An Analysis of Commercial Real Estate Returns: Is there a Smoothing Puzzle?

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Abstract

In this paper we investigate the commonly used autoregressive filter method of adjusting appraisal-based real estate returns to correct for the perceived biases induced in the appraisal process. Since the early work by Geltner (1989), many papers have been written on this topic but remarkably few have considered the relationship between smoothing at the individual property level and the amount of persistence in the aggregate appraised-based index. To investigate this issue in more detail we analyse a sample of individual-property level appraisal data from the Investment Property Database (IPD). We find that commonly used unsmoothing estimates overstate the extent of smoothing that takes place at the individual property level. There is also strong support for an ARFIMA representation of appraisal returns.

1 Introduction

One of the topics in real estate research that has received significant attention has been the treatment of appraisal-based returns. Recent evidence from a review of real estate articles suggests that research on this topic dominates the citation list in real estate journals (Domrow and Turnbull 2004). While attempts have been made to construct transaction-based returns series, use of appraisal-based returns remains common in the academic literature and is almost exclusively used in commercial research applications. There is a widespread belief among academics that such appraisal-based returns do not accurately represent the underlying movements of the commercial property asset class as biases are introduced in the appraisal process by appraisers seeking to dampen volatility in their price estimates. This view is based on the well known findings of Quan and Quigley (1991) and also confirmed empirically in Clayton, Geltner and Hamilton (2001). Other factors also induce econometric problems with appraisal-based indices, such as aggregation, and these issues have been discussed in Geltner (1993a) and Bond and Hwang (2005).

The general response to this problem has been to apply a statistical filter to the appraisal-based returns to remove all or part of the autocorrelation in the series. The corrected or "unsmoothed" series is then taken to more accurately reflect the movements in the "true" returns process. The most common statistical filtering procedures are based on Geltner (1991, 1993b) and Fisher, Geltner and Webb (1994). More recent work has been conducted by Cho, Kawaguchi and Shilling (2003), Edelstein and Quan (2004) and Bond and Hwang (2003, 2005) and a useful survey of the literature has been provided by Geltner, MacGregor and Schwann (2003). However, work on smoothed returns is not confined to real estate and is also discussed for other asset classes, such as hedge funds, by Getmansky, Lo and Makarov (2004).

Given the extensive volume of research on this topic and the many "unsmoothing" procedures that have been suggested, there has been little research investigating the statistical characteristics of an aggregate performance index and its relationship to the underlying property return process. Exceptions to this include Giacotto and Clapp (1992) who provide Monte Carlo evidence on appraisal smoothing behavior, and Edestein and Quan (2004) who compare appraisal returns with transaction information to assess the impact of smoothing.

The goal of this research is to investigate the nature and existence of three econometric problems common to appraisal-based return series. To do this we utilize data on individual property returns from the Investment Property Databank (IPD) for UK commercial real estate. This dataset is very similar to the NCREIF data commonly used in US research. Because of the similarity of construction methods it is believed that conclusions derived from using UK data will still have relevance to researchers using NCREIF data or similar appraisal-based data in other countries.

Our methodology is to use Monte Carlo simulations and bootstrapping techniques on a sample of individual property returns to generate alternative aggregate index series. Knowing the individual property returns allows us to form an estimate of the "true" underlying returns process using similar methods to Giacotto and Clapp (1992). The procedure clearly shows some interesting issues that, to our knowledge, have not been well discussed in the literature.

We find several interesting results. First, the smoothing level in an appraisal based index is not as large as in previous studies. At the individual property level, the smoothing parameter is as low as 0.14 when only smoothing is allowed for at the individual property level, while it could be up to 0.425 when both smoothing and nonsynchronous appraisal are considered. Therefore the usual smoothing coefficient, i.e., 0.89, estimated from an appraisal-based index is not supported by the smoothing level of individual properties. Second, we find evidence of nonsynchronous appraisal. The nonsynchronous appraisal problem arises when appraisers value properties (or use information for valuation) at irregular points of time.

The large difference in the smoothing levels between individual properties and the index constructed with these individual properties appears to be a puzzle – a "smoothing" puzzle. A few explanations are proposed to explain the puzzle. One possibility is that the sample estimates are biased because of a small number of observations in many individual properties. Using simulations we show that when the number of observations is small, i.e., less than 150, the estimated smoothing level appears to be lower than the true level or even negative. Another possibility is that aggregation effects exist as suggested by Bond and Hwang (2005). When individual properties suffer smoothing, the index constructed by cross-sectionally aggregating these individual properties shows a higher level of smoothing. Finally we propose the possibility of a highly persistent unobserved common factor in commercial real estate returns. Then although the smoothing level of individual properties is low, the aggregated process would be display a high level of persistance, driven by the persistent common factor (since the idiosyncratic components of individual properties are expected to be cancelled out by aggregation).

Our study has important inplications for both academics and practitioners. First, it is likely that commonly used statistical filtering procedures could over-unsmooth the appraisal index. The level of smoothing commonly suggested for a monthly appraisal index, e.g., 0.9 in the UK, seems to be too large. Individual properties do not show such a high level of smoothing, nor could any cross-sectional aggregation procedure or estimation bias in small samples be completely responsible for such a high level of smoothing. However we can not deny that these econometric problems could contribute to such a high level of smoothing in the appraisal index.

The layout of the paper is as follows. The next section discusses the unsmoothing problem and provides a brief overview of the related literature. Section 3 describes the methodology used in this study and the sampling procedure for the individual IPD property returns. Section 4 suggest investigates three explanations for the apparent smoothing puzzle observed. Section 5 concludes the paper.

2 Smoothing in Real Estate Returns

The work on smoothing in appraisal-based real estate returns is often motivated by the apparent low historical volatility relative to mean returns on benchmark indices such as NCREIF in the US or the IPD index in the UK. This smoothness looks particularly evident when the mean return to standard deviation ratio for real estate is compared to other asset classes such as equities or bonds. The academic arguments for the presence of smoothing in individual asset returns is based on the work of Quan and Quigley (1989, 1991). However, empirical approaches to unsmoothing aggregate or benchmark real estate indices had previously been suggested by Blundell and Ward (1987), Geltner (1989) and Ross and Zissler (1991). Extensive summaries of the smoothing literature can be found in Geltner and Miller (2001) and Geltner, MacGregor and Schwann (2003), to which the interested reader is referred for a detailed background to the smoothing debate. It is important to point out that not all researchers agree with the generally accepted view that smoothing is present in real estate data and Lai and Wang (1998) discuss a number of criticisms of the existing literature on smoothing.

