered by Davidson (2004) by generalizing the Fractional Integration GARCH process- that is, FIGARCH. The generalization involves embedding the unit amplitude restriction. The generalization formulation of the FIGARCH model was pioneered by Baillie, Bollersleve and Mikkelsen (1996)

conditional variance at time t is an infinite memory average of the squared realization of the series up to time t-1. The process is expressed by (9) through (12) where for all t: $\omega, \vartheta > 0$, ψ & $\beta < 1$, and $0 \leq \delta_v \leq 1$.

$$\varepsilon_t^* = \delta h_t \tag{9}$$

Following equation (9), a study by Baillie (1996) indicates the conditional variance in the fractional integration GARCH formulation - that is the FIGARCH (p,d,q) model is expressed as: $h_t^2 = \omega[1 - \beta(L)]^{-1} + \{1 - [1 - \beta(L)]^{-1}\psi(L) (1 - \mathcal{L})^\delta\} \varepsilon_t^2$ where: $(1 - \mathcal{L})^\delta$ is a fractional differencing operator defined by (3.10) with $C_1(\delta) = \delta$ and $C_2(\delta) = \frac{1}{2}\delta(1 - \delta)$ and so forth.

The conditional variance specification is expressed as follows:

$$(1 - \mathcal{L})^\delta = \sum_{k=0}^{\infty} \frac{\Gamma(\delta+1)L^k}{\Gamma(k+1)\Gamma(\delta-k+1)} \tag{10}$$

$$(1 - \mathcal{L})^\delta = 1 - \delta L - \frac{1}{2}\delta(1 - \delta)L^2 - \frac{1}{6}\delta(1 - \delta)(2 - \delta)L^3 \dots \dots \dots$$

$$= 1 - \sum_{k=1}^{\infty} C_k(\delta)L^k$$

where $1 \geq \delta \geq 0$ and L reflects a lag operator such that $\lambda(L) = 1 - \lambda_1 - -\lambda_1 \dots \dots - \lambda_q$. Thus, according to Davidson (2004) the HYGARCH model is obtained when $\lambda(L)$ in (15) is expressed as in (11) below. In this formulation, the conditional variance, δh_t , is positive with probability one and as mentioned above is a measurable function of \mathcal{F}_{t-1} which is generated by all information sets available up to time T_{t-1} ($y_{t-1}, y_{t-2}, y_{t-3}, \dots \dots$). When $0 < k < 1$ the process (11) is stationary and when $k > 1$ this expression is non stationary. The persistence behaviour in conditional variance is modelled by using the usual fractional differencing operator, $(1 - L)^\delta$ as defined by (10) above where δ is the amplitude of mean reversion tendency such that $0 < \delta < 1$. It is the fractional order parameter d, (which takes fractional values) which determines the nature and degree of the returns dependence. When $\delta = 0$, Davidson (2004) reveals equation (11) becomes an ordinary GARCH process:

$$h_t^2 = \omega + \sum_{i=1}^{\infty} \lambda_i L^i \varepsilon_t^2 = \omega + \lambda(L) \varepsilon_t^2 \tag{11}$$

$$\text{where: } \lambda(L) = 1 - [1 - \beta(L)]^{-1}\psi(L)\{1 + k(1 - \mathcal{L})^\delta - 1\} \tag{12}$$

The use of persistent and power transformed conditional variance filter in commercial property market is justified mainly because autocorrelations function of the volatility process decays at a hyperbolic rate based on information generated from macro economic conditions or general market dynamics and that the extent of such persistence depends on the intrinsic characteristics of the property. In fact, Furthermore, Quan and Quigley (1989, 1991) suggest that innovations in the valuation process varies with the completeness of the information sets of the pricing agents and the condition prevailing at the time a transaction is negotiated and/or concluded. Case and Shiller (1989) indicate residual component in the appraisals relative to the underlying true value are time varying and the variations over time are linked to the random arrival of potential buyers, behaviour of real estate market agents and exogenous market movements. Further, Case and Shiller (1989) highlight the noise component is never homoskedastic but rather increases with the interval between sales. In addition, Clayton et al. (2001) suggest that heterogeneity in properties making up the portfolio makes residual process sensitive to property value and consequently non constant. Finally, the convention assumption that the underlying data generating process of commercial property market is informationally efficient implies linearly propagating residual process after a transaction has been concluded, and thus, appraisal process must take into account both the initial (non accumulating noise in the prior transaction prices) as well as accumulation of the propagation of measurement errors in the underlying true value of the property after its previous transaction has taken place (Quan and Quigley, 1991).

Furthermore, it is well known that incremental information flow employed to revise previous estimates or expectation to contemporaneous estimates could be higher or lower depending on implicit characteristics of a property under appraisals as they relate to general market condition or macro economic variables and systematically varies over time due to business cycles and/or market dynamics (Engel, 1982 and Bollerslev, 1986 in the general financial literature). Indeed, Fisher et al. (2003) indicate marco-level transaction motivations for most part attribute changes over time in the flow of financial capital into and out of commercial property segments and subsequently induce an upward(downward) adjustment in transaction prices or market values as well as changes in liquidity. Childs et al. (2002a; 2002b) on the other hand show signal variation may arise as a result of hurried sale into a thin market, active/inactive resale market, or as a aftermath of purposefully acquisition of information as part of a due diligence process in addition to appraisal process, temporal aggregation or pricing model. Moreover, commercial real estate returns have non normal distributions, possibly negatively skewed t distribution with fat tails and excess kurtosis. It follows that the use of the normal distribution and constant variance assumption is unwarranted, causing major difficulties in estimating and reliably distinguishing the parameter's signal and casts doubt on subsequently

inferences. In addition, there is substantial evidence suggesting transaction density during up markets is greater than during falling market - that is, pro-cyclical variable liquidity. Essentially, these theoretical constructs cement the supposition that the nature and the extent of dispersion of appraisals relative to the underlying true value is not a simple pricing phenomenon linked to misconduct or lack of professionalism among pricing agents but rather an intrinsic phenomenon in the valuation process.

Finally, a number of studies present a striking set of empirical facts about the dynamics of the residual process and the extent of the effect of each new shock has on evolution of commercial property returns. Dolde and Tirtiroglue (1997) for instance, observe a tendency for news to cluster in time (i.e. volatility clustering) on housing returns, so do Wong et al. (2007) in real estate spot and forward returns. On the other hand, Crawford and Frantatoni (2003) illustrate that GARCH models present superior performance in forecasting housing returns, in terms of having lower root mean squared error (RMSE) than ARMA or Markov Switching processes in seven out of fifteen cases investigated. Moreover, empirical studies illustrate the propagation (transmission) of incremental information in the commercial property market displays is asymmetrical and uneven, suggesting that: i) market volatility not only varies over time but negative shocks generate higher volatility than positive innovations of the same magnitude and ii) investors react more when property values declines.

The above empirical and theoretical evidence is also supported by our preliminary analysis - see Appendix 2 on the dynamics of residual process for the monthly IPD index. Indeed, identifiable patterns of time varying variance illustrate that expected value of the noise terms, in absolute value, is not constant but rather larger for some periods than others. More specifically, the dynamics of the monthly IPD (UK) index clearly exhibit volatility clustering and the autocorrelation structure that is significantly persistent. These phenomena are marked as “A” & “B” and coincide with real estate market booms and depression in the late 1980s, mid 1990 and in the late 2000s as discussed above. Generally, Appendix 2 confirms the need for more careful modelling of innovations in the valuation process where time varying model may be in order. In short, the noise component is time varying and the variations depends on the completeness of the market information available to market participants as of that period of time or conditions of sale and thus, needs to be modelled by a time varying specification. This is important, because handling of time varying residual variance in a stable framework produces inefficient estimates and subsequently leads to flawed pricing model (Engle, 1982). In this perspective, failure to allow for heteroskedasticity in the noise component could induce a positive bias in the smoothing parameter.

Combined effects of level shifts and varying volatility

Although intermittent shifts on the level of the underlying pricing mechanisms and time varying residual component are two independent processes, it is imperative to handle them concurrently largely because the magnitude of bias in the smoothing parameter is a function of both expected number of breaks as well as volatility process. Differently stated, corresponding to stochastic shifts on the level of the process is an increase in expected volatility which in turn makes the sample autocorrelations in (9) converges to non zero value for any fixed lag as the sample size increases to infinity. Thus, in the presence of both effects – that is inter-temporal shifts on the level as well time varying volatility and volatility clustering, (6) is re-specified as in (13) where, β reflects the magnitude of variations in the conditional variance. Other variables are defined above. The order of existing moments, ψ , indicates volatility clustering where as $\delta_{figarch}$ measure the length of time shocks to the residual component takes to fade away.

$$\phi_{\xi}(\mathbf{1} - \mathcal{L}) (\mathbf{1} - \mathcal{L})^{\delta} (\mathbb{r}_{m,t} - \langle \mathbb{U}_0 + \sum_{\tau=1}^T \Omega_{\tau} I_{\{t > (t_{\tau} T)\}} \rangle) = \theta \varepsilon_{t-1}^* + \varepsilon_t^* \quad (13)$$

$$\begin{cases} I_{\{t > (t_{\tau} T)\}} = \begin{cases} 0 & \text{Unobserved} \\ 1 & \text{Observed if } \wp_t > \Delta \Psi_t \end{cases} \\ \varepsilon_t^* = \delta \mathfrak{h}_t \\ \mathfrak{h}_t = \omega + \langle 1 - [1 - \beta(L)]^{-1} \psi(L) \{1 + k (1 - \mathcal{L})^{\delta_{figarch}} - 1\} \rangle \varepsilon_t^2 \end{cases}$$

To control for the surge of reappraisals in the quarter end months⁶, we allow for the lag operator to have stochastic seasonal process as expressed in (14) where, the stochastic seasonal differencing parameter, $(\mathbf{1} - \mathcal{L}^s)^{\delta}$, is defined below:

$$\phi_{\xi}(\mathbf{1} - \mathcal{L}^s) (\mathbf{1} - \mathcal{L}^s)^{\delta} (\mathbb{r}_{m,t} - \langle \mathbb{U}_0 + \sum_{\tau=1}^T \Omega_{\tau} I_{\{t > (t_{\tau} T)\}} \rangle) = \theta \varepsilon_{t-1}^* + \varepsilon_t^* \quad (14)$$

$$\text{Where: } (\mathbf{1} - \mathcal{L}^s)^{\delta} = \mathbf{1} - \delta \mathcal{L}^s - \frac{\delta(1-\delta)\mathcal{L}^{2s}}{2} - \dots \dots \dots = \sum_{i=0}^{\infty} \pi_{0,i} \mathcal{L}^{i,s}$$

