Smoothing and Implications for Asset Allocation Choices

Model Selection or Calibration?

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Smoothing is the phenomenon that causes a lag effect and reduced volatility in valuation-based indices in comparison with the underlying market which is represented by accurate transaction-based indices. Indicators of smoothing are easily found in time series analyses of valuation-based indices, and the factors underlying those results have been extensively discussed in the literature. However, to date, this discussion has not resulted in a generally accepted quantitative measure of the extent to which returns should be unsmoothed in constructing mixed-asset portfolios.

Three main factors may cause smoothing in a valuation-based index: the aggregation process underlying the index construction; valuations spread over time (known as temporal aggregation); and inertia in individual valuations arising from anchoring to prior values in the absence of conclusive current market evidence, or in other words, thresholds applied by valuers (for example, 1% of capital value) before a change in value is reported.

From a practical standpoint, the issue of smoothing is critical for asset allocation choices in which the estimation of risk-return profiles of different asset classes appears to be key to the construction of function-maximizing portfolios. Following the Markowitz mean-variance model [1952], we would attribute a very high weight to real estate because valuation-based indexes show low levels of risk. However, institutional investors normally show a real estate weight ranging between 5% and 10% on average.[1] The difference between optimal and current real estate weights is frequently attributed to the understatement of the volatility in standard real estate indexes, such as the Investment Property Databank Index (IPD) and National Council of Real Estate Investment Fiduciaries (NCREIF)

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Property Index (NPI), and/or to the biased correlation or systematic risk due to the lag bias. A recent paper by Stevenson [2004] finds an improvement in performance obtained by including real estate in an international mixed-asset portfolio and, contrary to previous studies, points out that different unsmoothing models do not yield different allocation figures.

This article further investigates this issue by applying several unsmoothing techniques to identify the reasons why Stevenson [2004] and previous studies find different results. The next section provides a review of the literature on asset allocation and smoothing in real estate markets. The two subsequent sections explain, respectively, the data and methodology used in the empirical analysis and the full results for the U.K. market. The following section presents the main results for the U.S. and Australian markets, and the last section draws together the main findings and conclusions.

LITERATURE REVIEW

Several papers have studied the benefit of including real estate in a mixed-asset portfolio from either a domestic perspective—Fogler [1984], Firstenberg et al. [1988], MacGregor and Nanthakumaran [1992], and Byrne and Lee [1995, 2004]—or an international perspective—Ziobrowski and Curcio [1991], Newell and Worzala [1995], Chua [1999], Stevenson [1999, 2000], and Hoesli et al. [2002]. In both situations, results show a positive shift of the efficient frontier to the left (i.e., higher Sharpe ratios), but do not fully explain why portfolio managers hold less than optimal real estate weights. Other studies also look at the type of risk that should be considered for asset allocation decisions—Sing and Ong [2000], Cheng and Wolverton [2001], and Byrne and Lee [1999, 2004]. These studies identify different risk measures and compare relative portfolio allocations. They conclude that real estate weights vary significantly and the investor should choose the measure best describing his/her attitude towards risk.

However the problem arises when we question the reliability of real estate indexes in estimating the risk associated with this type of investment, whatever measure of risk we use. Clearly, current real estate weights in institutional portfolios in both the U.K. and U.S. suggest that the perceived risk is well above the risk reported by index providers such as IPD in the U.K. and NCREIF in the U.S. If, for example, we consider variance as the measure of portfolio risk, we know that two main factors impact its value—the variance of each asset class and the correlation coefficients between them—as expressed in the following equation:

$$value_t = \frac{rent_t}{caprate_t}$$

We also know that available real estate returns normally show both low volatility and low correlation coefficients with other asset classes. So, if we include real estate in a global portfolio, we inevitably expect and obtain a reduction in portfolio risk and an increase in the Sharpe ratio.

In a recent article, Fisher et al. [2007] also found similar Sharpe-maximizing portfolio allocations to real estate based on appraisal- versus transaction-based U.S. indexes, specifically, the MIT Center for Real Estate's Transaction-Based Index (TBI). The TBI-based allocation was smaller than the NPI-based allocation (43% versus 77%), but it was still very large and much larger than in current institutional portfolios.[2] This recent finding confirms that the smoothing issue is far from being overcome and then needs further discussion. Moreover, the extensive use of valuation-based indexes by portfolio managers and the lack of transaction-based measures in other markets make the smoothing issue especially relevant when international markets are considered.

In the real estate literature, the problem of underestimating risk is well documented and known as *smoothing*. Several sources of smoothing are identified either at the index level or the appraisal process of individual properties. In the latter case, Geltner [1997] defines valuation smoothing as the systematic past-market-value bias (i.e., the use of past comparables to value properties in a portfolio context) on the current valuation. Bowles et al. [2001] extend these findings by using sampling theory to measure confidence intervals for portfolio valuation errors and to define the minimum number of properties necessary to achieve a pre-determined level of accuracy at a portfolio level. Finally, Clayton et al. [2001] expand on Geltner [1989, 1997] and study appraisal smoothing caused by a temporal lag bias due to valuers using past information on transaction prices. They find that the weights used by valuers for new and old information are 0.815 and 0.175, respectively, with the first weight equal to 0.870 when the same valuer is responsible for two successive appraisals, and to 0.689 when a new valuer makes the appraisal, based on a tendency to be more conservative.

At a portfolio level, Geltner [1993a] analyzes the temporal aggregation effect—the use of several spot valuations occurring over a period of time to produce a real estate portfolio (i.e., index)—and finds that this type of smoothing reduces portfolio variance and beta by 33% and 50%, respectively. Furthermore, by proposing a financial technique developed by several authors—Bailey et al. [1963], Case and Shiller [1987], Clapp and Giaccotto [1992], and Gatzlaff and Haurin [1996]—Geltner [1999] measures the extent of smoothing that results from stale appraisals and suggests the use of a repeated-measures regression (RMR) based only on appraisals whose value has changed or been explicitly updated since the previous measurement.