To understand the issue of smoothing in real estate returns, consider the model of smoothing described in Bond and Hwang (2005). Start with the assumption that asset returns follow a mean plus noise process;

$$r_{it} = \mu_i + \sigma_i \varepsilon_{it} \tag{1}$$

where r_{it} is the log-return of asset i at time t, $\varepsilon_{it} \overset{iid}{\sim} N(0,1)$, and μ_i and σ_i are the expected return and standard deviation of the log-returns per unit of time respectively.

It is commonly assumed in models of smoothing that past information affects current price with an exponentially decreasing weight, that is, the innovation at time t, ε_{it}, is not fully reflected at time t, but over time with an exponential rate. When the rate is ϕ_{si}, the smoothed return process for asset i, r_{sit}, is

$$r_{sit} = \mu_i + (1 - \phi_{si})\sigma_i \varepsilon_{sit}, \tag{2}$$

where

$$\varepsilon_{sit} = \phi_{si}\varepsilon_{sit-1} + \varepsilon_{it}.$$

In this model, ϕ_{si} is an AR parameter for the level of smoothing, where $0 \leq \phi_{si} < 1$. Note that $1 - \phi_{si}$ in (2) is necessary to make the sum of the weights on past innovations one so that asset returns do not under or over reflect the innovations in the long run. The smoothed process in (2) can be written as

$$\begin{aligned} r_{sit} - \mu_i &= \phi_{si}(r_{sit-1} - \mu_i) + \sigma_{si}\varepsilon_{it} \qquad (3) \\ &= \phi_{si}(r_{sit-1} - \mu_i) + (1 - \phi_{si})(r_{it} - \mu_i), \end{aligned}$$

where $\sigma_{si} = (1 - \phi_{si})\sigma_i$. When $\phi_{si} = 0$, there is no smoothing and the return process in (3) is the same as the data generating process in equation (1). On the other hand, as ϕ_{si} becomes larger, the relative weight on the current information (ε_{it}) decreases and the past information ($\varepsilon_{it-1}, \varepsilon_{it-2}, ...$) becomes more important in the return process.

The variance and autocorrelation of the smoothed return process are

$$\begin{aligned} Var(r_{sit}) &= \frac{(1-\phi_{si})}{1+\phi_{si}}\sigma_i^2 \\ Cor(r_{sit}, r_{sit-\tau}) &= \phi_{si}^{\tau} \text{ for } \tau = 1, 2, ... \end{aligned} \tag{4}$$

The variance of smoothed returns decreases by $\frac{1-\phi_{si}}{1+\phi_{si}}$ times and thus is less volatile than the true process; i.e., $Var(r_{sit}) < Var(r_{it})$ for $0 \leq \phi_{si} < 1$. However, the expected return (μ_i) remains unchanged by the smoothing procedure.

Equation (3) forms the basis of the commonly used empirical approaches to unsmoothing real estate data. In particular, the methods of Fisher, Geltner and Webb (1994) and more recently Cho, Kawaguchi and Shilling (2003) essentially apply a version of this model to unsmooth aggregate real estate indices by applying the model to the real estate indices and then reverse engineering the equation to obtain estimates of ε_{it} as a measure of the unsmoothed real estate return (often with arbitrary assumptions placed on σ_i). In extending this model Bond and Hwang (2005) argued that while such an equation may explain smoothing for an individual asset (based on the arguments of Quan and Quigley 1991), it is not a complete model of real estate returns at an aggregate level (i.e. at the benchmark level to which most investors refer). To understand aggregate real estate returns, it is necessary to allow for timing errors in recording appraisals (nonsynchronous appraisal) and the impact of aggregation of individual asset return to form the benchmark index. Both of these issues have been raised by other researchers

(Geltner 1993a, Brown and Matysiak 1998), but had not been formally incorporated into a modelling strategy for aggregate returns.

The nonsynchronous appraisal issue arises when there is the discrepancy between the appraisal time point and the time point when the asset should be appraised, which creates the well known econometric problem of 'errors in variables' (see for example, Scholes and Williams 1977 and Lo and Mackinlay 1990). In the presence of nonsynchronous appraisal, Bond and Hwang show that returns on an individual real estate asset will follow an MA(1) of the form

$$r_{nit} - \mu_i = \sigma_{ni}\varepsilon_{it} + \theta_i\sigma_{ni}\varepsilon_{it-1}, \tag{5}$$

where the nonsynchronous returns (r_{nit}) depend on parameters θ_i and σ_{ni}. However, in practice it is likely that the two effects of smoothing and nonsynchronous appraisal will exist together. It can be shown that if the true return process becomes an AR(1) process when there is smoothing or a MA(1) process when the nonsynchronous appraisal problem exists, then when both effects are present the return process for an individual asset will follow an ARMA(1,1) process. That is

$$\begin{aligned} r_{cit} - \mu_i &= \sigma_{ni}(1 + \theta_i L)(1 - \phi_{si})\varepsilon_{sit}, \\ \varepsilon_{sit} &= \phi_{si}\varepsilon_{sit-1} + \varepsilon_{it}, \end{aligned}$$

where r_{cit} represents asset return at time t in the presence of the smoothing and nonsynchronous appraisal and L is the lag operator. This gives us

$$r_{cit} - \mu_i = \phi_{si}(r_{cit-1} - \mu_i) + \theta_i\sigma_{ci}\varepsilon_{it-1} + \sigma_{ci}\varepsilon_{it}, \tag{6}$$

where $\sigma_{ci} = (1 - \phi_{si})\sigma_{\eta i}$ and $\varepsilon_{it} \overset{iid}{\sim} N(0, 1)$ as in (1).

Finally it is necessary to consider the aggregation of the individual asset returns to form an index. Assuming $\sigma_i\varepsilon_{it} = \beta_i\epsilon_t + \eta_{it}$ where η_{it} is an idiosyncratic error and ϵ_t is a market-wide common factor, which are independent of each other and over time; $E(\eta_{it}\epsilon_t) = 0$, $\eta_{it} \sim iid(0, \sigma_\eta^2)$, and $\epsilon_t \sim iid(0, \sigma_\epsilon^2)$, it is shown in Bond and Hwang that the process obtained by cross-sectionally aggregating N ARMA(1,1) return processes is

$$r_{mt} - \mu_m = \sum_{\tau=0}^{\infty} E_c\left[\phi_{si}^{\tau}(\theta_i \epsilon_{it-1-\tau}^* + \epsilon_{it-\tau}^*)\right] \tag{7}$$

as $N \rightarrow \infty$, where

$$\epsilon_{it-\tau}^* = \frac{\sigma_{ci}}{\sigma_i}\beta_i \epsilon_{t-\tau},$$

and $E_c(.)$ represents cross-sectional expectation. In order to operationalise the model, assumptions need to be made about the distribution of the AR parameters in the model. If it is assumed that the AR parameters follow a Beta distribution as in Granger (1980), then we have the following ARFIMA(0,d,1) process;

$$(1 - L)^d(r_{mt} - \mu_m) = \theta\epsilon_{t-1}^* + \epsilon_t^*, \tag{8}$$

where $\theta = E_c(\theta_i)$, $d = E_c(\phi_{si})$ and $\epsilon_t^* = E_c[\epsilon_{it}^*]$.