⁶ Geltner (1989, 1991 and 1993) accounts for the impact of appraisals seasonality by invoking an infinite order moving average transfer function. Fisher et al. (1994) capture seasonality of reappraisals in the fourth quarter by including a fourth quarter lag dummy variable. Bond and Hwang (2007) add a fourth order autoregressive term for the US real estate market and a third order lag for the UK commercial property market. However, the use of liner seasonal adjustment filters do not necessary generate series which are free from periodic phenomenon/events.

$$\text{and: } \begin{cases} I_{\{t > (t_T)\}} = \begin{cases} 0 & \text{Unobserved} \\ 1 & \text{Observed if } \varphi_t > \Delta\Psi_t \end{cases} \\ \varepsilon_t^* = \delta h_t \\ h_t = \omega + \langle 1 - [1 - \beta(L)]^{-1} \psi(L) \{1 + k(1 - \mathcal{L})^{\delta_{figarch}} - 1\} \rangle \varepsilon_t^2 \end{cases}$$

One attractive feature of our analytical procedure is that it is flexible enough to estimate and capture other time series behaviours (seasonality and serial correlations in realized returns) governing returns generating process at different point in time and especially if only a few moments (mean, variance or correlations) of data generating process have changed overtime. In contrast, most previous studies have employed one generating process or one predetermined set of generating process that do not vary with time and it is not clear that empirical findings based on previous studies are representative of commercial real estate dynamics given the substantial structural changes in the market. However, estimates based on a sequence of spontaneously determined (regimes) segmented series much as are valid, could result in a loss of important signals and subsequently an efficiency loss than if all data sets were examined together. In addition, we employ a much larger number of generating mechanisms than previous studies. Thus, information on the propagation mechanism of the data generating process is used efficiently. Further, noise in the generating process are explicitly and accurately modelled as opposed to previous studies which recover the true stochastic behaviour of commercial property market while supposing the underlying returns generating process follows a random walk process and the market is informationally efficient. As mentioned elsewhere in this thesis, ad-hoc assumptions on the noise process do not allow a reasonable and reliable inference to be drawn, and in fact may lead to over/understating volatility process. More significantly, our specification accounts for correlation between the smoothing parameter and the error process or level shifts and subsequently it not only generates accurate and consistent estimates but also it allows correct inferences to be made.

Parametric specification and estimation strategy

Consistent to our assumptions, handling for changes on investors' expectations overtime as well as varying volatility process entails estimation of equation (19) which is purely a transformation of equation (14) where, $Z_{m,t}$ indicates a stationary index that holds constant the level of the underlying pricing process after properly differenced and demeaned. Other variables are defined above. It is expected that, if these two variables are the real factors driving the persistence behaviour of appraisal based series, then (15) should yield smoothing coefficient that is statistically insignificant.

$$\varnothing_{\xi}(\mathbf{1} - \mathcal{L})(\mathbf{1} - \mathcal{L})^{\delta} Z_{m,t} = \theta \varepsilon_{t-1}^* + \varepsilon_t^* \quad (15)$$

$$\text{where: } \begin{cases} \varepsilon_t^* &= \delta h_t \\ h_t &= \omega + \langle 1 - [1 - \beta(L)]^{-1} \psi(L) \{1 + k(1 - \mathcal{L})^{\delta_{figarch}} - 1\} \rangle \varepsilon_t^2 \end{cases}$$

Effectively, (15) calibrates the average level of smoothing at individual property level after isolating the effects of stochastic changes on the level of the underlying returns generating process of empirically observed appraisal based returns as well non-synchronous appraisal effects. In this framework, it is the combined effects of level shifts on data generating process as well as temporal aggregation and non synchronous appraisal effects which ascertain the nature and significance smoothing effect. A vector of the level shifts adjusted portfolio returns ($Z_{m,t}$) is generated by getting rid of all non linearity on the level of the data generating process. This entails subtracting the expected value of level shifts (i.e. $\overline{Z_{m,t}}$) from empirically observed portfolio returns ($r_{m,t}$) as in (16) along the lines Bos et al. (1999) and Hidalgo and Robinson (1996). Actually, Bos et al. (1999) reveal and demonstrate that expected value of the level shifts adjusted returns, $E(Z_{m,t})$, is expressed by (17) or simply as in (18) below.

$$Z_{m,t} = r_{m,t} - \sum_{\tau=1}^T \Omega_{\tau} I_{\{t > (t_{\tau} T)\}} \quad (16)$$

$$E(Z_{m,t}) = \overline{Z_{m,t}} = \frac{1}{T} \sum_{\tau=1}^k R_{m,t} - \frac{1}{T} \sum_t \sum_{\tau=1}^k U_{m,\tau} I_{\{t > (t_{\tau} T)\}} \quad (17)$$

$$\overline{Z_{m,t}} = \overline{R_{m,t}} - \frac{1}{T} \sum_{\tau=1}^k [T(1 - t_{\tau})] U_{m,\tau} \quad (18)$$

Model selection and particularly the lag order structure (i.e. p & q) is based on the structure of the sample Autocorrelations Function (ACF) and Partial Autocorrelations Function (PACF). Actually, a search over all constituent models is undertaken using both the Akaike and Bayesian information criteria beginning with maximum settings of $p=q=3$. An assessment of parameter significance is performed to select the best-fitting model. The current study estimates parameters of the analytical procedures discussed above by invoking the maximum likelihood estimator as implemented by PCGive (6.0) and GARCH (6.1) routines. The method has the smallest bias – estimates with minimum standard deviation (Souza, 2007).

The validity and adequacy of selected models involves performing tests regarding assumptions made on model parameters as well as testing for the whiteness of residuals. We employ the Augmented Dickey Fuller (ADF) test to examine the unit root process and Akaike information criteria to determine an appropriate number of the lagged independent variable to remove serial correlations. On the other hand, testing parameters assumptions is equivalent to testing the significance of lags

structure and, in our case it is performed by using the student type (t-ratio) test. The whiteness of residuals test is carried out by employing the Portmanteau test. We use the recursive residuals estimation technique to detect the presence of structural breaks in the series. Finally, test for parameter constancy is performed by employing the first step Chow (F-statistic) tests.

In short, the joint ARFIMA(p, δ, q)-HYGARCH(p, δ, q) process as defined by (15) has the capacity to approximate time varying volatility rather well but also it estimates the parameters driving the magnitude of persistence while accounting for dual long memory behaviours observed in both the conditional returns and transformed conditional volatility processes without suffering from the drift term. The expression manages the potential effect of intermittent shifts on the level of the data generating process that may occur without imposing a limiting condition/assumption on its structure – that is, how and when investors or pricing agents reverse their expectations. It allows for sub period risk and returns to govern parameters estimation as opposed to estimation process in the most of the previous studies which average over the various market conditions. In addition, it is flexible to estimate, it captures a number of time series behaviour of commercial real estate returns such as appraisals smoothing, nonsynchronous appraisals effects, seasonality of reappraisals, the effect of cross sectional aggregation, varying volatility and volatility clustering, persistent noise process and structural shifts on the data generating process. It does not lead to a loss of important signals as opposed to estimates based on a sequence of spontaneously determined (regimes) segmented series. Further, it is more flexible than a process in which transition from one regime to the other is not only abruptly but fixed based on either exogenous process or observable phenomena.

4. Data Description

The current analysis quantifies the effect of appraisal smoothing by employing data sets the private real estate market sourced from the monthly Investment Property Databank (IPD) index in the UK market over the January 1987 to January 2011 period. The index is the largest and well diversified valuation based database prepared from standing assets owned by its clients⁷ either directly or indirectly throughout the year effectively from 1987 with a fee based monthly valuations. The index is the most widely used as indicator of market performance or a benchmark for managers to gauge

⁷ Mainly from insurance and pension funds.

investment performance. It reflects a class of properties mostly preferred by institutional investors and measures unlevered returns from one open market value to the next. Performance measures are based on time weighted monthly patterns. Monthly returns are compounded to obtain annual returns. The series cover 25 years and in total there are 289 monthly observations. The database is well diversified in terms of property types, namely office, retail and industrial sectors with over 3,379 properties worth more than £32,709.2 million at the end of October 2013⁸.

[INSERT FIGURE 1]

Figure 1 summarises information on the profile of the monthly IPD (UK) capital growth rates from January, 1987 to January, 2011. Generally, the index is smoothed, upward sloping and where it is in a given period depends heavily on where it was the previous period. Moreover, Figure 1 indicates the profile has experienced major swings and the first swing indicates returns are trending upward from January 1987 to June 1988 and then marked by a sustained fall to negative 8 in May 1990. This is followed by a five year surge (high growth period) between 1990 and 1995 followed by a period of stable growth from July 1995 to December 2006. The impact of credit crunch and financial meltdown is vivid over the January, 2007 and December 2010. During that period, the monthly average realized capital growth rates is negative 5.3. The index bottoms up in January 2009. Further,

[INSERT TABLE 1]

Table 1 illustrates that index returns are marginally negatively skewed (-1.5157 to -0.87969) and display leptokurtic behaviour varying from 5.5706 to 3.6008. Effectively, normality is rejected at 95% level. Overall mean appreciation returns and long term standard deviation is 0.14083 and 1.1607 respectively. In addition, it shows that returns are highly correlated. On average, the first order serial correlation coefficient is around 0.9 and remains significant up to lag 10, meaning that

⁸ Source: Investment Property Databank, 2013

returns dependence from one period to the next is almost perfect and likely reflects the fact that market sentiment tends to be quite persistent, implying slow response to news.