Other authors suggest different techniques applied at the index level to yield an adjusted time series with higher volatility and lower autocorrelation. Quan and Quigley [1991] assume a random walk process for transaction prices and apply their updating valuation model to returns, following the model proposed by Geltner [1989]. Geltner [1993b], Geltner and Goetzmann [2000], and Cho et al. [2003]—with a generalized-difference specification—do not assume zero autocorrelation in true returns and use a first-order autoregressive reverse filter with judgmentally estimated parameters at both the aggregate and individual real estate levels. Fisher, Geltner and Webb [1994] apply Quan and Quigley's model by imposing an additional condition—the *true volatility* of commercial real estate valuation-based returns is approximately half the volatility of the stock market, for example, the Standard and Poor's (S&P) 500.

Chaplin [1997] allows for shifts in the parameter depending upon the existing growth state and introduces a double unsmoothing process to work out transformed series for both the capital growth and income return for the CBHP synthetic index (i.e., ERV and yields). Brown and Matysiak [1998] work on individual real estate data and propose a time-varying approach with maximum likelihood estimation and a Kalman filter. Wang [1998] uses a co-integration approach to derive a long-run unsmoothing parameter from a series of other variables.

In conclusion, previous studies highlighted a clear need for a better understanding of the estimation of real estate risk and its impact on asset allocation choices. In this article, we apply four different models and test whether optimal real estate weights are due to unsmoothing model selection or calibration (i.e., choice of parameter levels).

DATA AND METHODOLOGY

In this study we consider three different markets—the U.K., U.S., and Australia.

In the U.K. market, we use a dataset of annual total returns on U.K. equities, gilts, and cash (T-bills) from 1921 to 2005, taken from a standard source, the Barclays Capital *Equity-Gilt Study*. For the real estate market, we use two valuation-based indices from two different sources: 1) the Scott series from 1921 to 1970, and 2) the IPD Annual index from 1971 to 2005. The pre-1970 series is taken from an article by Peter Scott's 1994 book, *The Property Masters*, and is constructed as follows:

- from 1921 to 1939, a series of market rents and cap rates were used to create an income return (assumed to be equal to the cap rate) and capital growth rates

$$\left(cg_t = \frac{value_t}{value_{t-1}} - 1\right),$$

where $value_t$ represents the value of a property at time t and is computed as follows:

$$value_t = \frac{rent_t}{caprate_t}$$

- from 1946 to 1970, the IPD index construction method is applied to the real estate portfolios of two main insurance companies:

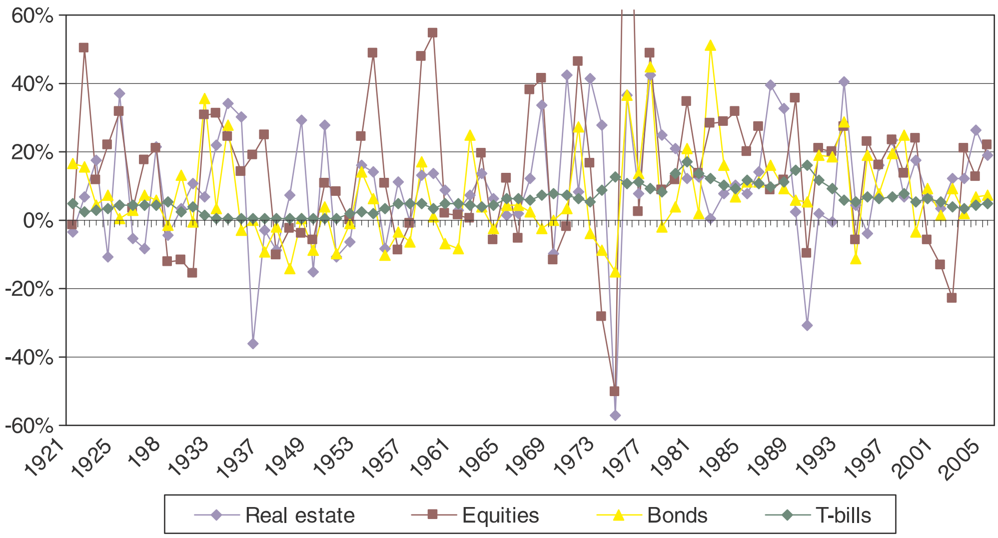
$$TR_t = \sum_{i=1}^{n} \frac{value_{i,t} - value_{i,(t-1)} - capex_{i,t} + NOI_{it}}{CV_{i,(t-1)} + \frac{1}{2}C_{i,t} - \frac{1}{2}NI_{it}}.$$

where
$NOI_{i,t}$ = *Net Operating Income of Property i at time t*

Because real estate data is not available between 1939 and 1945, these years are omitted from our analysis.

For the other two countries (U.S. and Australia), we use sources which maximize the length of the four time series and the consistency of our data (for comparability issues). We use the Morgan Stanley Capital International (MSCI) All Equity Index for both the U.S. and Australian markets. Real estate data is from the valuation-based indices provided by NCREIF in the U.S. and the

EXHIBIT 1
Historical Annual Returns for the Four U.K. Asset Classes



joint venture, Property Council of Australia/IPD, in Australia. Furthermore, for bond performance, we obtain the 10-year government bond benchmark computed by Datastream for the U.S. and the 10-Year Commonwealth Bank Bond Index for Australia. Finally, returns in cash are represented by the T-bill rate in both the U.S. and Australian markets. The sample period varies between the two markets and depends upon the availability of real estate indices. In the U.S., the sample period ranges from 1978 to 2005 and in Australia from 1985 to 2005.

Exhibit 1 shows the performance of the four asset classes in the U.K. for the entire period and Exhibit 2 contains the main descriptive statistics.

For the entire sample period, real estate shows the second highest performance (9.8%) after equities (14.8%), well above the average return of bonds (7.1%) and cash (6.0%). Real estate has the second lowest standard deviation (9.6%) and, consequently, the highest Sharpe ratio (39.9%). Equities and bonds have Sharpe ratios of 35.0% and 8.8%, respectively. In a mean-variance framework, we would then expect real estate to obtain a high portfolio weight, if we also take into account the small correlation coefficients with other asset classes, ranging between 0.15 for cash and 0.24 for equities.