Therefore, an index return process whose constituents suffer the smoothing and nonsynchronous appraisal problems follows a long memory process whose properties are summarized by an autocorrelation function with a hyperbolic decay rate. When the individual AR parameters follow the Beta distribution, we can directly estimate the average smoothing level and its variance from the autoregressive fractionally integrated (ARFIMA) (0,d,1) process since $d = E_c(\phi_{si})$ and $Var_c(\phi_{si}) = \frac{d(1-d)}{2}$. Therefore estimating d for an index return series is an alternative way of obtaining the average smoothing level of individual processes. Moreover Bond and Hwang show that when the market-wide common factor (ϵ_t) follows an AR(1) process, the index should be modelled by the ARFIMA(1,d,1) process, where the AR coefficient represents the persistence level of the common factor.

While there are strong theoretical arguments to favour the ARFIMA model of aggregate real estate returns as a basis to use in unsmoothing real estate returns, it is necessary to provide further evidence on the suitability of the assumptions made to develop the model (in particular the distribution of the AR parameters) and also to examine the performance of the model compared to the standard approach to unsmooth returns. To provide this evidence we first turn to an analysis of the individual appraisal returns for the properties which comprise the benchmark monthly IPD index in the UK. Using this information to calibrate the model, we provide simulation evidence to assess the suitability of the ARFIMA model to unsmooth appraisal-based returns.

3 Data and Smoothing Puzzle

3.1 Data

To conduct the analysis of the model we collect information on the appraised value (capital gain) series of individual properties belonging to the IPD monthly index (appraisals are conducted on a monthly basis). As the focus of this paper is on appraisal smoothing, the problem is more appropriately analysed by concentrating on the capital gain series rather than the total return (that are calculated by aggregating capital gains and rental income). Rental income in the UK, which may be a significant proportion of the total return, is usually only subject to change once every five years, and thus does not reflect either the smoothing or nonsynchronous appraisal problem.[1]

[1] However we note that the infrequent changes in rental income could create higher persistence in the total return series. See Banerjee and Urga (2005) for the discussion of the effects of structural breaks on the persistence.

The individual properties are the constituents of the UK IPD index, having been used to construct the IPD index from 1987 to 2005. We only analyse properties that have been included in the index for at least 60 months. This restriction is to prevent any econometric problems (i.e., small sample problems) faced when the AR and MA parameters are estimated. After allowing for this restriction we have a total number of 3409 properties, we then filter out 'outliers' whose characteristics are significantly different from most of the others and thus could lead to inappropriate inferences in the analysis. We remove outliers with the following procedure. Average returns of individual properties should be within three standard deviations of the average return, the monthly standard deviation of a property's returns should be less than 10 percent, and the maximum and minimum monthly returns should be less than 50 percent and larger than -30 percent respectively. By applying the procedures we remove 166 properties. Other outlier removing procedures are related to the estimates of the ARMA(1,1) model.[2] We face a large number of estimation errors or unusual estimates, and remove properties whose the standard errors of AR and MA estimates are larger than 5 or properties that have parameters that are not stationary or invertible. The additional filtering procedure removes 849 properties, the largest proportion of which is due to the nonstationarity and noninvertibility conditions imposed (621 properties). As suspected the filtered out properties have smaller numbers of observations (median observation is 85 months). After applying these filtering procedures we have 2394 properties which have been used for further analysis. These filtering procedures are arbitrary, but the statistical properties of the selected properties are, on the whole, not different from those of

[2]We use the ARMA(1,1) model rather than AR(1) model in order to select properties that can be used for both smoothing and nonsynchronous appraisal.

the original 3409 properties.

The statistical properties of the individual property returns data are summarised in Table 1. During the 18 years for which we have data available, the average monthly return of the individual properties is 0.25 percent with an average standard deviation of 2.32 percent. The statistics of the relevant index returns are reported in the last three columns in the table. The average return and standard deviation of the IPD capital gain index (IPDC) return are 0.29 and 0.79 percent respectively, while the IPD total return index reports an average return of 0.88 percent. Thus rental income consists of 68 percent of the total return. By way of comparison, returns on the FTSE Real Estate index are far more volatile and fat-tailed.

The average Sharpe ratio of individual properties is 0.12 (or in annual terms, 0.4), which is far less than 0.37 of the IPD capital gain index return. The difference is mainly due to the small standard deviation of the IPD capital gain return. This clearly shows that aggregation reduces volatility since idiosyncratic errors of individual properties are cancelled out by the aggregation. Therefore the high Sharpe ratio of the index does not automatically suggest that individual properties have similar Sharpe ratios. When the rental income, that is fixed in most cases, is included, individual properties have an average return of 0.88 percent with average standard deviation of approximately 2.32 (unchanged), giving a Sharpe ratio of 0.38. But this is still far less than 1.14 obtained from the IPD total index return. The Sharpe ratio of individual properties is one third of that of the index.

3.2 A Smoothing Puzzle

To analyse the issue of smoothing in real estate returns we first estimate the parameters for an AR(1) process for all the individual properties selected in our sample. The AR(1) process models only the impact of smoothing. The histogram of the estimated AR parameters is shown in Figure 1. The average value of AR parameters is only 0.141 with standard deviation of 0.156 (see panel B of Table 2). Around 16 percent of the estimated AR parameters are negative. The figure and statistics suggest weak evidence of smoothing: the estimated individual AR parameters are not significantly different from zero. On the other hand the AR estimate for the IPDC (IPD capital gain index series) return shows a high level of persistence; i.e., the AR parameter estimate is 0.886, with standard error of 0.032 (see panel A of Table 2).

One major problem with the AR process is that the AR parameter estimated is seriously downward biased if there is a negative MA component. In other words, as discussed in Bond and Hwang (2005), when individual properties suffer from nonsynchronous appraisal problems in addition to smoothing, the true process follows an ARMA(1,1) process with a negative MA coefficient. In this case the AR(1) process is a misspecified version of the true ARMA(1,1) process, and the AR estimates obtained from the AR(1) model are downward biased. Therefore we estimate an ARMA(1,1) process for the individual property returns to obtain AR and MA parameters, each of which represents smoothing and nonsynchronous appraisal. Figures 1B and 1C and Table 1 show some interesting patterns in the estimated AR and MA parameters. First, the average value of estimated AR parameters is 0.425 which is around three times higher than that of the AR(1) process in Figure 1A. The density function is negatively skewed and the median is much higher, i.e., 0.77. Thus the AR estimates from the ARMA(1,1) model suggest a much higher level of smoothing than those from the AR(1) model. Second, the average value of estimated MA parameters is -0.296 and the median is -0.58. As explained in Bond and Hwang (2005) these negative MA parameters suggest the existence of nonsynchronous appraisal. However when the statistics from individual properties are compared with those of the index in panel A of Table 2, the IPDC return still shows much higher levels of persistence. The estimated AR parameter is 0.952 from the ARMA(1,1) model.