[INSERT FIGURE 2]

This phenomenon is also echoed in Figure 2 which summarised information on autocorrelation and partial autocorrelations functions. However, if the correlation between contiguous returns is considered after correcting (“partial-out”) for any additional lags in between, the Partial Autocorrelation function (i.e. PACF) reveals that only the first two lags are significant and the remaining lags would be insignificant⁹. Save for the month of April, it seems that the high correlation between the IPD index return series is because returns at time t are related to previous returns. Nevertheless, the absence of spiking in the correlogram structure suggests that the impact of the seasonality of revaluation is less significant.

[INSERT TABLE 2]

In addition, results on our preliminary analysis on the structural shifts (Table 2) confirms that it is logically inconsistent to assume that the data generating process governing the profile of Figure 1 follows a random walk process. Actually, analysis indicates that the mean shifts overtime. In particular, we first reject the null of the constant data generating process in October 1989. The shift might have taken place when the UK economy experienced a boom in the housing market. The housing boom, which started in the early 1980s, increased house prices and stimulated consumer spending, which in turn resulted in remarkable increases in the rate of inflation. Consequently, the Bank of England increased interest rates to as high as 15% in the fourth quarter of 1989 in order to protect the value of the British pound. The costs of mortgage payments increased and led to a rising number of home repossessions and falling house prices (Osborn and Sensier, 2004). As a

⁹ Figure 2 indicates bars that are outside the lines suggest significant lags, as the lines are equal to two standard deviations of a normally distributed variable about zero at 5% critical value

consequence, consumer spending decreased and caused an economic slowdown which finally ended in the 1991 UK recession. The period of decline in property returns observed in May 1990 corresponds to the 1990 Gulf War. The second, structural change is detected around June 1993 but its impact appears to be gradual and continuously reflected in the market up to July 1994. The incidence corresponds to the change in monetary policy in 1992. The UK government through the Bank of England (UK) adopted an inflation targeting policy in 1992 that aims at keeping inflation at a low and stable level. Though the impact of the 1992 change in momentary policy was gradual and approximately took a year to be fully reflected in the real estate markets, it corresponds with the changes in the returns generating process and changes in models parameters. This is justified because inflation targeting policy turns out to be optimal and drives expectations of the market participants in their investment decisions and as a result investors and other economic agents make their investments decisions based on expected inflation rather than past inflation. In other words, a large swing of expectations is related to a large change in returns and/or trading volume. Instability in the profile of property returns from year-end 2006 through to the first quarter of 2009 corresponds to instability in the financial sector and the macro economy as a whole. That is, the plummet in house prices resulted in mortgage defaults and foreclosures, which in-turn lead to the decline in the price of mortgage backed securities and devaluation in equity prices – a phenomenon commonly referred to as the credit crunch and financial meltdown which sweeps across all economies, particularly US, Europe and East Europe.

5. Empirical Results

Data exploration has revealed that property index is characterized by major fluctuations, periodicity, trends and cycles that reflect good times or bad times over 1987 to 2011 period. The focus of the current section is to determine whether smoothing in appraisals is not attributed to the lack of contemporaneous market information, and that smoothing parameter implied by statistical models which allow for just one market state is a ballpark figure reflecting the constant market condition. This econometric problem is explored by employing equation (6) which is expressed as $(1 - L)^\delta(1 - \varphi L)r_t = \mu + (1 + \theta L)\varepsilon_t$ where, δ_τ captures the average level of appraisal lag; $\varphi_{\xi\tau}$ approximates sensitivity of commercial property returns in response to unobservable market wide value affecting factors; θ measures the impact of non synchronous appraisals and \mathcal{L}^s denotes $r_{m,\tau-s}$ where s reflects three month seasonality in reappraisal. Equation (6) quantifies smoothing effect by allowing just one market state and after accounting for the impact seasonality of reappraisal, non

synchronous appraisal as well as stale appraisals have on the data generating process. In other words, the model does not allow for mean shifts or time varying noise components. The model is estimated for the full sample and three sub periods, namely from January, 1987 to April, 1990; from May, 1990 to December 2007 and from January, 2008 to January 2011. The sub series are exogenously determined based on empirically observed phenomenon, namely the housing recession of the late 1989, the Gulf War in early 1990 as well as credit crunch and financial meltdown of the late 2007. Model estimation is performed by using the ARFIMA exact maximum likelihood routine in OxMetric 6.10 console and in particular PcGive 6.10. On the other hand, model selection and particularly the choice of optimal number of lags is guided by the ACF and PACF (see Figure 2) above as well as the Akaike and Bayesian information criteria. A search over all constituent models (see Table 3) was undertaken beginning with maximum settings of AR and MA equals to four. This led to the following ARFIMA.1, d, 1 model being selected.

[INSERT TABLE 3]

5.1 Smoothing in appraisal

Following the procedure outlined above, Table 4 presents properties of the smoothing parameter for the overall market index and sub periods series. A number of different and interesting patterns emerge. Most notable, the point estimate of the average level of smoothing effect at asset level based on the full sample is approximately 30% and statistically significant, suggesting a partial response of appraisals to the arrival of price sensitive information. The speed of adjustment is infinitely low, signifying that it takes approximately 5 months for deviation between appraisals and unobserved true asset values to be fully eliminated¹⁰ other things being equal. Such a pattern parallels the popular hypothesis that appraisals lag behind asset value and flatten periodic fluctuations in property values.

Sub-period estimates are quite surprising. Smoothing parameters vary from negative 23% to positive 45% depending on the sub period analyzed. In particular, the smoothing parameters tend to be negative or insignificant when there is an increased uncertainty in the market. This phenomenon is

¹⁰ The partial adjustment parameter is 0.2881 which translates to an average of $\left[\left(\frac{1}{1-0.2881}\right) - 1\right] * 12 = 4.856$ months other things being equal.

detected from January 1987 to April, 1990 and again from January 2008 to January 2011. The negative smoothing parameter could be linked to a number of factors, namely the higher ex-ante risk, which implies that sellers accept whatever price buyers are willing to pay and thus properties are sold immediately or the mix of the properties transacted reflects a higher proportion of lower values properties. It may also be the case that valuers overreact to price sensitive information, resulting in overstating appraisals. Alternatively, appraisers could be very cautious and subsequently downplay the importance of rapid rises or declines. Either way, negative smoothing parameters implies that appraisals are not serially correlated, and that the price formation process has no memory and innovations have are transitory effects rather than permanent. In empirical sense, this implies that information is quickly and fully incorporated into property value as it arrives – the evidence against smoothing tendency. More important is the fact that, negative smoothing parameters parallel the average level of smoothing as proxied by serial correlations of frequently valued commercial properties which range from negative 0.346 to positive 0.416 – e.g. Brown and Matysiak (2000) and Bond et al. (2012). The question whether few transactions that do take place in a downturn truly represents market prices is beyond the scope of this study.

[INSERT TABLE 4]

Empirical estimation of the smoothing effect from May, 1990 to December, 2007 is around 45%, implying that innovations decay slowly at hyperbolic rate and market information is slowly incorporated into pricing mechanisms. The 95% confidence interval varies from $0.3263 \leq \delta \leq 0.5763$ and statistically significant. Surprisingly however, the real estate market is characterized by a five year high growth period followed by a period of stable – gradual and sustained growth. Taking into consideration that the intensity of the smoothing parameter indicates the extent to which previous market information feeds into the current appraisal estimates or the rate of information flow, indeed, the evidence signifies that pricing agents under react significantly to new market signals during the period of stable growth. The average lag is nearly 10 months. The lack of information on market pricing could be rationalized in terms of three interrelated facts. First, it is likely that sellers do not face liquidity shocks and as a result, they can always wait for the best prospective buyers. Thus, lower ex-ante risk lead to even higher correlations between adjacent returns and subsequently higher magnitude of the smoothing parameter even if uncertainty in the market is lower. The problem will be magnified if potential buyers have lower time values and thus search longer.

Alternatively, the mix of properties being sold is biased towards expensive properties, resulting in longer expected marketing period and subsequently higher smoothing parameter. It may also be the case that actual prices overstate properties values. This is consistent to the usual belief that sellers who synchronize their business operations with market cycles, are likely to liquidate higher valued or well performing properties in upmarket and lower value properties/ non performing properties in the down market.

5.2 Dynamics of the real estate market portfolio

Furthermore, Table 4 summarises information on the impact of stale or artificial seasonality of appraisal have on property indices. One can immediately see that smoothing due to partial adjustments in property indices linked to stale or seasonality of reappraisal is lowest (1%) when realized capital growth rates is negative – that is, from 2008 to 2011. Generally, the rate is highest in absolute value (i.e. 49%) from 1987 to 2007, when the market generates positive returns and is marked by a high growth period or by a sustained period of stable growth. The evidence suggests that most properties are not appraised every month but rather information accumulates on the quarter ends months and subsequently induces spurious smoothing in aggregate series by 21% on average. On the other hand, the impact of non-synchronous appraisal effects is weak statistically, implying that aggregating appraisals estimated at different points in time as if were estimated at the same point is less likely to induce spurious autocorrelations on either aggregate or individual property returns series. The evidence is consistent whether analysis is based on full sample or sub series. Indeed, this is consistent to findings reported in Bond and Hwang (2007) or Bond et al. (2012). In addition, Table 4 reveals that the market wide common factor appears to be highly persistent than the smoothing of the constituting properties. The first order autoregressive parameter is around 0.57 on average. Nevertheless, sub-periods estimates are quite dispersed. It is nearly 1.47 over the 1990 – 2007 period, almost three times as large the parameter based on the full sample and it is twice as much the smoothing parameter for 2008 to 2011 period. Surprisingly, the average level of smoothing at index period over 1990 to 2007 is around 0.35 and much lower than the lagging tendency at individual property level in this period. To this effect, systematic lagging behaviour of property indices is governed by a number of factors ranging from; appraisal smoothing, non synchronous appraisal effects, persistence characteristics of real estate common factors as well as the partial adjustment in an index caused by the fact that most properties are not updated in each month but rather updated once a year or simply because most of the individual values in each

month are stale valuations. Moreover, the significance of each of this factor is very sensitive to market conditions. While the impact of smoothing in appraisal is most pronounced when the market is stable and followed by a period of sustained growth, its effect tends to diminish where there is increased volatility, signifying that as opposed to market noise, transactions noise increases when variations on property prices is minimum¹¹. On the other hand, market wide common factors are highly persistent when market is highly volatile so does the impact of non synchronous appraisal effects. Amazingly, the impact of seasonality of reappraisal has mixed results.