If the sample is split into two subperiods corresponding to the Scott series and the IPD Annual index, there are some significant differences. Until 1970, the average return of real estate (7.1%) was slightly smaller than the return of bonds (7.2%), and only 110 bps higher than the return of cash (6.0%). The real estate standard deviation (8.1%), however, was below that of equities and bonds, with real estate second to equities in terms of Sharpe ratio (11.5% versus 32.5%). In the subsequent sample period (1971-2005), correlation coefficients between real estate and either equities or bonds were slightly smaller, and the correlation coefficient between real estate and cash switched from being positive in the first period (0.12) to being negative in the second one (–0.22). Finally, the summary statistics clearly show that for all assets kurtosis and skewness lead to the rejection of normality in both periods.

Because the results for the real estate market differ between the subsamples, empirical results are presented for both subsamples and the entire period. Most reliance is placed on the 1971-2005 sample which is based on the more reliable estimates of real estate performance and guarantees a consistency with the methodologies used in the other two markets we analyze.

Exhibit 3 shows the performance of the four asset classes in both the U.S. and Australia markets throughout the sample period, and Exhibit 4 contains the main descriptive statistics.

U.S. real estate (9.8%) shows the second highest performance after equities (14.4%), slightly above the average return of bonds (8.9%), but well above the return of cash (5.9%). Real estate also has the second lowest standard deviation (6.4%), and therefore the highest Sharpe ratio (62.3%),

EXHIBIT 2
Descriptive Statistics of the Four U.K. Asset Classes

Panel A: sample 1921 - 2005

	Real Estate	Equities	Bonds	T-Bill
Average	9.8%	14.8%	7.1%	6.0%
Standard Deviation	9.6%	25.1%	13.1%	4.1%
Skewness	0.12	1.82	1.03	0.70
Kurtosis	-0.06	10.02	1.42	-0.03
Sharpe Ratio	39.9%	35.0%	8.8%	
1st Order Serial Correlation	0.30	-0.12	0.02	0.91
2nd Order Serial Correlation	0.04	-0.11	0.22	0.81
Real Estate	1.00	0.24	0.19	0.15
Equities		1.00	0.52	0.10
Bonds			1.00	0.29
T-Bill				1.00

Panel B: sample 1921 - 1970

	Real Estate	Equities	Bonds	T-Bill
Average	7.1%	12.5%	7.2%	6.2%
Standard Deviation	8.1%	19.3%	13.8%	4.2%
Skewness	0.74	0.57	0.99	0.53
Kurtosis	0.39	-0.62	1.07	-0.35
Sharpe Ratio	11.5%	32.5%	7.1%	
1st Order Serial Correlation	0.12	0.16	0.01	0.92
2nd Order Serial Correlation	0.01	-0.28	0.22	0.81
Real Estate	1.00	0.27	0.18	0.12
Equities		1.00	0.32	-0.09
Bonds			1.00	0.01
T-Bill				1.00

Panel C: sample 1971 - 2005

	Real Estate	Equities	Bonds	T-Bill
Average	12.9%	17.5%	11.7%	9.1%
Standard Deviation	10.3%	30.8%	14.6%	3.6%
Skewness	-0.60	1.95	0.73	0.38
Kurtosis	0.85	9.80	0.94	-0.66
Sharpe Ratio	37.6%	27.4%	18.4%	
1st Order Serial Correlation	0.28	-0.25	-0.15	0.80
2nd Order Serial Correlation	-0.16	-0.03	0.06	0.51
Real Estate	1.00	0.19	0.05	-0.22
Equities		1.00	0.62	0.10
Bonds			1.00	0.15
T-Bill				1.00

with that of equities and bonds approximately 10% and 20%, respectively, behind real estate. In a mean-variance framework, we would then expect real estate to obtain a high portfolio weight, especially if we also consider the small correlation coefficient with equities (0.07) and bonds (−0.20). However, as the correlation with T-bills is quite high (0.48), we would expect a substitution effect between the two assets, with the T-bill weight increasing as the real estate weight decreases.

Australian real estate shows both an average return (10.4%) and risk (9.2%) between those of equities (13.9% and 16.0%) and bonds (10.8% and 7.6%). These figures differentiate Australia from the other two markets, with real estate showing only the third highest Sharpe ratio (28.6%) after those of bonds (39.1%) and equities (38.2%). In a mean-variance framework, however, we may still expect real estate to have a high weight due to the diversification offered by this asset class, showing correlation coefficients near zero with both equities and bonds. Again, since the correlation with T-bills is quite high (0.48), as in the U.S. market, we may expect a substitution effect between the two assets.

Finally, for both the Australian and the U.S. market, summary statistics clearly show that normality is rejected for all assets (i.e., see kurtosis and skewness figures).

Unsmoothing Techniques

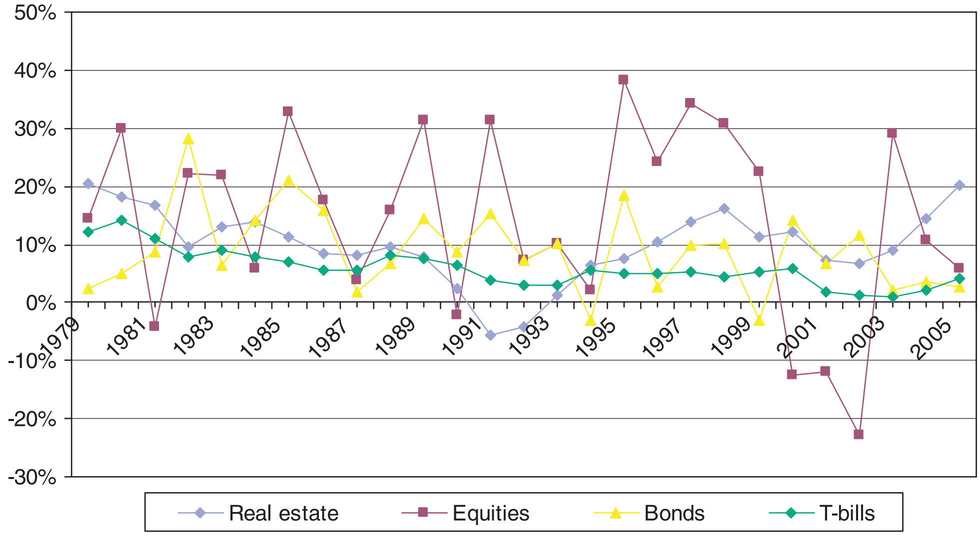
Unsmoothed capital appreciation, or growth, rates are obtained with four different models: first- and second-order autoregressive filters as in Geltner [1993b], volatility weight as in Fisher et al. [1994], and market growth states as in Chaplin [1997]. Only procedures using real estate time series properties, as opposed to methods relying on indirect linkages with other variables, such as Wang [1998], have been used. Time-varying methods as in Brown and Matysiak [1998] have not been used due to the small number of observations available with annual data. Finally, the method proposed in Cho et al. [2003] was not applied because it represents a specification only slightly different from that in Geltner [1993b] and the differentiation of returns seems to be redundant.