This leads to an intriguing set of results, both the AR(1) and ARMA(1,1) models show a high level of smoothing in the index. However at the individual property level, the smoothing level is far less than that obtained for the index. This large difference in the smoothing levels, which we call 'smoothing puzzle', needs to be explained.

4 Some Explanations for the Smoothing Puzzle

In this section we propose three alternative explanations to explain the smoothing puzzle. The first explanation concerns whether the large number of negative AR estimates observed (negative smoothing) actually represents the true probability density function of the individual AR parameters. We address this concern by showing the existence of estimation biases in relation to small samples. The second explanation is if cross-sectional aggregation increases the persistence level in the index, the idea proposed by Bond and Hwang (2005). The last explanation we investigate is whether the underlying common factor in real estate is efficient. It may not be solely the issue of appraisal smoothing in individual properties that contributes to the high persistence levels in the index. There could be other common factors that explain the high persistence in the index.

4.1 Is Negative Smoothing Possible?

In the sample estimates there are many negative AR estimates and positive MA estimates that are not consistent with smoothing and nonsynchronous appraisal respectively. Negative smoothing suggests that appraisers overreact to information and higher valuations follows lower valuations, and vice versa. However, the AR and MA estimates are noisy; many of them are not significantly different from zero. Moreover there may be the biases in the estimates from the assets that have been included in the IPD index for only a relatively short period of time. The correlation coefficient between AR estimates and the number of observations is positive and significant, i.e., 0.183. Thus the properties that have been included in the index for short periods of time are likely to show lower or negative AR estimates. As shown in Figure 2 the majority of properties have less than 150 months of observations and this could create small sample problems for our estimates. If we only consider the properties that have stayed in the index for longer than 150 months, Figure 3 shows that most of the AR estimates are positive while the MA estimates are negative. The median AR estimate is 0.83 and the median MA estimate is -0.67. Thus we observe a high value for the AR parameters of properties in the index for longer time periods. This raises the possibility that small samples create a downward bias (or upward bias) in AR estimates (MA estimates). However for the majority of the properties whose history is shorter than 150 months, this explanation does not hold.

We hypothesize the possibility of estimation bias for the properties that have shorter monthly observations. In order to test the hypothesis, we perform simulations as follows. We generate 1000 ARMA(1,1) series under the assumption that AR and MA parameters are distributed as in Figures 3B and 3C. To explain smoothing we only allow positive AR parameters. Each

ARMA(1,1) series have 60 observations to allow for us to evaluate the small sample bias. For the generated ARMA(1,1) series we estimate AR(1) and ARMA(1,1) models whose histograms are reported in Figure 4.

In the AR estimates from the AR(1) process, there is hardly any difference between Figures 3A and 4A. On the other hand for the ARMA(1,1) process Figures 4B and 4C show a clear difference from Figures 3B and 3C respectively. Even if the true AR parameters are significantly left skewed and have the mass around 0.83 (figure 3B), the small sample estimates of AR parameters are far less skewed and have many negative AR estimates. Similarly the estimates of the MA parameter are upward biased.

Therefore the distributions of AR and MA estimates in Figures 1B and 1C could be affected by a large number of small observations. Taking into account the downward bias in AR estimates implies we could have a much higher level of smoothing than suggested by the original estimates. As in Figure 3B the smoothing level could be 0.83, which is the median of the AR estimates that comes from the properties included in the IPD index for more than 150 months. However, since these biases decreases with the number of observations, our choice of 60 observations provides one extreme case and thus in reality the effects of the small sample bias could be smaller than those in our simulations

4.2 The Effects of Cross-sectional Aggregation

Bond and Hwang (2005) suggest that the persistence level of an index (cross-sectionally aggregated process) is not necessarily equivalent to the average persistence level of individual properties. When there is smoothing and thus AR parameters are positive, an index created by aggregating the individual AR processes becomes more persistent and thus the smoothing level calculated with the index could be inflated. In order to investigate if cross-sectional aggregation increases the persistence level of the index, we construct an index return series by aggregating the 2394 AR(1) series, each of which is generated with the estimated AR parameters. For the constructed index return series, we estimate AR(1) and ARMA(1,1) models. The procedure is repeated 1000 times and the results are summarised in Panel A of Table 3.

The estimated AR parameter for the pseudo index returns is 0.128, on average which is similar to the average value of the AR parameters of the individual properties, i.e., 0.141. The result indicates that if the AR(1) process represents the true process for the measure of smoothing, in the index level we do not observe high smoothing, i.e., 0.886 by aggregation. The ARMA(1,1) model also does not support the high persistent level; the average AR estimate for the ARMA(1,1) model increases by 0.1 but is not significant. These two models of individual asset returns do not explain why we observe the high level of persistence in the benchmark IPDC index.

We repeat a similar bootstrapping technique except this time using an ARMA(1,1) model as the underlying base model; An index return series is created by aggregating the 2394 ARMA(1,1,) series each of which are generated with the estimated AR and MA parameters. For the constructed index return series, we estimate the AR(1) and ARMA(1,1) models. The procedure is repeated 1000 times and results are summarised in Panel B of Table 3. As explained in Bond and Hwang (2005) we observe larger average values of the AR and MA parameters from the simulations than the true values in the first two columns. However because of the large number of negative AR parameters, the upward bias is not as severe as predicted by Bond and Hwang (2005). Interestingly the AR parameter from the AR(1) process is still very low, i.e., 0.138.

The results in Table 3 suggest that we can explain some of the high smoothing level in the index due to the issue of cross-sectional aggregation. Cross-sectional aggregation of individual asset returns increases smoothing levels at the aggregate level by 0.1 to 0.15. However, it is possible that the difference between the two level of persistence (at the individual property level vs the index level) is explained by both the cross-sectional aggregation and the estimation bias explained in the previous section. Either one of the explanations does not seem to resolve the puzzle, but combining the two could be the answer.

4.3 Persistent Common Factors

Another possible explanation is that there may be unobserved common factors that are highly persistent. By cross-sectionally aggregating individual property returns, idiosyncratic errors will disappear, and only common factors survive the aggregation (see Bond and Hwang 2005 for further discussion). If markets are efficient the common factors should not be autocorrelated. However in our case the unobserved common factors (ϵ_t) could be autocorrelated since it is hard for arbitraguers to exploit the persistence of the unobserved common factors of the highly illiquid commercial property market. In addition the common factors may reflect changes in macroeconomic factors that move slowly over time.

