Alternative investments: the stability of the co-movements between asset classes

Keith Elliott[1] **and Gianluca Marcato**[2]

School of Real Estate & Planning
Henley Business School
University of Reading
Reading RG6 6UD

[Current Draft: 25th May 2010]

ABSTRACT

In an asset allocation process, correlations are particularly important if one includes 'alternative investments' such as real estate, commodities and hedge funds, which have been proclaimed to provide diversifying benefits within the overall portfolio context. While many studies have found that correlations between assets are time-dependent within each asset class, we focus on the correlations between asset classes to see if they change over time.

The co-movement between asset classes is firstly examined using rolling correlation analysis and by statistical testing of the both the correlation and covariance matrices to see if they are stable over time. The technique of semi-correlation is then used in order to differentiate asset class returns between up- and down-movements. We find that there are a number of assets for which correlations generally increase in down states (e.g. all types of equities). Hedge funds and balanced commodities also show substantially higher correlations to most other assets in down states. Furthermore, we find that gilts are the only asset class that becomes less correlated to most other assets during down markets, thus confirming their importance as a key diversifier in a multi-asset portfolio. Finally, once real estate indexes are adjusted to account for smoothing, we show

[1] Email: k.e.w.elliott@reading.ac.uk, Tel: +44 (0)118 378 8175, Fax: Tel: +44 (0)118 378 8172.
[2] Email: g.marcato@henley.reading.ac.uk, Tel: +44 (0)118 378 8178, Fax: Tel: +44 (0)118 378 8172.

that several correlation coefficients increase, suggesting that original time series may be overstating the benefits of diversification.

1. Introduction

The importance of measuring correlation between assets is at the very heart of the asset allocation process, as in a standard mean-variance model (Markowitz 1952), where the covariance matrix is a key input, along with asset returns and standard deviations. In the modern multi-asset class world one of the main reasons used to justify the inclusion of a wider variety of asset classes in a portfolio is the increase in diversifying power; for an overall view see for example Terhaar, Staub, and Singer (2003). Many academic studies have concluded that real estate adds to the risk/ return performance of investors' portfolios many due to its relatively low correlation with equities and bonds, e.g. Peyton and Lotito (2007). Furthermore, diversification effects are also often cited as one of the main advantages of including hedge funds in a portfolio – e.g. Agarwal and Naik (2000b)– even if Kat (2003) states that the diversification effects of hedge funds may be overstated and that they may not combine very well with equity investments.

A large section of literature has studied correlation across financial assets and, within this, a section has been focused on correlations changing over time – e.g.Kaplanis (1988), Longin and Solnik (1995), Solnik, Boucrelle, and Le Fur (1996) and Groenen and Franses (2000). However; most of these studies are mainly focused on the returns between different equity markets, while this study analyses the correlations between asset classes to see if they move over time.

This paper aims to test the following hypothesis in the context of a modern multi-asset investment portfolio in a time frame that includes most of the 2007 to 2010 financial crises: firstly we expect cross-asset class correlation matrices to be unstable over time; Secondly we envisage coefficients to increase in downward market trends and decrease in upward markets. The 2007 to 2010 financial crises is the most major negative world financial event to have impacted investors since hedge funds have become more 'mainstream' investments, although events in 1998 are also of considerable importance to multi-asset class portfolios. These findings would have implications on the wide asset class portfolio because the increased diversifying power that adding 'alternative' assets is supposed to have may be at their weakest when it is most needed.

This article will set out as follows; there will be a overview of the relevant literature followed by an overview of the data used as well as some basic analysis of that data. Section 4 will present an analysis of the rolling correlations of the assets. In Section 5 we will present statistical analysis of the correlation and covariance matrices over different time periods using two different statistical tests. While in section 6 the method of semicorrelation will be described and then empirical results using the method will be presented. Finally Section 7 offers some overall conclusions.

2. Literature review

A number of articles have proven that correlations between some types of assets vary over time and many different methods have been used to come to this conclusion, from the very simple to the quite complex. Some papers include analysis using a rolling correlation framework and this trends to show quite easily numerically or even more clearly; graphically the dynamic nature of correlation. For example for international equity indices (Solnik, B.H., Boucrelle, C. and Le Fur, Y. 1996), for international real estate equities (Sebastian and Sturm 2007) and for hedge fund strategies in Tobias (2007).