In short, a number of points can be emphasized from the preliminary analysis with respect to smoothing effect. First, if the incidence of smoothing is contingent upon the quality of market information, the evidence does not appear to be consistent with the popular belief among real estate professional that smoothing in appraisal is attributed to the lack of contemporaneous market information. Indeed, this preliminary analysis implies that professional valuers face a significant problem in forming opinion of values in deep markets and when assets are continuously traded than when there are reduced level of liquidity and subsequently little market information rely on. Second, analysis indicates that smoothing effect varies across market conditions and actually it is negligible for two out of three market regimes, implying that smoothing parameter based on the full sample is not only a ballpark figure reflecting the average tendency across various market conditions but it also does not reflect the constant market condition. Indeed, if parameters are sensitive to sampling periods, then inter-temporal shifts on investors' expectation play a significant role in driving the process of price formation. This being the case, the smoothing parameter does not relate to autocorrelations produced by real estate pricing agents decisions, but might reflect a misspecified response function due, at least in part, to structural shifts in the underlying process. Differently stated, the smoothing effect based on the full sample is biased and the bias reflects jumps or seasonality in the pricing process. More significantly, is the fact that, if we link results in Table 4 with the evidence presented on section 3, it follows immediately that the failure to adjust for intermittent shifts on the level of the process when quantifying the smoothing effect, serial correlations on the data generating process enter and distort the serial correlation of empirically observed returns, resulting in biased smoothing parameter. The magnitude of bias increases, other thing being equal, with the number and size of shifts. This being the case, the conventional wisdom that appraisals are significantly smoothed relative to the underlying true values cannot be justified. In fact, the evidence lends a strong support to the idea that evidence of smoothing effect implied by previous models can

¹¹ Our findings parallel results in Chaplain (1997) but at odd with Clayton et al. (2001) who observe the highest appraisal lag when transaction density in real estate market is low.

be due to more than the optimal behavioural response in the presence of market uncertainty, there is also the effect of misspecified generating mechanism at work. Still remains to be seen, however, is whether such a bias is statistically significant. Section 5 helps to address this issue.

Another serious inference from Table 4 concerns the validity of the implemented model – that is, all standard post regression diagnostic test statistics repulse the whiteness of residual autocorrelations, non-normality and, hence reject the goodness of fit of this model. The homoskedasticity assumption is rejected at 1% level in favour of heteroskedasticity effect, implying that: i) volatility process displays asymmetric response to changes in prices; ii) abnormal returns tend to occur more frequently than expected under normal assumption; and iii) volatile periods are characterized with large abnormal returns in absolute value alternate with more quite periods of smaller returns. If these effects cannot be identified and properly managed could distort the magnitude of the smoothing parameter. This leads to the main argument of the current thesis, namely to what extent smoothing effect in appraisals is attributed to sporadic shifts in investors’ expectations, time varying volatility or both? These issues are addressed below.

5.3 Effects of sporadic shifts in investors’ expectation

The focus of the current section is to examine the impact of sporadic shifts on the level of generating mechanism on the magnitude and significance of the smoothing parameter. In particular, we illustrate that when structural shifts in the mean are properly adjusted, the average level of smoothing at asset level is lower than previously thought. We benchmark this empirical fact by using expression (8) given as: $\phi_{\xi\tau}(\mathbf{1} - \mathcal{L}^s)(\mathbf{1} - \mathcal{L}^s)^{\delta\tau}\mathbf{z}_{m,\tau} = \theta\varepsilon_{t-1}^* + \varepsilon_t^*$. Actually, (8) employs level shifts adjusted returns, $\mathbf{z}_{m,\tau}$, rather than empirically observed returns. The resulting index holds constant the level of the data generating process. All model parameters are defined above. Table 5 summarises estimates on five alternative models. As discussed above, the first option allows for just one market state and is only valid if and only if appraisals were sampled from one stochastic process. If this is not the case, option one yields biased estimates. Option two to five, allow for two and five states of market condition respectively. We employ the recursive method of PcGive 13.1 on Oxmetrics 6.1 package to estimate various market states. The recursive estimation aims to throw light on the relative future information aspect - that is, parameter constancy. The significance of the structural break is determined by using Break-point F-tests. On the other hand, lag lengths were identified using the Akaike information criteria. In addition, Table 5 summarises information on sensitivity of level shifts adjusted returns on fundamental factors, non synchronous appraisals,

seasonality, break point dates, TBs, as well as relative changes on returns generating process which is given as Δ/ϑ where, Δ denotes the size of the level shift and ϑ is a standard deviation of the ARFIMA(3,d,1) process.

[INSERT TABLE 5]

A number of serious inferences can be drawn from information summarised in Table 5 above. Most notable, the magnitude of smoothing weakens considerably relative to unadjusted index returns when potential effects of structural shifts on the mean are identified and managed. The impact of structural shifts in response to unique market signals cannot be overstated. The evidence indicates that the atrociousness of bias on the smoothing parameter is lower and converges at geometric rate to an index generated without level shifts as the number of level shifts accounted for become more frequent, and significantly disappear after adjusting for five structural shifts in the mean. The average level of smoothing effect is 11% and on average much lower than the 30% smoothing effect based on a model which allows for just one market state, signifying that the average lag in appraisals declines from 5 months to just 2 months or the impact is nearly twice as large when time series properties of returns in the private real estate markets are not properly identified and accounted for.

In empirical sense, the evidence lends a strong support to the idea that smoothing parameters based on conventional linear models which allows just one state or which do not take into account the effect of level shifts on the underlying pricing mechanism are upward biased and essentially mask what can be significant structural changes – inter-temporal shifts on investors’ expectations. Results also indicate that we cannot completely ignore the ravages of structural shifts as the degree of bias increases, other things being equal, in the number and magnitude of shifts. Taking the latter for example, the bias on the smoothing parameter is highest when very few fundamental changes on returns generating process are taken into account. On the other hand, there is a direct relationship between appraisal lagging bias and the magnitude of shifts as measured by the variance of analytical procedure. When the size of shift is 1.23 for instance, smoothing effect is nearly 30%, it is 12% when the size of shift is approximately 0.93 when computation is performed based on an index which eliminates all curvatures that could bias appraisal smoothing, that is after controlling for five level shifts. Likewise, volatility declines as the as persistence of appraisals is correctly estimated by adjusting for one, two or more changes on returns generating process. Indeed, this empirical fact

signifies and confirms three important facts: i) appraisal smoothing and in particular appraisal lagging bias tends to be higher when market volatility is higher; (ii) appraisal noises tend to be higher relative to market noises when the magnitude of shifts is considerably higher and vice versa; and that (iii) shocks which are larger in size persist for longer period than smaller shocks other things being equal. In short, these facts indicate smoothing effect is driven by the relative size of the market wide and transaction noises as well as number of shifts in the generating process. Equally important, is the fact that, although coefficients are not robust at 1% level, on average, the speed of adjustment in appraisals in response to the arrival of price sensitive information is almost 90% and much higher than previously thought. Immediately this implies that, the nature of valuation process becomes irrelevant in explaining significant serial correlations in appraisal based series, and that spurious serial correlations induced by sporadic shifts on the level of the process is quite significant and possibly accounts for mixed and conflicting results documented in the literature.

Furthermore, Table 5 indicates that the impact of non synchronous appraisal effect in explaining the behaviour of property indices is marginally understated if sporadic shifts on the level are not properly identified and managed. For instance, the contribution of non synchronous appraisals effects on serial correlations of aggregate returns is only 2.6% when estimation is based on a procedure which allows for just one market state. Surprisingly, the effect is nearly 6.7% after adjusting for one level shift and approximately 9.4% after accounting for all non linearity in the profile of empirically observed aggregate returns. Nevertheless, all parameters are positive and change slowly as non linearity tendency is taken into account., signifying that the time difference between the appraisal time point and the time point when appraisals ought to be appraised though is trivial tends to be biased downward if level shifts are ignored. It is not surprising that the non synchronous appraisal effects appear to be significant after controlling for level shifts as ignoring structural shifts parallels inducing averaging effect. In contrast, the seasonal effect parameter is inversely related to number of breaks, which basically means that, overlooking structural breaks, the impact of seasonality in reappraisal is exaggerated. In addition, Table 5 reveals that the real estate common factor is highly persistent with an average autoregressive parameter of around 0.56. The parameter hardly changes in response to the evolution of generating process, suggesting that property indices are persistent mainly because signals from fundamental factors are partially incorporated into the pricing process.

5.4 Sensitivity of Persistence to Time Varying Volatility

The current section examines the magnitude of smoothing effect if the noise component is allowed to evolve overtime while the mean of the process is constrained to be constant. The focus is to determine whether ignoring time varying noise component leads to a bias in the smoothing parameter. The use of persistent, conditional variance filter is justified mainly because the dynamics structure of commercial property returns is neither stationary nor normally distributed but rather is negatively skewed, with over 5 excess kurtosis and characterized by heteroskedasticity effect. Parameters are estimated by using equation (6) which allows the noise term not only to vary overtime but also propagates as a HYGARCH process. Following our procedure, results are summarized in Table 6. Two issues worth to be emphasized. First, is the fact that, the average level of persistence in volatility is nearly 0.6 and positive, signifying that the expected value of the noise term, in absolute value, is not constant but rather larger for some periods than others. As well, the hyperbolic parameter is significantly different from zero, signifying that there is a tendency for the propagation of incremental information flow in the commercial property to exhibit asymmetrical and uneven behaviours. If this is the case, market volatility not only varies over time but negative shocks generate higher volatility than positive innovations of the same magnitude. In addition, market participants react more in down markets than in up markets.

Second, when the noise component is allowed to evolve overtime, smoothing effect declines considerably. The smoothing parameter is around 11% or an average lag of 2 months, an on average smaller than the 30% smoothing effect based on the transformation techniques which do not allow for time varying volatility. In empirical sense the evidence suggests not only appraisals respond quickly to the arrival of new market information related to property values, but also indicates randomness in the noise components is great enough to distort estimation of the smoothing parameter if not properly identified and managed.