To investigate the effects of the persistence of a common factor on the persistence in the index level, we simulate the common factor as follows. The proportion of the common factor to the idiosyncratic errors is set to 30 percent since the standard deviation of the IPD capital gain index return is around 30 percent of that of the individual properties. In other words if we treat the IPDC return as a common factor, its standard deviation is around

30 percent of the individual property returns. Thus

$$\sigma_i \varepsilon_{it} = \beta_i \epsilon_t + \eta_{it},$$

where $\epsilon_t \tilde{} N(0, 0.3^2)$ and $\eta_{it} \tilde{} N(0, 0.7^2)$.[3] Although we use the relative size of the standard deviation of the IPDC return we do not use the IPD index return for ϵ_t, since the dynamics of the IPD index return is likely to be affected by smoothing and nonsynchronous trading. Therefore we generate the common factor as

$$\epsilon_t = \phi_f \epsilon_{t-1} + \xi_t,$$

where we set ϕ_f = 0.1, 0.3, 0.5, 0.7, and 0.9. We set $\beta_i \tilde{} N(1, \sigma_\beta^2)$, and tried various values for σ_β but the results do not change.[4] Thus we report the results with $\sigma_\beta = 1$.

When the common factor follows an AR(1) process with the AR parameter ϕ_f, the index follows an ARFIMA(1,d,1) process analytically, where the AR parameter shows the persistence level of the unobserved common factor, ϕ_f, the long memory parameter d represents the level of smoothing in individual properties, and the MA parameter represents nonsynchronous appraisal. The last row of panel A of Table 2 reports that the smoothing level of individual properties is 0.332, the persistence of the common factor is 0.591, and the nonsynchronous appraisal explains the negative MA of -0.287. The smoothing level of individual properties in panel B of table 2 is 0.425 (average AR estimate) which is close to 0.332. The simulation results in Table 4 indicate that when ϕ_f is 0.7 to 0.9, the estimates of the ARFIMA(1,d,1) model in panel A of table 2 could be obtained.

[3] We also used different combinations of idiosyncratic errors to common factor, but the results do not change in a meaninful way.

[4] This is because $E(\beta_i) = 1$ regardless of σ_β^2. We set $E(\beta_i) = 1$ since the factor f_t is the market factor as the beta in CAPM.

Therefore an unobserved common factor could explain the difference in smoothing level between individual properties and index. The close comparison between simulation and estimation results indicates that the unobserved common factor could be highly persistent, but on the other hand smoothing level could be much smaller, i.e., 0.425.

5 Conclusion

This paper has investigated the appropriateness of commonly used stochastic processes to explain some of the "stylised facts" of real estate returns at an individual property level and an aggregate index level. This is important as many of the "unsmoothing" procedures used by researchers are based on assumptions about how appraisers' behaviour impacts on individual property returns but are almost always applied to aggregate index returns. We believe that this severely overestimates the level of smoothing that actually takes place at the individual property level.

Our analysis of individual property level appraisals lead to an intriguing "puzzle", we observed low levels of smoothing in individual property level returns yet a high level of persistence in aggregate index returns. Clearly models of appraisal smoothing that apply AR filters to the aggregate index will overstate the extent of smoothing and may give misleading information about the nature of "true" property returns. We investigated three possible explanations for this puzzle. The first explanation concerned the extent to which estimation errors (in particular small sample biases) may have impacted on the estimates of the stochastic processes at the individual property level. These biases may have underestimated the extent to which smoothing is a problem at the individual property level. We found some evidence to suggest that the downward bias in the smoothing parameter is greater for those properties with fewer observations in the sample. As many of the properties which comprise the monthly IPD index had only been in the index for less that ten years, it is possible that this could account for some of the discrepancy observed. The second was that aggregation of individual property returns lead to high levels of persistence at an aggregate level. Using the work of Bond and Hwang (2005) we considered the process of aggregation and found that while this can account for some of the difference between smoothing at the individual property level and persistence at an index level, it may not account for all of it. Finally we investigated another possibility, that the stochastic process underlying individual appraisal-based property returns is more complex than previously thought. While most of the literature has focused on the autoregressive component to smoothed returns and more recently consideration has been given to an ARMA process to capture both smoothing and nonsynchronous appraisal, there may be evidence of a common factor representation to individual level appraised returns. On the statistical evidence presented, this explanation also describes the puzzle between the low level of smoothing at the individual property level and the high level of persistence of the aggregate index. If this model is appropriate, it would have important implications for our understanding of the property market at the micro level and further raise questions about market efficiency and the nature of the appraisal process.

In terms of advice to researchers on using unsmoothing procedures, there is strong evidence that simple AR filtering models are not appropriate. There is some evidence to support the use of the ARFIMA representations put forward by Bond and Hwang (2005). These models are the only ones that go some way to capturing the complexity of the relationship between individual property returns and the aggregate property index. Of the models put forward by Bond and Hwang the ARFIMA (1,d,1) is better able to capture appraisal smoothing "puzzle" found in the analysis of individual property returns. However further work is required to understand the nature of the process which gives rise to the common factor representation of property returns.

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Table 1 Statistical Properties of Individual Property Returns

	Capital Gains of Individual Properties			Indices		
	Mean	Standard Deviation	Number of Observations	IPD Capital Gain Index	IPD Total Return Index	FTSE Real Estate Index
Mean	0.25	2.32	107.96	0.29	0.88	0.95
Median	0.25	2.12	99.00	0.22	0.82	1.29
Maximum	1.77	8.42	225.00	2.88	3.61	18.01
Minimum	-1.76	0.50	60.00	-2.24	-1.76	-30.87
Std. Dev.	0.37	0.99	38.58	0.79	0.77	5.79
Skewness	-0.24	1.30	1.15	0.32	0.25	-0.88
Kurtosis	4.34	5.55	3.93	0.75	1.21	3.69
Jarque-Bera	201.33	1319.96	610.63	9.21	16.00	156.68
Probability	0.00	0.00	0.00	0.00	0.00	0.00
Autocorrelation with Lag 1				0.88	0.88	0.17

Note: The individual properties are the constituents of the UK IPD index, which have been used to construct the IPD index from 1987 to 2005 (to be confirmed). We take properties that have ever been included in the index for at least 60 months. With this restriction we initially take a total number of 3409 properties, and then filter out `outliers' whose properties are significantly different from most of the others. Outliers are removed with the following procedure. Average returns of individual properties should be within the three stadard deviations of the average returns, monthly standard deviation of property returns should be less than 10 percent, and maximum and minimum monthly returns should be less than 50 percent and larger than -30 percent respectively. Using estimates of the ARMA(1,1) model we also remove properties whose the stadardard errors of AR amd MA estimtes are larger than 5 or properties that are not stationary or invertible. After applying these filtering procedures we have 2394 properties which have been used for analysis.