One popular batch of techniques for testing whether correlations and covariances change over time is to use statistical testing of the correlation or covariance matrices. These tests are beneficial as they give a result with a degree of statistical significance; however, they only compare the matrices at 2 fixed points in time. Therefore they may need to be performed multiple times to establish how often they change over time. A good number of studies have used these statistical tests in order to assess the stability of the covariance or correlation matrices over time. They mainly use the test that was created in Jennrich (1970) as well as sometimes the linked Box M (Box 1949) test. A number of papers have used the Jennrich test to discover that the correlation matrix of a number of different groups of international equity indices are not stable over time (Kaplanis 1988, Longin and Solnik 1995; Bracker and Koch 1999). It has also been used to discover that for some of the periods compared, the correlation matrices of national real estate equity indices were not stable (Eichholtz 1996), while this also tends to be the case when looking at different indirect real estate indices (Schinder 2009) . Lee (2006) uses the Box M test to assess the stability of the covariance matrices and correlation of the ten IPD market segment indices for the U.K. property market; he finds that many of these are not stable. He also expands this work using a different test in order to test the stability of the individual covariances between 2 indices. Kaplanis 1988 also used the Box Test for testing of the covariance matrix in this article mentioned above.

A paper that uses a technique which is based on similar principles to the semicorrelation method which I will use in this paper is Goldstein and Nelling (1999). The authors use an interesting methodology that allows correlations to be compared in periods of advantaging and declining equity markets. Advancing markets are defined as those periods in which the return of the domestic equity market exceeds the return on 3 month T-bills. Their article addresses whether correlation between both equity and mortgage REITs, and difficult types stocks and bonds (and also to inflation) changes depending on the state of the equity markets. Overall they find that there a large difference between REIT correlations depending upon conditions in the equity market. They find that the correlation between Equity REITs and the S&P 500 is 0.350 in advancing equity markets, while in declining equity markets it is substantially higher. The difference is less severe with mortgage REITs: a 0.383 correlation (advancing equity markets), and 0.491 (declining equity markets). The results were also found to be similar when the correlations of the 2 types of REITs with small stocks are analyzed. In declining markets both types of REIT's negative correlation with inflation appears to be higher as well. While mortgage REIT's correlations with government and corporate bonds were found to more highly correlated in advancing markets than they are in declining markets.

There are only appears to be four published papers which use semicorrelation in as a method in detail. All of these describe the method as 'semicorrelation' except in Gabbi (2007) were it is described as 'semi-correlation'. Thus I will refer to it as semicorrelation.

Erb, Harvey and Viskanta (1994) were the first authors to use the semicorrelation method as part of their analysis in order to determine whether correlations are different depending on the state of economic activity. They used the semicorrelation analysis to establish whether correlations are different between different countries when segmented by ex post returns. The method was applied in order to measure if correlations are different between G7 countries equity returns' depending on whether the markets were either both rising, both falling or out of cycle with one another. To calculate the semicorrelation coefficients Morgan Stanley Capital International (MSCI) total return indices were used, as well as a U.S. government bond portfolio that was calculated by Ibbotson Associates. The period that was studied was from January 1970 through December 1993. The authors find that the international cross-correlations are considerably higher in down-down markets than up-up markets. In fact the average negative semicorrelation is found to be in many cases to be almost double that of the positive semicorrelation with some of the differences between individual cross-correlations being considerably higher. For example the authors highlight that the United States-Germany correlation is 8.6 (up-up states) and 52.3 (down-down states). When it is applied across two asset classes (in the correlation between U.S. equities and U.S. government bonds) the method also seems to be consistent. The down-down correlation was, at 27, over double that of the up-up correlation (12.7) showing clearly that the correlation between US equities and bonds are also found to be higher during times when both sets of returns are below their average.