[INSERT TABLE 6]

5.5 The combined effects of shifts on the level of DGP and Varying Volatility

The current section illustrates that when both the effect of structural shifts on the mean and varying volatility are properly identified and managed, the average level of smoothing effect is lower than previously thought, and actually it is consistent with proxies for smoothing parameter of frequently valued commercial properties – that is, the average level of serial correlations. This empirical evidence is generated based on equation (14) which essentially considers the case where varying expectations and noisy component are intrinsic characteristics of commercial property markets. This leads to time varying data generating mechanism in which both the mean and error terms vary overtime. The two variables are examined together largely because they move together and actually one facilitates the other; and second, both of which play a significant part in explaining the magnitude of smoothing parameter. It is, therefore, clear from Table 7 that the smoothing effect decreases even in the presence of both effects. For the purpose of comparison, the effect declines from 28.8% (or 9 months lag) based on a model which allows for just one market state with constant variance to 6.65% (or one month lag) after filtering out three structural shifts on the mean while letting the noise component evolves overtime, signifying that the failure to allow for structural shifts and varying volatility exaggerates smoothing effect. The academic literature is full of studies which quantify smoothing effect without allowing for instability in the data generating process and report appraisal smoothing effect is quite substantial varying from 0.45 to 0.9 – e.g. Geltner, (1991; 1993), Barkham and Geltner (1994, 1995), Bond and Hwang (2007). More importantly, is the fact that, the smoothing effect in our analysis is actually consistent with 0.15 the first order serial correlation coefficients of frequently valued properties as reported in Brown and Matysiak (1998, 2000), Clayton et al. (2001) and Bond et al. (2012) inter-alia. Our analysis corroborates the premise that without a proper specification of the underlying generating mechanism, evidence in favour of appraisal smoothing could be the relic of ad-hoc assumptions made about the underlying process as highlighted for example in Quan and Quigley (1991) and Lai and Wang (1998).

[INSERT TABLE 7]

In addition, Table 7 illustrates that the magnitude of persistence in the real estate market wide common factor would be significantly downward biased if either structural shifts on the mean, or varying noise process or both are not identified and recognized. The average first order serial

correlation based on equation (14) for example, is 0.9 on average much higher than 0.56 based on expression (6). Notwithstanding, market wide common factors are highly persistent and induce significant averaging effect in property indices despite of the fact that properties making up portfolio are characterized by insignificant serial correlation effect. This is consistent to Bond et al. (2012), Fu (2003) and Brown and Matysiak (2000) just to name a few. Definitely, the observed coefficient of temporal lag bias in portfolio returns series is significantly higher than 0.25 that could be observed in a portfolio made up of frequently valued commercial properties¹² or whose constituents evolve randomly (Brown, 1985; Brown and Matysiak, 2000).

On the other hand, the effect of intra-year information flow on the behaviour of aggregate series is significantly different from zero and generally much higher when quantified by a process which identifies and recognizes effects of shifts on the level or time varying innovations or both. The impact of non synchronous appraisal effect is nearly 30% based on expression (14) as oppose to just 2% based on (6) above. In empirical sense this implies that, much as appraisals follow a random walk process, a significant proportion (i.e. 30%) do not reflect true value at the point when indices are prepared. This is inconsistent with Bond and Hwang (2007) or Bond et al. (2012) in which the authors invoke a fractional integration process without allowing for instability in the data generating process and observed insignificant evidence of non synchronous effects in appraisals. On the other hand, the magnitude of smoothing in portfolio returns series that is directly related to stale appraisals and/or seasonality of reappraisals is around 18 -20%. For sure, the evidence suggests that ignoring time variations on residual processes as well shifts in investor expectation understate the effect of non-synchronous appraisals or overstate the impact of stale appraisals have on persistence of aggregate commercial property returns.

6. Conclusions

Building on previous works on real estate smoothing we show that previously estimated smoothing parameters are biased upward due to the failure of adjusting for structural shifts in mean and/or

¹² Brown and Matysiak (2000) demonstrate the average serial correlation of the capital growth rates of frequently valued commercial properties is negative 0.027 (0.416) for retail sector, 0.027(0.345) for office properties and negative 0.039(0.26) for industrial returns. The maximum autocorrelation between successive changes in values are reported in brackets. As well, they indicate that the average autocorrelation based on a random sample of 30 properties from 1986 – 1995 is 0.124 and its upper limit approaches 0.389.

varying volatility. The combined effect of these two phenomena not only ascertains the nature and magnitude of the smoothing effect, but it also identifies a level of around 10% (i.e. an average lag of 2 months) in the long run when the dynamics of the two components are correctly specified. More importantly, we show that the relationship between the smoothing effect and the combined effect of time varying volatility and occasional shifts on the data generating process is dynamic and the bias in the smoothing parameter increases in the number and size of shifts, other things being equal. Moreover, our analysis reveals that the smoothing effect in appraisal-based returns can be correctly estimated by invoking a stationary fractional integration ARMA process with occasional shifts and time varying noise process as this model is capable of accommodating our prior knowledge about changes in market conditions. In addition, property indices are persistent mainly because market wide common factors are partially incorporated into the pricing process and due to the fact that indices are partially updated. The true impact of stale appraisals, non-synchronous appraisals seasonality of reappraisals also depends on proper specification of data generating process, but we also find that market wide common factors are still highly persistent even after controlling for instability in the data generating process. Finally, an interesting inference, in light of the above findings, is that real estate markets are well functioning with adequate liquidity that allows price sensitive information to transfer and aggregate very quickly into opinion of value, resulting in high quality appraisals.

References

- Baillie, R.T., 1996, Long memory processes and fractional integration in econometrics. *Journal of Econometrics*, 73, 5-59.
- Barkham, R., and Geltner, D., 1994, Unsmoothing British valuation-based returns without assuming an efficient market. *Journal of Property Research*, 11(2), 81-95.
- Barkham, R., and Geltner, D., 1995, Price discovery in American and British property markets. *Real Estate Economics*, 23(1), 21-44.
- Bos, C.S., Franses, P.H., Ooms, M., 1999, Long memory and level shifts: re-analyzing inflation rates. *Empirical Economics* 24, 427-449.
- Blundell, G.R. and Ward, C. W.R., 1987, Property portfolio allocation: A multifactor model *Land Development Studies*, 4, 145-156
- Brown, G., 1985, The information content of property valuations. *Journal of Valuation*, 3 (4), 350-62.
- Brown, G.R. and Matysiak, G.A., 1998, Valuation smoothing without temporal aggregation, *Journal of Property Research*, 15, 89-103.
- Brown, G. and Matysiak, G., 2000, Sticky valuations, aggregation effects, and property indices. *Journal of Real Estate Finance Economics*, 20, 1, 49-66
- Bond S. et al., 2004, Liquidity in Commercial Property Markets. Investment Property Forum Research Report.
- Bond, S.A. and Hwang S., 2007, Smoothing, nonsynchronous appraisal and cross-sectional aggregation in real estate price indices. *Journal of Real Estate Economics*, 35, 3, 349-38.
- Bond, S.A., Hwang S. and Marcato, G., 2012, Commercial real estate returns: An anatomy of smoothing in Asset and Index. *Journal of Real Estate Economics*, 40 (3), 637 - 661.
- Case, K. E., and Shiller, R. J., 1989, The efficiency of the Market for Single-Family Homes. *American Economic Review*, 79(1), 125 - 37.
- Chaplin, R., 1997, Unsmoothing valuation-based indices using multiple regimes. *Journal of Property Research*, 14(3), 189-210.
- Chau, K. W., MacGregor, B. D. and Schwann, G., 2001, Price discovery in the Hong Kong real estate market. *Journal of Property Research*, 18(3), 187-216.
- Childs P.D., Ott, S.H., & Riddiough, T. M., 2002a, Optimal valuation of noisy real assets. *Journal of real estate economics*, 30(3), 385-414
- Childs P.D., Ott, S.H., & Riddiough, T. M., 2002b, Optimal valuation of claim on noisy real assets: Theory and an application. *Journal of real estate economics*, 30(3), 415-443
- 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.
- Clayton, J., Geltner, D. and Hamilton, S., 2001, Smoothing in commercial property Valuations: Evidence from individual appraisals. *Real Estate Economics*, 29, 337-360.
- Crawford, G. and Fratantoni, M., 2003, Assessing the forecasting performance of Regime-Switching, ARIMA and GARCH models of house prices. *Real Estate Economics*, 31, 223-43.
- Davidson, J., 2004, Moment and memory properties of linear conditional heteroscedasticity models, and a new model. *Journal of Business and Economic Statistics*, 22, 16 - 29.
- DeWit, D., 1993, Smoothing bias in in-house appraisal based returns of open-ended real estate Funds. *Journal of Real Estate Research*, 8(2), 157-170.
- Diaz, J. and Hansz, J.A., 1997, How valuers use the value opinions of others. *Journal of Property Valuation and Investment*, 15(3), 256-260.