Table 2 Estimates of AR(1) and ARMA(1,1) Models

A. Estimates for the IPD Capital Gain Index Returns

	AR Parameter	MA Paramater	d Parameter	AR3 Parameter
AR(1) Process	0.886 (0.032)			
ARMA(1) Process	0.952 (0.023)	-0.319 (0.071)		
ARFIMA(1,d,1) Process	0.591 (0.171)	-0.287 (0.138)	0.332 (0.147)	0.249 (0.105)

B. Estimates for the 2394 Individual Properties Returns

	Estimated Models		
	AR(1) Process	ARMA(1,1) Process	
	AR Parameter	AR Parameter	MA Paramater
Mean	0.141	0.425	-0.296
Median	0.130	0.770	-0.580
Standard Deviations	0.156	0.631	0.601
Skewness	0.218	-1.078	0.918
Kurtosis	4.161	2.586	2.325

Notes: The models in panel A are estimated using 225 monthly returns of the IPD Capital Gains index from January 1987 to September 2005. The estimates in panel B are calculated using 2394 individual properties described in Table 1.

Table 3 Estimates of AR(1) Model and Simulated Index from AR(1) Process

A. Estimates from Simulated Index Returns Using AR(1) Process

	Data generating Process: AR(1) Process	Estimated Models		
		AR(1) Process	ARMA(1,1) Process	
	AR Parameter	AR Parameter	AR Parameter	MA Paramater
Average Estimate	0.141	0.128	0.248	-0.145
Standard Errors of Estimates	(0.156)	(0.066)	(0.354)	(0.359)

B. Estimates from Simulated Index Returns Using ARMA(1,1) Process

	Data Generating Process: ARMA(1,1) Process		Estimated Models		
			AR(1) Process	ARMA(1,1) Process	
	AR Parameter	MA Paramater	AR Parameter	AR Parameter	MA Parameter
Average Estimate	0.425	-0.296	0.138	0.565	-0.442
Standard Errors of Estimates	(0.631)	(0.601)	(0.073)	(0.411)	(0.422)

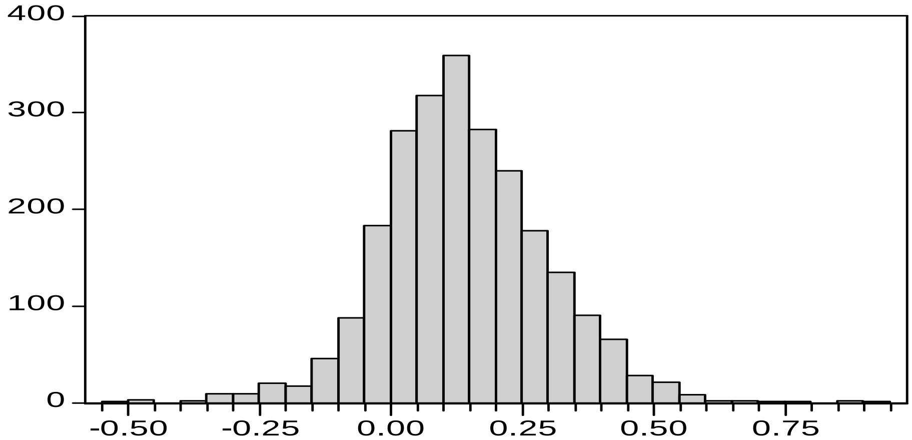
Notes: The table summarises the simulation results. We construct an index return series (225 observations) by aggregating the 2394 AR(1) series each of which are generated with the estimated AR parameters. Error terms are drawn randomly from the normal distributions whose standard deviations are set to estimated standard deviations of residuals. For the constructed index return series, we estimate the AR(1) and ARMA(1,1) models. The procedure is repeated 1000 times

Table 4 Simulations for Common Factors

	Persistence of Common Factor	Estimated Models					
		AR(1) Process	ARMA(1,1) Process		ARFIMA(1,d,1) Process		
	AR Parameter	AR Parameter	AR Parameter	MA Paramater	d Parameter	AR Paramater	MA Paramater
Average Estimate	0.100	0.241	0.499	-0.287	0.114	0.174	-0.066
Standard Errors of Estimates		(0.071)	(0.325)	(0.348)	(0.314)	(0.467)	(0.454)
Average Estimate	0.300	0.444	0.529	-0.112	0.070	0.285	0.068
Standard Errors of Estimates		(0.064)	(0.164)	(0.190)	(0.281)	(0.418)	(0.309)
Average Estimate	0.500	0.627	0.641	-0.025	0.081	0.458	0.080
Standard Errors of Estimates		(0.058)	(0.095)	(0.119)	(0.272)	(0.342)	(0.204)
Average Estimate	0.700	0.798	0.787	0.029	0.151	0.624	0.044
Standard Errors of Estimates		(0.040)	(0.054)	(0.089)	(0.258)	(0.283)	(0.171)
Average Estimate	0.900	0.940	0.930	0.081	0.318	0.771	-0.073
Standard Errors of Estimates		(0.022)	(0.026)	(0.067)	(0.256)	(0.254)	(0.193)

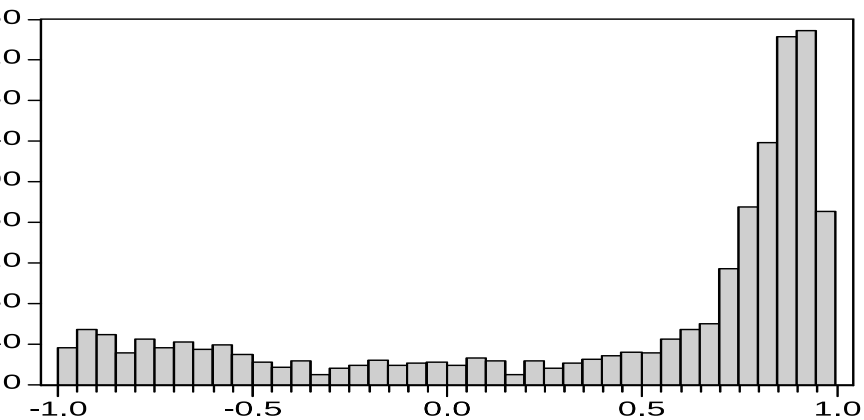
Notes: The table summarises the simulation results. We construct an index return series (225 observations) by aggregating the 2394 AR(1) series each of which are generated with the estimated AR parameters. Error terms are drawn randomly from the normal distributions whose standard deviations are set to estimated standard deviations of residuals. For the constructed index return series, we estimate the AR(1), ARMA(1,1), and ARFIMA(1,d,1) models. The procedure is repeated 1000 times. As in Table 2 ARMA(1,1) processes are generated using the estimated AR and MA parameters.