The first unsmoothing procedure is the first-order autoregressive reverse filter (FOARF). Unsmoothed

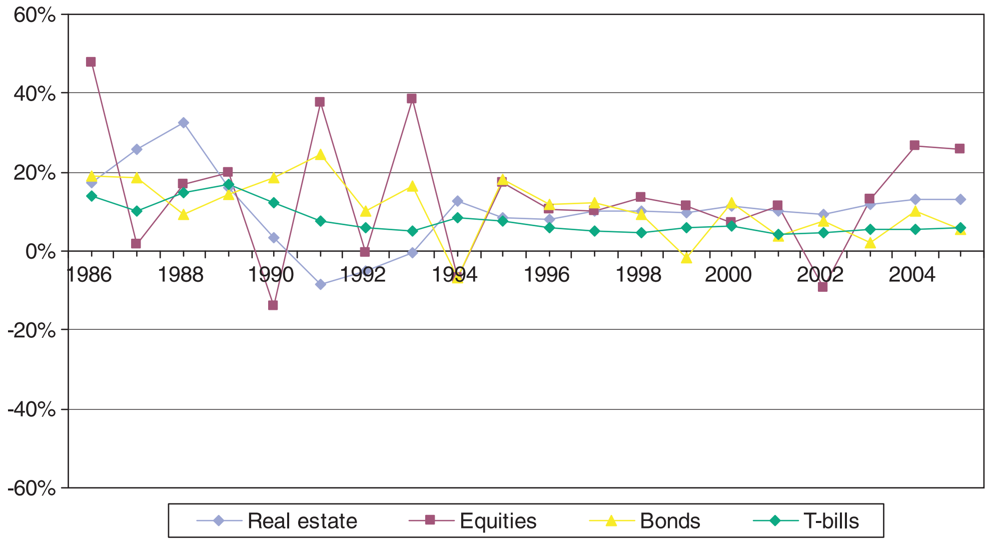
E X H I B I T 3

Historical Annual Returns for the Four U.S. and Australian Asset Classes

Panel A: U.S. Market



Panel B: Australian Market



capital growth rates for real estate investment (ucg_t) are computed as follows:

$$ucg_t = \frac{[cg_t - \alpha_1 \star cg_{t-1}]}{(1-\alpha_1)}$$

where cg_t is the capital growth of the valuation-based index at time t and α_1 is the unsmoothing parameter.

Three main assumptions are implied in this model. First, the values of the mean for the adjusted and unadjusted series are equal. Second, the model holds over time (i.e., stationarity). And finally, purely random errors are left out of the index (i.e., there is no noise).

An autoregressive process with more than one lag provides a more generalized model. However, with annual returns we believe there is no *a priori* reason to assume an autoregressive process of order higher than two, and so we restrict the analysis to a second-order autoregressive reverse filter (AR2):

$$ucg_t = \frac{cg_t - (\alpha_1 \star cg_{t-1} + \alpha_2 \star cg_{t-2})}{(1 - \alpha_1 - \alpha_2)}$$

The third method applies the technique proposed by Fisher, Geltner and Webb [1994] with a first-order autoregressive specification to obtain a full information value index (FIVI). Residuals are computed from (cg_t–$\alpha_1 \star cg_{t-1}$), and their volatility is used to compute the weight

$$\left(w_0 = \frac{2 \star \sigma_{\text{resid}}}{\sigma_{\text{equity}}} \right)$$

that is necessary to obtain the unsmoothed capital appreciation rate from the following equation:

$$ucg_t = \frac{(cg_t - \alpha_1 \star cg_{t-1})}{w_0}$$

Finally, different phases of the market cycle will plausibly result in changes to the unsmoothing parameter.

Following Chaplin [1997], it is assumed that the unsmoothing parameter is higher in falling than in rising markets; that is, valuers will tend to resist downward adjustments more than upward ajdustments. Second, it is assumed that the stronger the capital appreciation (depreciation), the higher (lower) the unsmoothing parameter, or in other words, the understatement of change will be greater in fast-moving markets.

Different unsmoothing parameters are then applied for different market growth states (STATES). First, the parameter is fixed for returns lying between the mean and the mean plus its standard deviation. For returns outside this range, new parameters are obtained by adding a varying coefficient to the fixed parameter:

- 0.10 for returns included between the mean plus 1 standard deviation and the mean plus 2 standard deviations;
- 0.20 for returns above the mean plus 2 standard deviations.
- 0.05 for returns included between the mean and the mean minus 1 standard deviation;
- 0.15 for returns lying between the mean minus 1 standard deviation and minus 2 standard deviations; and
- 0.25 for returns below the mean minus 2 standard deviations.

Unsmoothed capital growth rates are computed as for a first-order autoregressive filter, but with varying unsmoothing parameters:

$$ucg_t = \frac{[cg_t - \alpha_1 \star cg_{t-1}]}{(1 - \alpha_1)}$$

After the computation of unsmoothed capital growth rates with the four different techniques described above,

EXHIBIT 4
Descriptive Statistics for the Four U.S. an Australian Asset Classes

Panel A: US market (sample 1978 - 2005)

	Real Estate	Equities	Bonds	T-Bill
Average	9.8%	14.4%	8.9%	5.9%
Standard Deviation	6.4%	16.2%	7.2%	3.2%
Skewness	-0.64	-0.53	0.61	0.78
Kurtosis	0.67	-0.47	0.59	0.74
Sharpe Ratio	62.3%	52.6%	42.5%	
1st Order Serial Correlation	0.79	0.05	-0.14	0.86
2nd Order Serial Correlation	0.45	0.09	0.09	0.69
Real Estate	1.00	0.07	-0.20	0.48
Equities		1.00	0.20	0.21
Bonds			1.00	0.07
T-Bill				1.00

Panel B: Australian market (sample 1986 - 2005)