- Diaz, J. and Wolverton, M., 1998, A longitudinal examination of the appraisal smoothing hypothesis. *Real Estate Economics*, 26(2), 349–358.
- Diebold, F.X., Inoue, A., 2001, Long memory and regime switching. *Journal of Econometrics*, 105, 131–159.
- Dolde, W. and Tirtiroglu, D., 1997, Temporal and spatial information diffusion in real estate price changes and variances. *Real Estate Economics*, 25, 539–65.
- Edelstein, R.H. and Quan, D.C., 2006, How does appraisal smoothing bias real estate returns measurement? *The Journal of Real Estate Finance and Economics*, 32 (1), 41–60.
- Eichholtz, P. M.A. and Hartzell, D. J., 1996, Property shares, appraisals and the stock market: An International perspective. *Journal of Real Estate Finance and Economics*, 12: 163-178
- Engle, R.F., 1982, Autoregressive conditional heteroskedasticity with estimates of the variance of UK inflation. *Econometrica*, 50, 987-1008.
- Fisher, J., Geltner, D. and Webb, J., 1994, Value indices of commercial real estate: A comparison of index construction methods. *Journal of Real Estate Finance and Economics*, 9, 137-164.
- Fisher, J. D., Miles, M. K. and Webb, R.B., 1999, How reliable are commercial appraisals? Another look. *Real Estate Finance*, 16(3), 9-15
- Fisher, J. and Geltner, D., 2000, De-lagging the NCREIF index: transaction prices and reverse-engineering. *Real Estate Finance*, 17(1), 7 – 22.
- Fisher, J., Gatzlaff, D., Geltner, D., Haurin, D., 2003, Controlling for the impact of variable liquidity in commercial real estate price indices. *Real Estate Economics*, 31, 269–303.
- Fu, Y., 2003, Estimating the lagging error in real estate price indices. *Real Estate Economics*, 31(1),
- Gallimore, P., 1994, Aspects of information processing in valuation judgement and choice. *Journal of Property Research*, 11, 97-110
- Gallimore, P., 1996, Confirmation bias in the valuation process: A test for corroborating evidence. *Journal of Property Research* 13(4): 261–273.
- Gallimore, P. and Wolverton, M. L., 2000, The objective in valuation: a study of the influence of clients feedback. *Journal of Property Research*, 17(1), 47 – 58.
- Geltner, D., 1989, Bias in appraisal-based returns. *Journal of the American Real Estate and Urban Economics Association*, 17, 338-352.
- Geltner, D., 1991, Smoothing in appraisal based Returns. *Journal of the American Real Estate and Urban Economics Association*, 13, 15-31
- Geltner, D.M., 1993, Estimating market values from appraised values without assuming an efficient market. *Journal of Real Estate Research*, 8(3), 325–345.
- Geltner, D., MacGregor, B.D. and Schwann, G.M., 2003, Appraisal smoothing and price discovery in real estate markets. *Urban Studies*, 40, 1047-1064.
- Getmansky, M., Lo, A. W. and Makarov, I., 2004, An econometric model of serial correlations and illiquidity in hedge fund returns. *Journal of Financial Economics*, 74, 529 – 609.
- Giaccotto, C. and Clapp, J., 1992, Appraisal based real estate returns under alternative market regimes. *Journal of American Real Estate and Urban Economics Association*, 20, 1-24.
- Granger, C.W.J. and Hyung, N., 2004, Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. *Journal of Empirical Finance*, 11(3), 399-421.
- Hansen, B.E., 1992, Tests for parameter instability in regression with I(1) processes. *Journal of Business and Economic statistics*, 10(3), 321 – 335.
- Hansz, J. A., 2004, The use of a pending mortgage reference point in valuation judgement. *Journal of Property Investment and Finance*, 22 (3), 259-268.

- Hansz, J. A. and J. Diaz I., 2001, Valuation bias in commercial appraisal: A transaction price feedback experiment. *Real Estate Economics*, 29(4), 553-656.
- Hidalgo, J. and Robinson, P. M., 1996, Testing for structural change in a long-memory environment. *Journal of Econometrics*, 70, 159–174.
- Ibbotson, R. G. and Siegel, L., 1984, Real estate returns: A comparison with other investment. *Real Estate Economics*, 12(3), 219 – 249.
- Lai, T. and Wang, K., 1998, Appraisal smoothing: The other side of the story. *Journal of Real Estate Economics*, 26(3), 511–535.
- Liow, K. H. and Webb, J. R., 2008, Non linear return dependence in major real estate markets. *Journal of Property Research*, 25(4), 285-319
- Lizieri, C., Satchell, S., Worzalla, 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(3), 339 – 355
- Lizieri, C. and Satchell, S., 1996, Interactions between property and equity markets: An investigation of linkages in the United Kingdom 1972-1992. *Journal of Real Estate Finance and Economics*, 15, 11-26.
- Lizieri, C., and Satchell, S., 1997, Property company performance and real interest rates: A regime switching approach. *Journal of Property Research*, 14, 85–97.
- McAllister, P., A. Baum, N. Crosby, P., Gallimore, and Gray, A., 2003, Appraiser Behaviour and Appraisal Smoothing: Some Qualitative and Quantitative Evidence. *Journal of Property Research*, 20(3), 261-280.
- MacGregor, B. D. and Nanthakumaran, N., 1992, The allocation to property in the multi asset portfolio: the evidence and theory reconsidered, *Journal of Property Research*, 9(1), 5–32.
- Myer, N. and Webb, J., 1994, Statistical properties of returns: Financial Assets versus Commercial Real Estate. *Journal of Real Estate Finance and Economics*, 8, 267-282.
- Nelson, C. R., and Plosser C. I., 1982, Trends and random walks in macroeconomic time series: Some evidence and implications. *Journal of Monetary Economics*, 10, 139-162.
- Perron, P., 1989, The Great Crash, the oil price shock, and the unit root hypothesis. *Econometrica*, 57(6), 1361-1401.
- Quan, D.C. and Quigley J., 1989, Inferring an investment return series for real estate from observations on sales. *Journal of the American Real Estate and Urban Economics Association*, 17(2), pp. 218–230.
- 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.
- Souza, L.R., 2007, Temporal aggregation and bandwidth selection in estimating long memory. *Journal of Time Series Analysis*, 28(5), 701-722
- Wong, S. K., Chau, K.W. and Yiu, C. Y., 2007, Volatility transmission in the real estate spot and forward markets. *Journal of Real estate Finance Economics*, 35, 281-293.

Tables and Figures

Table 1: Descriptive Statistics – Monthly IPD Appreciation returns index 1987(1) – 2011(6)

Description	Full Sample (1987:1 – 2011:1)	Sub Sample 1: 1987:1 - 1990:4	Sub Sample 2: 1990:5 - 2007:12	Sub Sample 3: 2008:1 - 2011:1
observations	289	40	212	37
Mean	0.1408	0.99323	0.14493	-0.8042
Standard Deviation	1.1627	0.81803	0.83738	2.0258
Skewness	-1.5157	-0.32861	-1.0530	-0.5855
Excess Kurtosis	5.5706	-0.76028	5.6846	0.07446
Minimum	-5.8390	-0.6337	-4.1746	-5.8390
Maximum	3.0068	2.4006	2.881	3.0068
Asymptotic Test - $\chi^2(2)$	484.32 [0.000]**	1.6833 [0.4310]	324.62 [0.0000]**	2.1228 [0.3460]
Normality Test - $\chi^2(2)$	67.716[0.000]**	2.2896 [0.3183]	59.869 [0.0000]**	2.5636 [0.2775]
Portmanteau (24) $\chi^2(24)$	1148.1[0.0000]**	79.603 [0.0000]**	545.66 [0.0000]**	103.40 [0.0000]**
Unit Root Tests (T-stats)	-3.245** (0.0004)	-3.551** [0.0006]	3.444** [0.0074]	-3.156** [0.0012]
Number of lag	2	1	2	2
Autocorrelations				
1	0.90446	0.79225	0.8124	0.8994
2	0.82512	0.73037	0.6835	0.7583
3	0.76276	0.57369	0.6391	0.6426
4	0.66628	0.45409	0.5204	0.5198
5	0.5882	0.32879	0.4551	0.4109
10	0.25678	-0.012482	0.1923	-0.0052
<p>Notes: A unit root test model is given by $\Delta Y_t = \psi Y_{t-1} + \sum_{i=1}^k \gamma \Delta Y_{t-i}$. We employ AIC - Akaike Information Criteria to choose the AR lag length. As usual, ** denotes significant at 1% tests whereas * implies significant at 5% tests. Given that $E[\rho(k)] = 0$ and $var = 1/T$ then the 95% confidence interval for k is therefore $\pm 1.96 / \sqrt{T}$. For the 99% confidence interval, the 0.995 probability point of the normal cdf is 2.57. The 99% CI is therefore $\pm 2.57 / \sqrt{T}$. A $\rho(k)$ outside this CI is evidence that the model residuals are not random</p>				

Table 2: Instability Patterns in the Appreciation Returns Indices

Type of IPD Index	Recursive Residuals Test : 1-Step Chow Tests			
	Break point (k = tP)	Break Fraction t= k/T	F-Statistic	Reflect
Monthly IPD ALL CAP index	October , 1989			Housing boom
	May-90	0.128	F(1, 37) = 15.236 [0.0004] **	The 1990 Gulf war
	December, 1993	0.27	F(1, 79) = 7.9179 [0.0062] **	F
	December, 2005	0.28	F(1, 81) = 10.410 [0.0018] **	
	September, 2008			
	December, 2009			

Note: As usual, * denotes significant at 90% confidence interval, and ** indicates 95% confidence interval.

Table 3: Model Selection

S/N	Model	Information Criteria			Remarks	Selected Model
		Log Likelihood.	AIC.T	AIC		
1	ARFIMA (0,d,1)	-224.8500	457.7138	1.5837		
2	ARFIMA (1,d,0)	-207.6300	423.2526	1.4645		
3	ARFIMA (1,d,1)	-207.4800	424.975	1.4705		
4	ARFIMA (2,d,0)	-207.5374	425.0748	1.4708		
5	ARFIMA (0,d,2)	-223.0806	456.1612	1.5784		
6	ARFIMA (2,d,2)	-204.9972	423.9945	1.4671		
7	ARFIMA (3,d,1)	-203.0368	420.0736	1.4535		V
8	ARFIMA (3,d,1)	-205.6300	423.2624	1.4645	AR(2) fixed	
9	ARFIMA (3,d,2)	-200.6448	417.2897	1.4439		
11	ARFIMA (4,d,3)	196.3907	412.6615	1.4278		
12	ARFIMA (4,d,4)	196.1507	414.3014	1.4335		

Notes: Estimation output comprises of estimated coefficients, standard errors and t-probability (t-values). The t-values are given by t-distribution with T-s degree of freedom, where S denotes number of model parameters estimated (i.e. $S = 1+p+q+k+1$). AIC in this case (AIC.T) is given by $(-2*\log \text{likelihood} + 2S)$. AIC represents AIC.T over sample size (T). Reported Mean and Variance are of dependent variable. The BIC is given by $-2*\log \text{likelihood} - S*\ln T$

Table 4: Empirical estimations of unsmoothing parameters across regimes in the monthly IPD index 1987(1) – 2011(1)