Figure 1A Histogram of AR Estimates of AR(1) Process



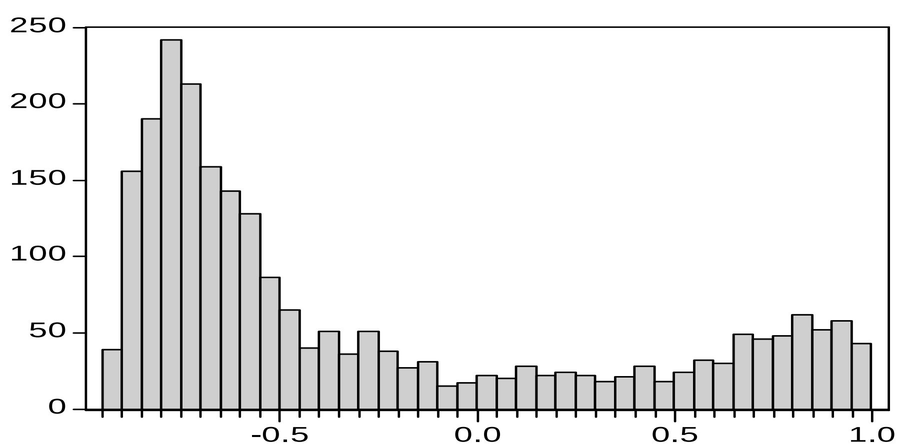
Statistics of AR Estimates	Mean	Median	Std. Dev.	Skewness	Kurtosis
	0.141	0.130	0.156	0.218	4.161

Figure 1B Histogram of AR Estimates of ARMA(1,1) Process



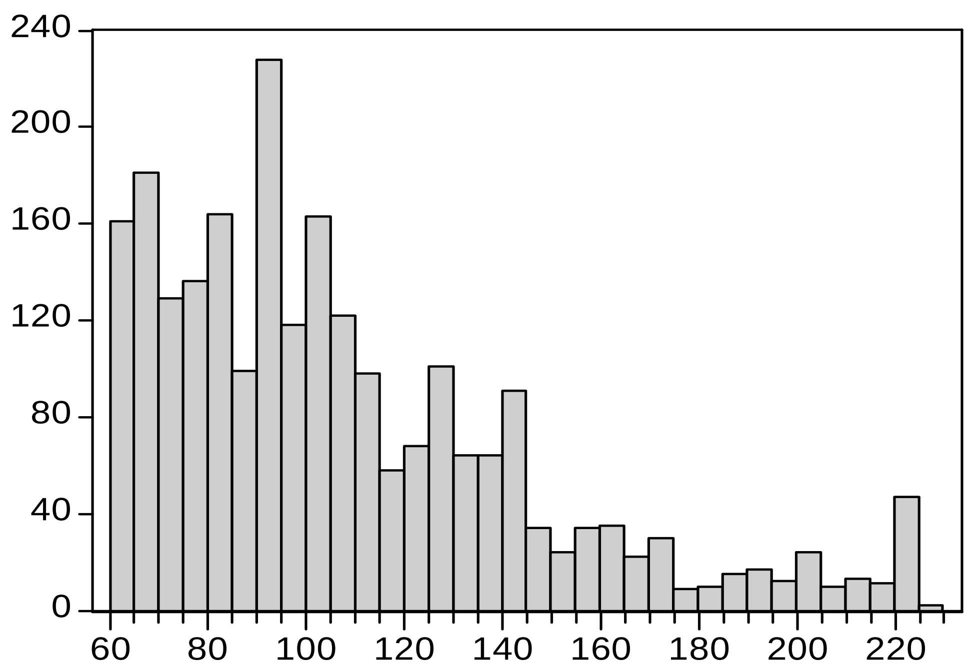
Statistics of AR Estimates	Mean	Median	Std. Dev.	Skewness	Kurtosis
	0.425	0.770	0.631	-1.078	2.586

Figure 1C Histogram of MA Estimates of ARMA(1,1) Process



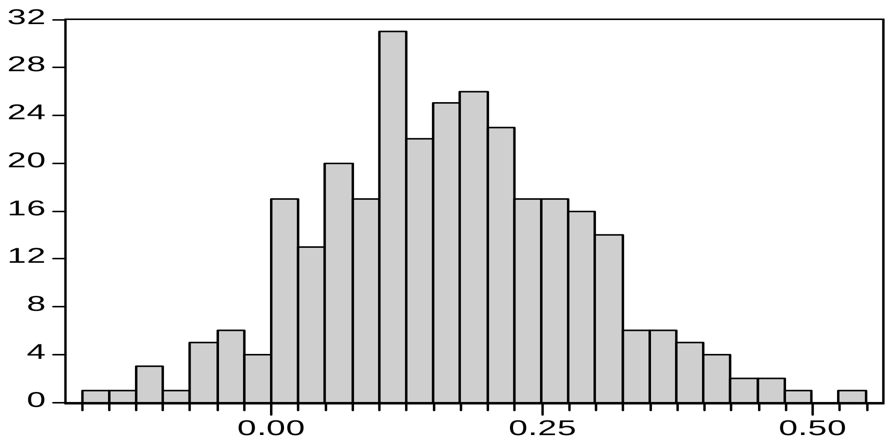
Statistics of AR Estimates	Mean	Median	Std. Dev.	Skewness	Kurtosis
	-0.296	-0.580	0.601	0.918	2.325

Figure 2 Frequency Count of Observations by Number of Months in Sample



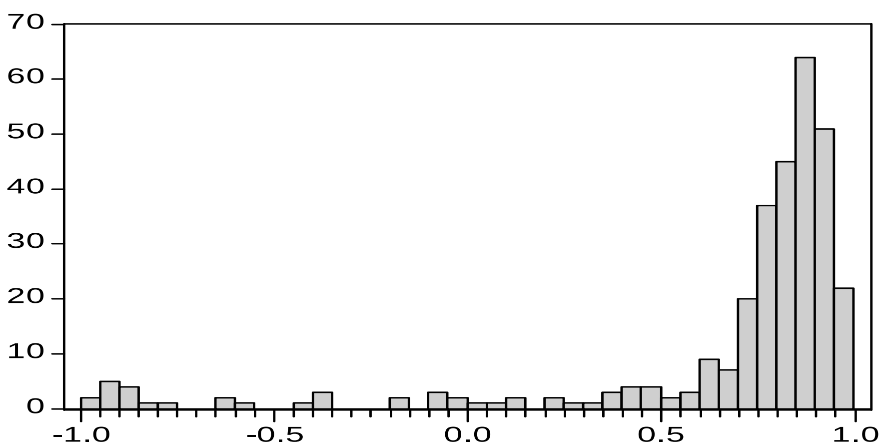
Statistics of months in sample	Mean	Median	Std. Dev.	Skewness	Kurtosis
	107.961	99.000	38.581	1.146	3.932