	Real Estate	Equities	Bonds	T-Bill
Average	10.4%	13.9%	10.8%	7.8%
Standard Deviation	9.2%	16.0%	7.6%	3.8%
Skewness	0.18	0.32	-0.51	1.34
Kurtosis	1.53	-0.03	0.26	0.65
Sharpe Ratio	28.6%	38.2%	39.1%	
1st Order Serial Correlation	0.71	-0.56	-0.02	0.79
2nd Order Serial Correlation	0.19	0.34	0.34	0.57
Real Estate	1.00	-0.04	-0.21	0.47
Equities		1.00	0.38	0.12
Bonds			1.00	0.33
T-Bill				1.00

EXHIBIT 5
Minimum and Maximum Average Return, Standard Deviation, and Sharpe Ratio with Varying Unsmoothing Parameters

		FOARF	AR2	FIVI	STATES
	Panel A:	**sample 1921 - 2005**			
Average return	Max	14.7%	14.7%	14.7%	14.7%
	Min	*10.9%*	*10.7%*	*11.7%*	*11.2%*
Standard deviation	Max	25.3%	25.3%	25.3%	25.3%
	Min	*10.5%*	*11.6%*	*12.3%*	*12.2%*
Sharpe ratio	Max	46.5%	40.4%	58.5%	42.8%
	Min	*34.4%*	*34.4%*	*34.4%*	*34.4%*
	Panel B:	**sample 1921 - 1970**			
Average return	Max	9.1%	8.6%	9.7%	9.1%
	Min	*8.4%*	*8.4%*	*8.2%*	*8.2%*
Standard deviation	Max	11.1%	10.7%	10.6%	11.1%
	Min	*9.1%*	*9.3%*	*10.0%*	*10.2%*
Sharpe ratio	Max	58.8%	54.2%	63.6%	55.3%
	Min	*47.3%*	*47.3%*	*47.3%*	*47.3%*
	Panel C:	**sample 1971 - 2005**			
Average return	Max	16.2%	16.2%	16.2%	16.2%
	Min	*12.2%*	*12.4%*	*12.4%*	*12.2%*
Standard deviation	Max	26.7%	26.7%	26.7%	26.7%
	Min	*7.9%*	*10.2%*	*7.9%*	*8.6%*
Sharpe ratio	Max	40.3%	31.5%	66.4%	35.7%
	Min	*26.3%*	*26.3%*	*26.3%*	*26.3%*

we obtain an income return (uir_t) recalibrated for the unsmoothed capital value index ($ucgi_t$) as follows:

$$uir_t = \frac{inc_t}{ucgi_{t-1}}$$

where inc_t is the income at time t and $ucgi_{t-1}$ represents the unsmoothed capital growth index at time $t-1$.

The unsmoothed total return for private real estate at time t (utr_t) is finally derived from the sum (at time t) of the two components—the unsmoothed capital growth and the unsmoothed income return:

$$utr_t = ucg_t + uir_t$$

Portfolio Construction and Simulation

To test for the impact of smoothing on asset allocation choices, we simulate the construction of 100 portfolios for unsmoothing parameters ranging from 0.01 to 1.0 in steps of 0.01. All portfolios maximize the Sharpe ratio and lie on the efficient frontier in a mean-variance environment. To test the sensitivity of asset class weights to the variation of the unsmoothing parameter, it is assumed the simulated portfolio is fully invested with no borrowing and the only constraints are:

- The total sum of weights is unity: $w_{re} + w_{equities} + w_{bonds} + w_{cash} = 1$;
- Each single weight is positive: $w_{re} \geq 0, w_{equities} \geq 0, w_{bonds} \geq 0, w_{cash} \geq 0$;

U.K. RESULTS

Exhibit 5 shows the minimum and maximum values of average return, standard deviation, and Sharpe ratio obtained for U.K. portfolios, maximizing the Sharpe ratio with a varying unsmoothing parameter. First, it may be noted that differences between smoothed and unsmoothed figures are, for each measure, greater in the second subperiod than in the first. This reveals a higher sensitivity of the real estate index (and consequently real estate weight) to smoothing in the latter period. The maximum average return is 14.7% overall compared to 9.1% and 16.2% in the two subperiods. The standard deviation ranges between 11.1% and 9.1% in the 1921-1970 period and between 7.9% and 26.7% in the 1971-2005 period. The four different unsmoothing models show very small differences in minimum and maximum values of their average returns which are always around 9% and 16.2%, respectively, in both periods, with standard deviations of around 9-10% and 8-10%, respectively.

The resulting Sharpe ratios show increasing differences between minimum and maximum values during the last 35 years. In panel C of Exhibit 5, the Sharpe ratio shows a minimum value equal to 26.3% for all unsmoothing methods and, contemporaneously, a

EXHIBIT 6

Minimum and Maximum Portfolio Weights with Varying Unsmoothing Parameters

		FOARF	AR2	FIVI	STATES
	Panel A:	sample 1921 - 2005			
Property weight	Max	76.0%	67.0%	80.8%	69.8%
	Min	*0.0%*	*0.0%*	*0.0%*	*0.0%*
Equity weight	Max	100.0%	100.0%	100.0%	100.0%
	Min	*24.0%*	*33.0%*	*19.2%*	*30.2%*
Bonds weight	Max	0.0%	0.0%	0.0%	0.0%
	Min	*0.0%*	*0.0%*	*0.0%*	*0.0%*
Cash weight	Max	0.0%	0.0%	0.0%	0.0%
	Min	*0.0%*	*0.0%*	*0.0%*	*0.0%*
	Panel B:	sample 1921 - 1970			
Property weight	Max	70.0%	59.2%	71.4%	59.7%
	Min	*0.0%*	*0.0%*	*0.0%*	*0.0%*
Equity weight	Max	54.7%	54.7%	54.7%	54.8%
	Min	*30.0%*	*35.1%*	*28.6%*	*37.3%*
Bonds weight	Max	0.0%	0.0%	0.0%	0.0%
	Min	*0.0%*	*0.0%*	*0.0%*	*0.0%*
Cash weight	Max	45.3%	45.3%	45.3%	47.1%
	Min	*0.0%*	*5.7%*	*0.0%*	*3.1%*
	Panel C:	sample 1971 - 2005			
Property weight	Max	60.1%	56.3%	51.2%	52.9%
	Min	*0.0%*	*0.0%*	*0.0%*	*0.0%*
Equity weight	Max	79.1%	79.1%	79.1%	79.1%
	Min	*10.2%*	*20.2%*	*3.1%*	*12.3%*
Bonds weight	Max	20.9%	20.9%	20.9%	20.9%
	Min	*7.2%*	*9.3%*	*5.3%*	*7.2%*
Cash weight	Max	28.8%	14.3%	43.3%	28.8%
	Min	*0.0%*	*0.0%*	*0.0%*	*0.0%*

maximum value ranging between 31.5% (AR2) and 66.4% (FIVI).