Variables	Sample Period - 1987:1 - 2011:1				Regime 1987:1 - 1990:4				Regime 1990:5 - 2007:12				Regime 2008:2 - 2011:1			
	ARFIMA (3,d,1)				ARFIMA (3,d,1)				ARFIMA (3,d,1)				ARFIMA (3,d,1)			
	d	AR(1)	AR(3)	MA	d	AR(1)	AR(3)	MA	d	AR(1)	AR(3)	MA	d	AR(1)	AR(3)	MA
Estimates	0.2881	0.5755	0.2059	0.0261	-0.2273	1.4670	-0.4934	-1.0000	0.4453	0.3524	0.4825	0.0254	-0.0478	0.8580	0.0126	0.3669
STD	0.1695	0.1803	0.0874	0.1176	0.2104	0.0212	0.0147	0.0964	0.0706	0.1264	0.0785	0.1244	1.1700	0.9421	0.6118	0.3902
t-prob	1.6999	3.1919	2.3555	0.2217	-1.0802	69.1674	-33.4706	-10.3767	6.3063	2.7877	6.1485	0.2038	-0.0408	0.9107	0.0206	0.9404
Mean	0.14				0.99				0.1449				-0.77			
Variance	1.35				0.67				0.70				4.18			
LL	-205.63				-16.95				-95.86				-42.63			
AIC	423.26				45.89				203.73				97.25			
Post Regression diagnostic Tests																
Asymptotic test	Chi ² (2) = 392.49[0.000]**															
Normality test	Chi ² (2) = 133.19[0.000]**															
ARCH from lag	F(2,200) = 31.071[0.000]**															
1- 2																
RSS	104.685															
Notes: ** implies significant at 1% level																

Table 5: Empirical estimates of unsmoothing factors for the Monthly IPD (UK) capital gain aggregate index

Model Specification: $\phi_{\xi}(1 - \mathcal{L})(1 - \mathcal{L})^d (r_{m,t} - \langle U_0 + \sum_{\tau=1}^T \Omega_{\tau} I_{\{t > (\tau T)\}} \rangle) = \theta \varepsilon_{t-1}^* + \varepsilon_t^*$ Where: $I_{\{t > (\tau T)\}} = \begin{cases} 0, & \text{Unobserved} \\ 1, & \text{Observed if } \rho_t > \Delta \Psi_t \end{cases}$																		
Model	Number of Market states allowed	d		AR(1)		AR(3)		MA(1)		Average appraisal lag in Month	%chd	Bias (%)	Vol of the ARFIMA process (ϑ)	Break Points				
		Coef.	T-stats	Coef.	T-stats	Coef.	T-stats	Coef.	T-stats					TB = 1	TB = 2	TB = 3	TB = 4	
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	TB = 1	TB = 2	TB = 3	TB = 4
Model 1	ARFIMA(3, d, 1)	1	0.2881 [0.1695]	1.70	0.5755 [0.1803]	3.19	0.2058 [0.0874]	2.36	0.0260 [0.1176]	0.22	5		144.4	1.3473				
Model 2	ARFIMA(3, d, 1)	2	0.2537 [0.1851]	1.37	0.5693 [0.1919]	2.97	0.2007 [0.087]	2.30	0.0669 [0.1136]	0.61	4	11.94	115.2	1.2249	2008:1			
Model 3	ARFIMA(3, d, 1)	3	0.2577 [0.1832]	1.41	0.5604 [0.1910]	2.93	0.2058 [0.086]	2.40	0.0718 [0.1131]	0.64	4	10.55	119.3	1.2279	1994:1	2008:1		
Model 4	ARFIMA(3, d, 1)	4	0.1810 [0.2254]	0.80	0.5748 [0.2312]	2.49	0.1895 [0.0871]	2.18	0.0928 [0.1153]	0.81	3	37.17	53.5	0.9801	1993:6	2007:7	2009:8	
Model 5	ARFIMA(3, d, 1)	5	0.1179 [0.2118]	0.56	0.6316 [0.2005]	3.15	0.1654 [0.0898]	1.84	0.0936 [0.1137]	0.82	2	59.08	0	0.9290	1993:6	2004:3	2007:7	2009:8

Notes: In this framework, the autoregressive parameter, $AR(1)$, measures the degree of persistence of unobserved common factors, the moving average parameter $MA(1)$, captures the impact of non synchronous appraisals and the long memory parameter, $d(0 - 0.5)$, approximate the average level of smoothing at individual property level. On the other hand, while the third order autoregressive parameter, $AR(3)$, measures approximate the impact of seasonality of reappraisal, Volatility of the ARFIMA(3,d,1) process represents the magnitude of the level shift where as Δ denotes the size of the level shift. Relative level shift is computed by dividing the size of the level shift at given break point by the standard deviation of the ARFIMA(3,d,1) process – that is, ϑ . For shifts on investors expectation, the size of the shift is given $\mu_{\lambda} I_{\{t > (\tau T)\}}$

Table 6: Sensitivity of appraisal lag to time varying volatility

		Model Specification: $\phi_{\xi}(\mathbf{1} - \mathcal{L})(\mathbf{1} - \mathcal{L})^d(r_{mt} - \mathbb{U}_m) = \theta \varepsilon_{t-1}^* + \varepsilon_t^*$ $\varepsilon_t^* = \delta h_t = h_t^2 = \omega + \sum_{i=1}^{\infty} \lambda_i L^i \varepsilon_t^2 = \omega + \lambda(L) \varepsilon_t^2$															Average lag in Months	Bias in the smoothing parameter
		ARFIMA(3, d, 1)							HYGARCH(1,d,1)									
		d		AR(1)			MA(1)		d		Arch(Phi(1))		Grch(Beta(1))		HY(Alpha)			
		Coef.	Coef.	T-stats	Coef.	T-stats	Coef.	T-stats	Coef.	T-stats	Coef.	T-stats	Coef.	T-stats	Coef.	T-stats		
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Overall Capital Gain Index	1	0.2881	0.1114 [0.092]	1.208	0.9041 [0.018]	51.26	-0.3415 [0.089]	-3.804	0.8485 [0.5177]	1.639	0.2461 [0.3479]	0.6876	0.5838 [0.4793]	1.218	0.1761 [0.2707]	0.651	2	61.33
<p>Notes: In this framework, the autoregressive parameter, $AR(1)$, measures the degree of persistence of unobserved common factors, the moving average parameter $MA(1)$, captures the impact of non synchronous appraisals and the long memory parameter, $d(0 - 0.5)$, approximate the average level of smoothing at individual property level. On the other hand, the third order autoregressive parameter, $AR(3)$, measures approximate the impact of seasonality of reappraisal. In addition, the Beta(1) captures the effects of heteroskedastics volatility while the hygarch (HY(alpha) approximate asymmetrical reaction to news arrival. Finally, bias in the smoothing parameter is a proportion of the average level of smoothing at individual property level based on the joint ARFIMA-GARCH process to the ARFIMA (1,d,1).</p>																		

Table 7: The combined effects of level shifts on DGP and time varying volatility on the extent of appraisal lag

Model		Number of Shifts	Model Specification: $\phi_{\xi}(1 - \mathcal{L})(1 - \mathcal{L})^{\delta}(\mathbb{r}_{m,t} - \langle \mathbb{U}_0 + \sum_{\tau=1}^T \Omega_{\tau} I_{\{t > (t_{\tau} T)\}} \rangle) = \theta \varepsilon_{t-1}^* + \varepsilon_t^*$													
			where: $\begin{cases} I_{\{t > (t_{\tau} T)\}} = \begin{cases} 0, & \text{Unobserved} \\ 1, & \text{Observed if } \phi_t > \Delta \Psi_t \end{cases} \\ \varepsilon_t^* = \delta h_t h_t = \omega + \langle 1 - [1 - \beta(L)]^{-1} \psi(L) \{1 + k(1 - \mathcal{L})^{\delta} f_{igarch} - 1\} \rangle \varepsilon_t^2 \end{cases}$													
			ARFIMA(3, d, 1)							HYGARCH(1,d,1)						
			d		AR(1)		MA(1)			d		Arch(Phi(1))		Garch(Beta(1))		HY(Alpha)
		Coef.	T-stats	Coef.	T-stats	Coef.	T-stats	Coef.	T-stats	Coef.	T-stats	Coef.	T-stats	Coef.	T-stats	
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Model 1	1	0.1086 [0.088]	1.225	0.9108 [0.022]	41.63	-0.3442 [0.1488]	-2.313	0.7817 [0.8887]	0.8797	0.1215 [2.2357]	0.0544	0.410 [2.514]	0.1632	0.1993 [0.2971]	0.6708
	Model 2	3	0.0665 [0.1015]	0.655	0.8914 [0.0196]	45.40	-0.3293 [0.086]	-3.813	0.815 [0.3348]	2.434	0.4074 [0.6246]	0.6522	0.5790 [0.3891]	1.488	0.2327 [0.2541]	0.9158
	Model 3	4	0.0114 [0.1011]	0.1128	0.8926 [0.0134]	66.71	-0.2801 [0.1005]	-2.788	0.8466 [0.2312]	3.661	0.1536 [0.6762]	0.2272	0.3631 [0.6221]	0.5837	0.1799 [0.1968]	0.9148

Notes: In this framework, the autoregressive parameter, $AR(1)$, measures the degree of persistence of unobserved common factors, the moving average parameter $MA(1)$, captures the impact of non synchronous appraisals and the long memory parameter, $d(0 - 0.5)$, approximate the average level of smoothing at individual property level. On the other hand, the third order autoregressive parameter, $AR(3)$, measures approximate the impact of seasonality of reappraisal. In addition, the Beta(1) captures the effects of heteroskedastics volatility while the hygarch (HY(alpha) approximate asymmetrical reaction to news arrival. Finally, bias in the smoothing parameter is a proportion of the average level of smoothing at individual property level based on the joint ARFIMA-GARCH process to the ARFIMA (1,d,1).