Figure 3A Histogram of AR Estimates of AR(1) Process



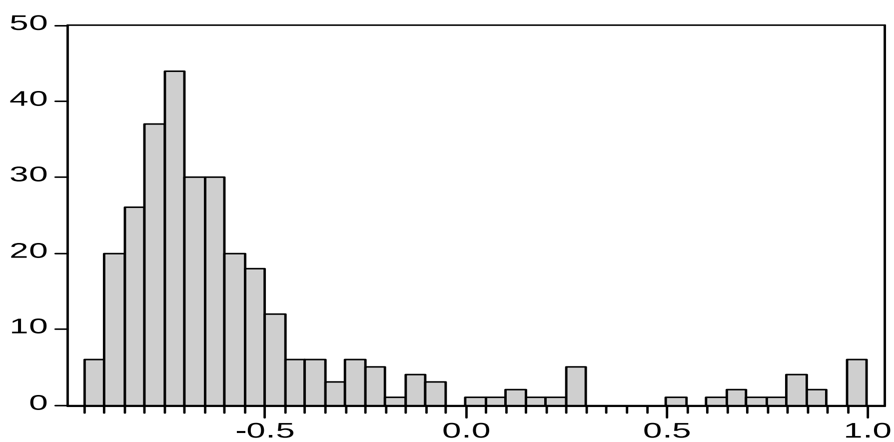
Statistics of AR Estimates	Mean	Median	Std. Dev.	Skewness	Kurtosis
	0.166	0.166	0.121	0.145	2.956

Figure 3B Histogram of AR Estimates of ARMA(1,1) Process



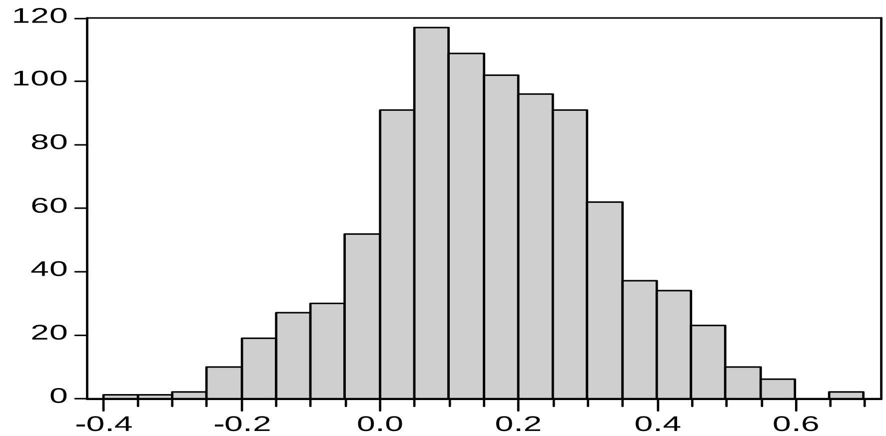
Statistics of AR Estimates	Mean	Median	Std. Dev.	Skewness	Kurtosis
	0.675	0.830	0.435	-2.609	9.077

Figure 3C Histogram of MA Estimates of ARMA(1,1) Process



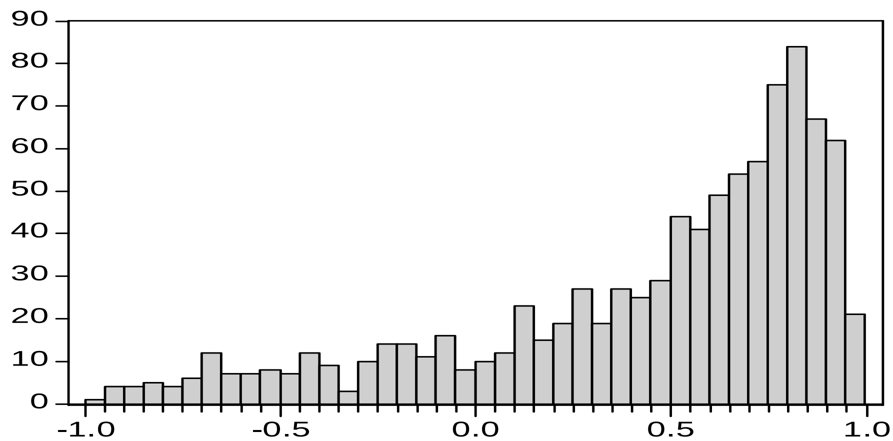
Statistics of AR Estimates	Mean	Median	Std. Dev.	Skewness	Kurtosis
	-0.538	-0.670	0.414	2.261	7.710

Figure 4A Histogram of AR Estimates of AR(1) Process



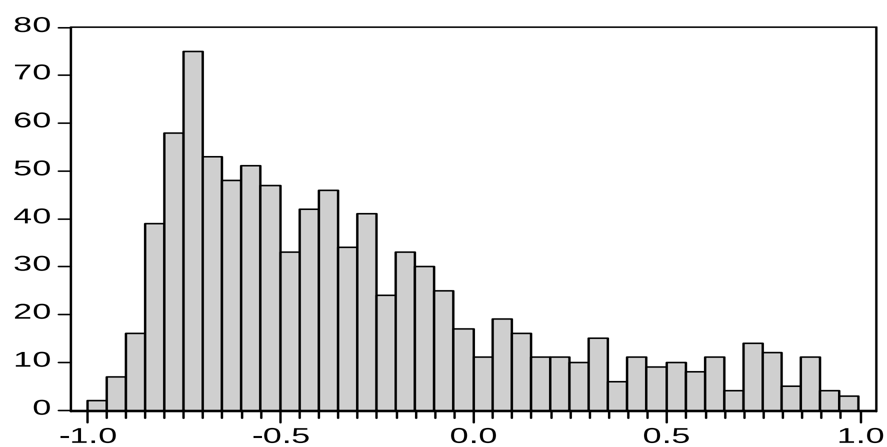
	Mean	Median	Std. Dev.	Skewness	Kurtosis
True AR Parameters	0.181	0.173	0.112	0.328	2.981
Statistics of AR Estimates	0.156	0.150	0.166	0.051	2.961

Figure 4B Histogram of AR Estimates of ARMA(1,1) Process



	Mean	Median	Std. Dev.	Skewness	Kurtosis
True AR Parameters	0.797	0.840	0.163	-2.166	8.551
Statistics of AR Estimates	0.449	0.609	0.463	-1.156	3.447

Figure 4C Histogram of MA Estimates of ARMA(1,1) Process



	Mean	Median	Std. Dev.	Skewness	Kurtosis
True MA Parameters	-0.647	-0.700	0.200	1.572	6.370
Statistics of AR Estimates	-0.301	-0.413	0.458	0.963	3.094