Overall, there are larger differences between minimum and maximum values than between unsmoothing methods. This result supports our initial belief that calibration (i.e., choice of the parameter) is much more important than model selection.

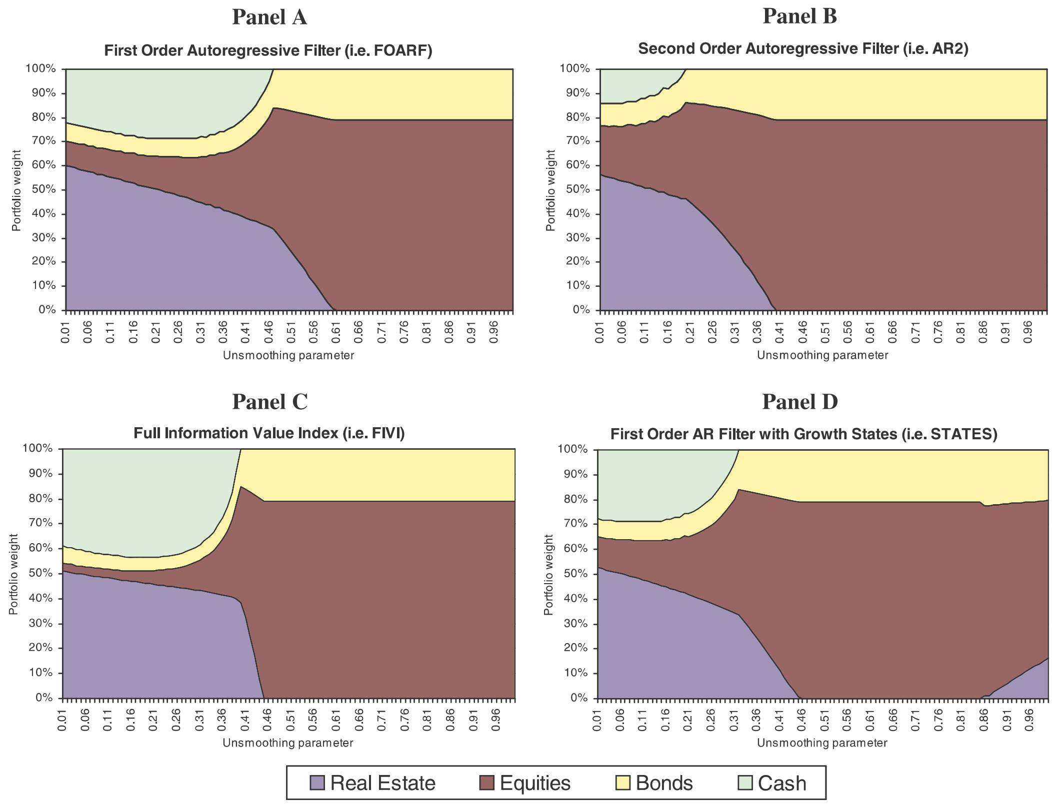
Next, we focus our analysis on the obtained asset allocation. Although bonds do not form a part of any portfolio constructed using the 1921–1970 sample, they were always represented (minimum weight of 5.3%) within portfolios based on the 1971–2005 sample. Equities always show a minimum weight equal to 19.2% for the whole sample (FIVI), but their weight decreases from the first to the second sample (e.g., from 28.6% to 3.1% for FIVI). Real estate reaches an optimal weight around 80% using the whole sample, and 71.4% and 60%, respectively, in the first and second subperiods. Finally, cash is not represented in the asset allocation based on data over the entire period, but does have a significant percentage weight in portfolios run on the two subperiods.

We now focus our analysis on the impact that each unsmoothing method and its calibration have on asset allocation choices, only discussing results obtained using the second sample (1971–2005).

The first-order autoregressive filter yields asset class weights as represented in Exhibit 7 Panel A. Real estate is included with a very high percentage in the mixed-asset portfolio. With original data, it shows a 60% weight which diminishes as the unsmoothing parameter increases, and disappears when the parameter is greater than 0.60. Finally, if a parameter ranging between 0.50 and 0.60 is applied, as previously done in the literature, the computed weights tend to be similar to those currently held in U.K. institutional funds, in the range of 5%–10%. With a parameter equal to either 0.56 or 0.58, the indicated optimal portfolio has a Sharpe ratio of 24.9% or 25.8%, and is constructed of 11% or 5.9% real estate, 69.6% or 74.1% equities, and 19.2% or 20% bonds, respectively. These results show a very high sensitivity of allocation choices to the unsmoothing parameter.

Similarly, the second-order autoregressive process shows a decreasing real estate weight as the unsmoothing parameter increases as shown in Panel B of Exhibit 7. However, the minimum parameter necessary to obtain

EXHIBIT 7
U.K. Portfolio Weights with Varying Unsmoothing Parameter



a zero real estate weight is lower (0.40) than the one shown by FOARF due to the inclusion of a second-order parameter. If 0.38 or 0.36 is used as the first-order parameter and 0.10 as the second-order parameter, the indicated portfolio is composed of 5.7% or 11.6% real estate, 74.4% or 69.4% equities, and 20.0% or 19.0% bonds, respectively.

The third unsmoothing method shows similar portfolio compositions to the first method. However, this model is even more sensitive to the unsmoothing coefficient as shown in Panel C of Exhibit 7. The real estate weight tends to fall rapidly, from 40% to 1%, if we increase the unsmoothing parameter from 0.40 to 0.45. Past this parameter, this asset class disappears completely from the Sharpe-maximizing portfolio. With a parameter of 0.44, the portfolio is composed of 7.9% real estate, 72.4% equities, and 19.7% bonds. And cash tends to gain a higher weight with the FIVI unsmoothing method than with FOARF.