Figure 1: A profile of the Monthly IPD (UK) Appreciation Index from 1987 to 2011

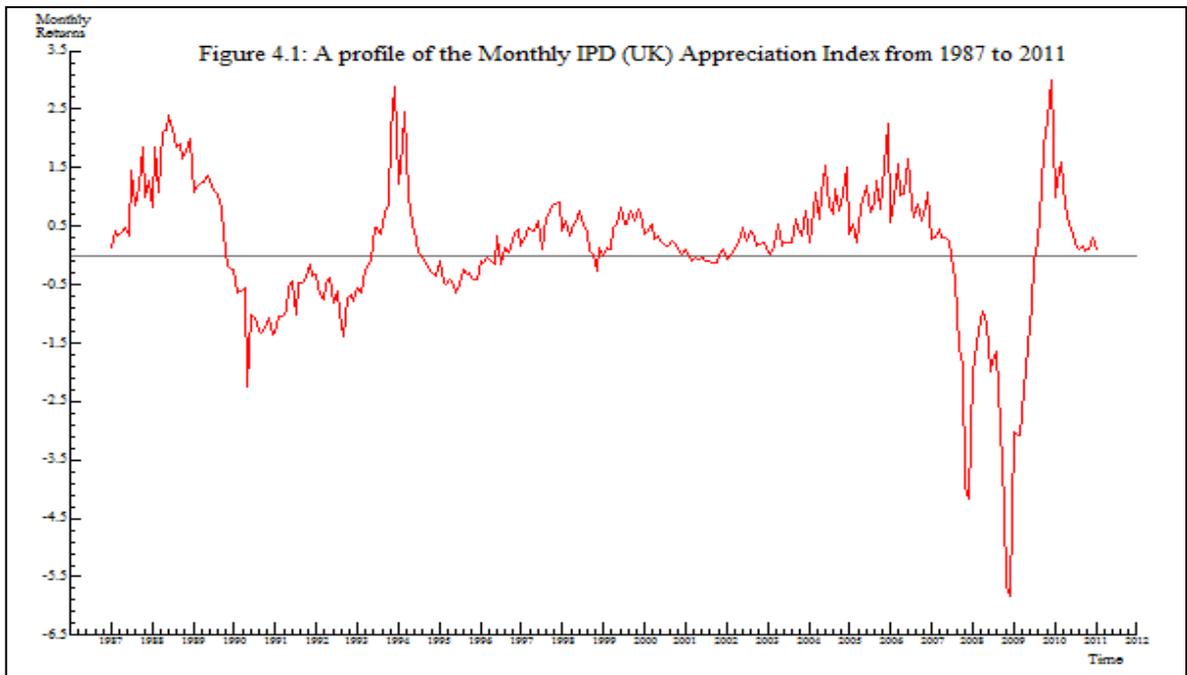
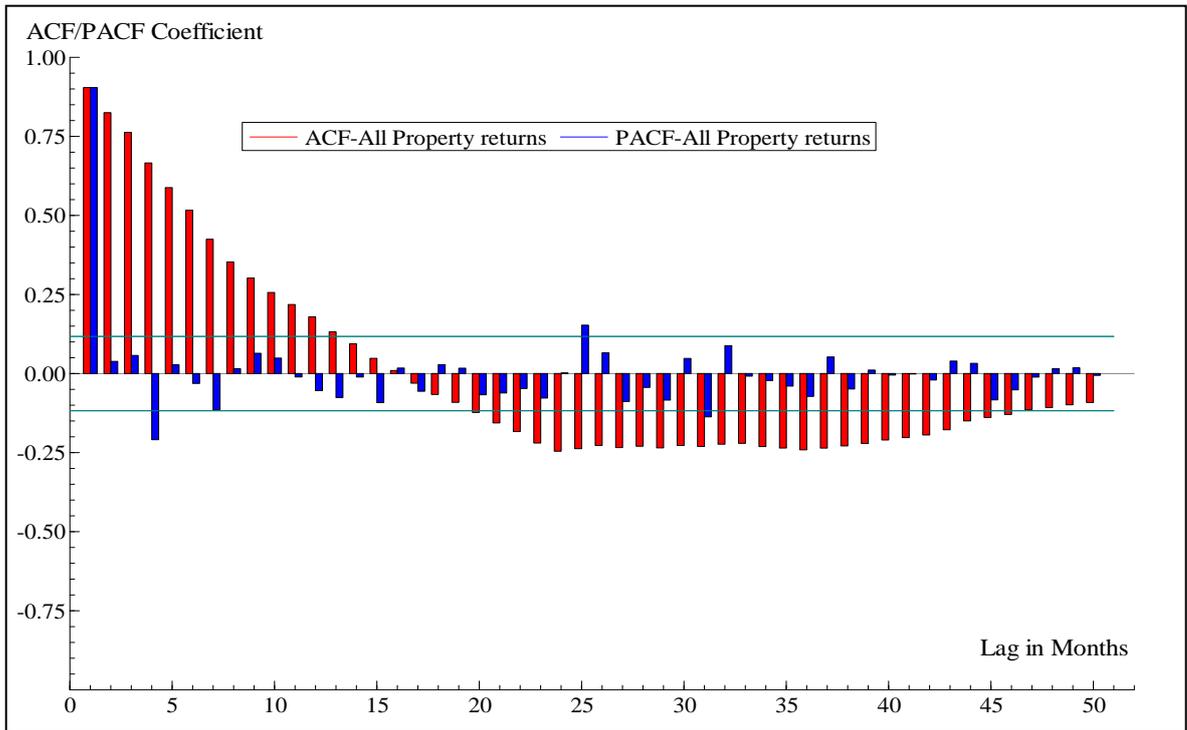


Figure 2: Sample Autocorrelation Function (ACF) and Partial Autocorrelations Functions (PACF) for the Monthly IPD (UK) Capital Growth Rates Index from 1987 to 2011



Appendix 1: Empirical estimation of lagging effect and un-smoothing factors

Study	Country	Data Source	Time - Period	Returns Frequency	Nominal/ Real	Model used	Smoothing Factor implied by models	Lagging effect	Volatility of		Variance adjustment factor	AR(1) of	
									Smoothed index (%)	Transformed index (%)		Smoothed Index	Transformed Index
Ross and Zisler (1991)	US	EAI/RN	1978-85	Q	N		0.65 - 0.9		2	9 -13	4.5-6.5		
MacGregor & Nanthakumaran (1992)	UK	JLW	1970-77	M & Q	R	2.13	0.54		2.45	4.7	1.92 – 2.86		
Geltner (1993)	US	EAI/RN	1978-86	A	N		0.4 -0.75	1yr	4.5-5.2	8.3-8.7	1.67-1.84	0.572-0.63	0.22-0.33
Fisher et al. (1994)	US	R-NCREIF	1979-92	A	R		0.4-0.7	2yrs	5.2	8.19-14.42	1.58-2.77	0.72	-0.94-0.16
Barkham and Geltner (1994)	UK	JLW	1970-92	A	N		0.63	1yr	11.8	15 -20	1.27–1.69	0.28	0.034– 0.04
Barkham and Geltner (1995)	UK	JLW	1970-92	A	N		0.63	1yrs	11.8	18	1.52	0.29	0.04
Barkham and Geltner (1995)	US	EAI/RN	1975-92	A	N		0.4	2yrs	5.0	8.0	1.6	0.61	0.31
Newell and MacFarlane (1996)	UK	R-NCREIF	1987-92	A	N			1Q	1.1	13.1	3.45	0.91	
Gatzlaff and Geltner (1998)	US	R-NCREIF	1981-96	A	N			1yr	3.86	4.07	1.05	0.61	0.21
Brown and Matysiak (1998)	UK	Appraisals	1987-95	M	N		0.5-0.62		3.64	3.64		0.12	
Geltner and Goetzman (2000)	US	R-NCREIF	1977-98	Q	N			2-3yrs	3.66	4.26	0.9-1.2	0.70	0.55
Brown and Matysiak (2000)	UK	Appraisals	1979-82	M	N	2.13	0.176		3.69	3.69	0	-0.039-0.027	
Brown and Matysiak (2000)	UK	IPD	1979-82	M	N	2.13	0.81-0.85		0.87-1.27	3.24-4.94	3.7 – 3.9	0.87 -0.90	0.85 -0.89
Clayton et al. (2001)	Canada	appraisals	1986-96	A	N		0.18 – 0.3	1-3Q	0.53 ^a	0.67 ^a	1.26	0.18	
Chau et al. (2001)	H. Kong	JLW	1984-96	Q	N		0.367-0.38	1-3Q	16.9-24	16.9-24		<0.14	
Fisher et al. (2003)	US	R-NCREIF	1982-01	A	N			3yrs	5.22	8.3-12.9	1-2.5	80.1	0.06-0.08
Fu (2003)	US	R-NCREIF	1978-02	Q	R		0.9	1yr	1.7	2.84	1-2.5	0.7	-0.7
Booth & Marcato (2004)	UK	IPD	1980-01	A	N		0.6		8.79	16.48	1.875	0.41	0.17
Maurer, et.al (2004)	UK	JLW	1987-02	A	R	2.13			2.34 -8.96	6.54-13.1	1.46- 2.79	0.35	0.06
Maurer, et.al (2004)	German	AMMEX	1987-02	Q	R	2.13			2.34	6.54	2.79	0.76	0.02
Maurer, et.al (2004)	US	RN	1987-02	Q	R	2.13			5.59	13.35	2.23	0.78	0.45
Maurer, et.al (2004)	UK	JLW	1987-02	Q	R	2.13			2.38	7.66	3.22	0.86	0.27
Pagliari et al. (2005)	US	R-NCREIF	1980-01	A	N		0.4		5.91	9.31	1.575		
Fisher et al. (2007)	US	R-NCREIF	1984-05	A	N			3yrs	1.7	3.7-11.2	1-6.7	79.5	
Bond & Hwang (2007)	US	R-NCREIF	1978-03	Q	N		0.4-0.9		1.7	3.7	01-Apr	0.7-0.9	<-0.3
Bond & Hwang (2007)	UK	IPD	1988-03	M	N		0.465		0.477	3.515	6.6	0.89-.948	0.1
Bond et al. (2012)	UK	Appraisal	1985-05	M	N		0.42		2.32	8.42	NA	0.141	

Notes: ^a The standard deviation reported in this study reflects the standard deviation of the average of reported overall capitalization rates.

Appendix 2: Time varying volatility and clustering patterns for the monthly IPD(UK) Total Index from 1987 to 2011 period