Finally, the growth states model shown in Panel D in Exhibit 7 identifies a relationship between weights and the unsmoothing parameter that is very similar to the one shown by FOARF. Unsmoothing parameters are slightly shifted to the left; that is, smaller parameters are needed to indicate the same asset allocations. With the main unsmoothing parameter for returns falling between the mean and the mean plus one standard deviation set at either 0.43 or 0.41, we obtain exactly the same weights we have described for the 0.58 or 0.56 parameters applied to the FOARF method, because in this fourth model the reported parameter only represents the minimum parameter."[3] This is also the reason why real estate reappears in the optimal portfolio when the unsmoothing parameter is greater than 0.90.[4]

Furthermore, in the last part of our empirical analysis we compose three benchmarks with fixed weights as follows:

- Risk-averse investor (i.e., Benchmark 1): real estate 10%, equities 65%, bonds 20%, and cash 5%;
- Risk-lover investor (i.e., Benchmark 2): real estate 5%, equities 75%, bonds 15%, and cash 5%; and

EXHIBIT 8
U.K. Sharpe Ratio with Varying Unsmoothing Parameter

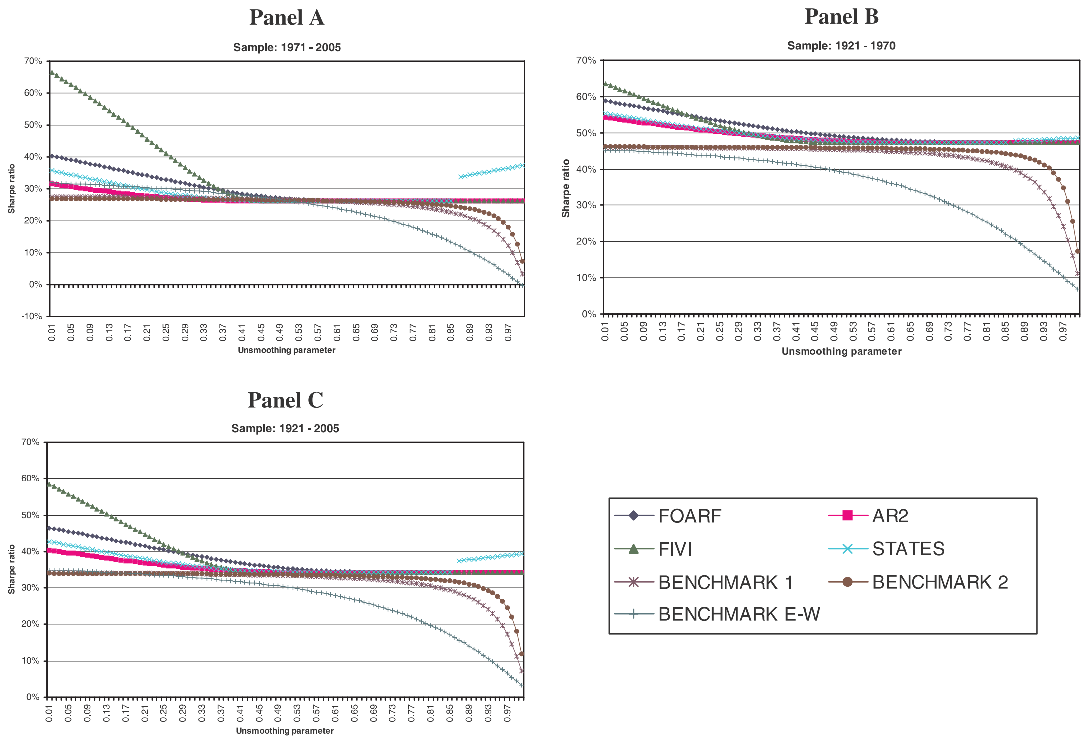
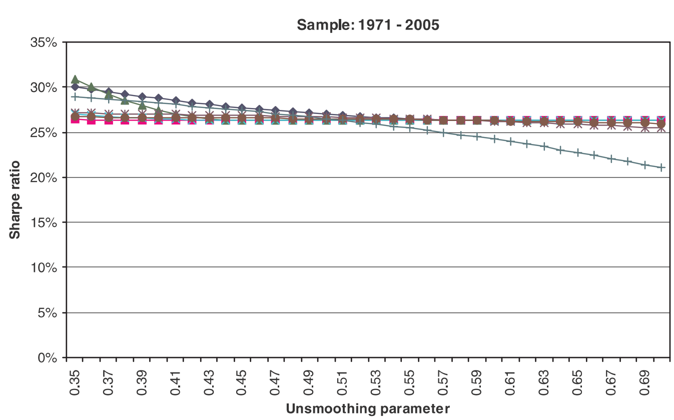


EXHIBIT 9
U.K. Sharpe Ratio with Varying Unsmoothing Parameter between 0.35 and 0.70



- Equally weighted (i.e., Benchmark E-W): real estate 25%, equities 25%, bonds 25%, and cash 25%.

We then compare the Sharpe ratio of these benchmarks with the one of optimal portfolios. Exhibit 8 shows that, for each sample period, there is a range of unsmoothing parameters that makes the Sharpe ratio of optimal portfolios equal to one of the three benchmarks (excluding the equally weighted portfolio). Particularly, focusing on the second subsample, Exhibit 9 shows a window of Exhibit 8 Panel A, where the unsmoothing parameter only ranges between 0.35 and 0.70. The plot suggests the existence of an implicit range of unsmoothing parameters that portfolio managers probably have in mind when they make asset allocation choices.

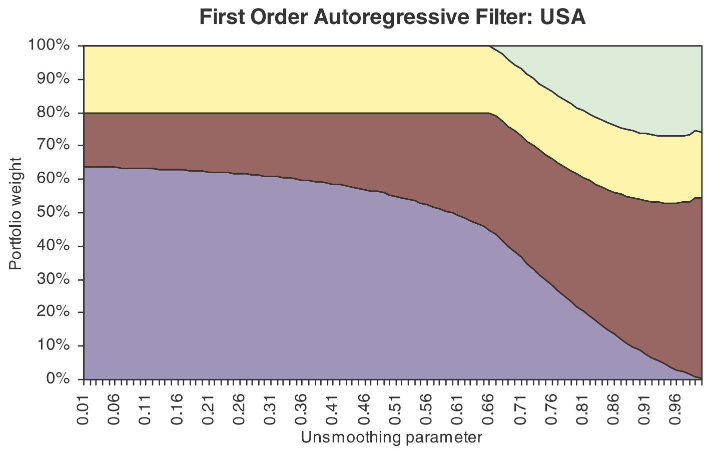
U.S. AND AUSTRALIAN RESULTS

In this article, we also compare the U.K. results with the ones obtained in U.S. and Australian markets. Exhibit 10 reports the main results respectively for the U.S. and Australia using a FOARF unsmoothing model.[5] These

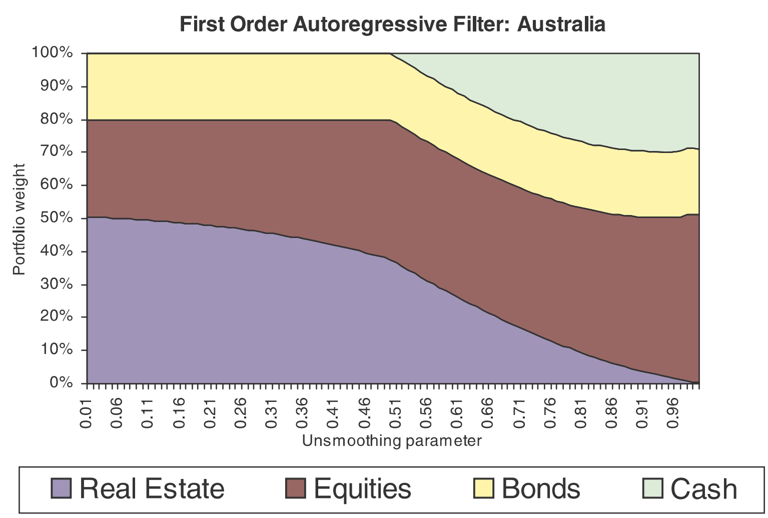
EXHIBIT 10

U.S. Portfolio Weights with Varying Unsmoothing Parameter (FOARF)

Panel A



Panel B



results reinforce the findings achieved in analyzing the U.K. market for the period 1971–2005,[6] with real estate weights decreasing as the unsmoothing parameter increases.

However some differences should be noticed. First, for both the U.S. and Australia, the unsmoothing parameter has a significant impact on the overall portfolio weighting, much bigger than for the U.K. This is due to a much higher autocorrelation coefficient in these two markets (0.79 and 0.71, respectively) compared to those in the U.K., where the first-order serial correlation is only equal to 0.28. This result also suggests the existence of greater inefficiencies in U.S. and Australia than U.K. valuation-based indexes to be "corrected" in portfolio optimization tools for asset allocation choices.

Second, the maximum weight of equities in both the U.S. and Australian portfolios (55% and 50%, respectively) never reaches the 80% level of the U.K. when the unsmoothing parameter is approximately equal to 1. This is simply due to the relative risk-return profile of bonds, which is much more appealing in the former two countries than in the U.K.

Third, we see a substitution effect between real estate and cash, due to a correlation coefficient near 0.50, in both the U.S. and Australian markets. When the unsmoothing parameter increases, the real estate weight decreases and, along with it, the portfolio weight in cash increases.

CONCLUSION

Portfolio managers normally hold a less than optimal weight for real estate assets. Previous studies unsmoothed real estate returns to increase the level of risk and to change correlation coefficients with other asset classes. Contrary to Stevenson [2004] who finds no difference in the application of two different unsmoothing methods, other research found that model selection has a significant impact on real estate weights.

In this article, a possible explanation for these opposite results is found in *calibration*. Portfolio simulations show that unsmoothing model specification has little impact on asset allocation choices. However, we find that all unsmoothing methods are highly sensitive to the choice of the parameter. This result reinforces and develops Stevenson's conclusion, and highlights calibration, rather than model selection, as the key issue when unsmoothing real estate data. Consequently, previous studies supporting the importance of model selection may be biased due to the choice of different and not comparable parameters for different models. We then conclude that real estate research should focus more on calibration than on model specification.

Finally, a comparison of the Sharpe ratio obtained for four portfolios (using different unsmoothing methods) and three benchmarks revealed the existence of an implicit unsmoothing parameter (or, at least, a range of implicit parameters) that is included in the range 0.40-0.60. This range is in line with coefficients used in previous studies. Because some of these articles determine the level of this parameter qualitatively, as a theoretical weight given to past information, further research should analyze the underlying unsmoothing parameter that best fits the data-generating process of real estate returns.

For practical use, we suggest adopting the simplest form of unsmoothing method, FOARF, with a parameter included in that range.

ENDNOTES

We would like to thank David Downs, David Geltner, David Ling, Colin Lizieri, Kerry Vandell, Seah Kiat Ying, and the participants at the 2005 ARES Conference, 2007 International AREUEA Conference, and 2007 APRU Symposium for useful comments. We also thank the Investment Property Forum for providing a research grant and valuable suggestions through a research steering committee.

[1]Source: Investment Property Databank: UK IPD Digest 2007.

[2]Corgel and deRoos [1993] also find that "weights may be sensitive to the effects of recovery across several correlation regimes." Particularly, since they find that different models not only increase the volatility, but also the mean, of return distributions, they doubt the applicability of unsmoothing methods.

[3]With a STATES method, the reported unsmoothing parameter shown in Exhibit 7 as the x-axis is applied only to returns between the mean and the mean plus one standard deviation. To that parameter, a value of between 0.05 and 0.25 is added depending upon the growth state of the market.

[4]Too many observations are unsmoothed with a parameter greater than 1. This level is not acceptable on both theoretical and empirical grounds and results from that point onward are consequently unrealistic and to be disregarded.

[5]We did not show the results obtained with other unsmoothing procedures because they yield similar results to those already obtained for the U.K. market. We find that unsmoothing model selection makes a small impact on asset allocation choices. Moreover, since unconstrained weights determined very high allocations to bonds, we decided to limit their weight to 20% in order to make the results comparable with the U.K. where the maximum weight for bonds was 20%.

[6]Among the U.K. results available, the ones referring to the second sample period should be preferred for both certainty of performance measurement and similarity of time periods with the other two markets.

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