Newell and Acheampong (2001) use semicorrelation to analyse the correlations of listed property trusts (LPTs), which are one of the main vehicles of indirect property investment in Australia with both Australian stocks and bonds. Of the 4 studies that use semicorrelation as a method this is the most that examines the most asset classes. They use monthly data from January 1980 to June 2000, comparing the UBS Warburg LPT total return series with ASX All Ordinaries index series (equities) and the UBS Warburg government bond index series (bonds). The authors find that there are substantial differences in correlations between the overall correlations and the all states of semicorrelation for the relationship between LPTs and equities. Common down-down correlations were much higher at 0.80 than both up-up correlations (0 .18) and the overall correlation of 0.63. However; for the correlation between LPTs and bonds, semicorrelation analysis does not find any substantial difference between up-up markets and down-down markets, which had semicorrelation co-efficients of 0.19 and 0.21 respectively. Overall this study is important as it documents that the increasing down-down correlations may be seen in some cross-asset class correlations and not in others.

In his article on the correlations amongst geographical areas and business sectors Gabbi (2007) also uses semicorrelation as a method to address correlation change. He uses it along with a forecasting technique in order to try and forecast the direction of equity returns and thus correlations. He used daily equity returns data (local currency) from 23 sector and 22 country indices versus the MSCI World Index to produce semicorrelation coefficients calculated over 120 rolling periods. As 6 month rolling periods were used (which is moved forward two weeks at a time); the correlations reported are average values. The author's findings support those of Erb, Harvey and Viskanta (1994); that correlations in down-down markets are higher than up-up ones. He found that for countries the down-down correlations were 80.22% on average were as the up-up correlations averaged 72.68%. Similarly the findings for sectors displayed average correlations for the down-down markets were 84.67%, while the up-up correlations averaged 79.79%. He also reports the volatility (as measure by their standard deviation) of the up-up and down-down rolling semicorrelation coefficients are less volatile than the overall correlations. Gabbi goes on to use semicorrelation in portfolio optimization by attempting to forecast the direction of equity returns.

The most recent article that uses semicorrelation as a tool for analysis is Schindler (2009) which compares listed real estate companies over time. The author uses the FTSE EPRA/NAREIT monthly indices for 13 different countries for the period January 1990 and December 2006 for the semicorrelation part of his study. When compared with the average values of the other markets all 13 analyzed listed real estate indices showed increased correlation in down-down markets when compared to up-up environments. The authors point out that the general range of these average correlation coefficient is between 0.07 and 0.30 in down-down phases, compared with between 0.02 and 0.16 in up-market phases. This gives a maximum difference between the down-down and up-up phases of 0.247 in the Netherlands and a minimum difference of 0.0416 in Switzerland. Looking at individual cross-correlations about 75% of these had greater correlations in down-down markets than up-up markets. The greatest difference between the correlations in the two states was the U.K. and Hong Kong correlation which was a negative value of 0.168 in the up-up and a positive value of 0.3949, a change of 0.563.

Some of these studies use ARCH type models in order to prove that correlation changes over time and in some cases what factors drive it (for example in Longin and Solnik 1995 for international equities). This line of research also includes paper using models from the dynamic conditional correlation family, first used by Engle (2002). A number of other papers have investigated correlation change using regime shifting techniques e.g. Ang and Bekaert 2002). Other techniques used included in papers that are connected to these issues include extreme value theory (Longin and Solnik 2001). Although we will not use any of these types of techniques within this paper they are still important in this area.

3. Data

3.1 Data description

Published indices have been used as proxies for all asset class returns, the total return or equivalent indices have been used in each case. All data has been downloaded from DataStream or Bloomberg. All have been kept in their local currency, which for all the commodities, overseas equities and hedge funds is in dollars. In a practical sense we can assume that investors will hedge their exposure as best they can (however; this will incur a cost).

In order to represent domestic equities I have used the FTSE 100 index with is a market capitalization weighted index of the 100 biggest companies in the U.K. The FTSE All-share index could have been used to include medium and small cap. equities; however, due to the large weighting of the FTSE 100 in this index it would make little difference to the results. As well as domestic equities I include a proxy for international equities as there is a large amount of research that suggests that these provide at least some diversifying power. To represent overseas equities I have used the Overseas MSCI World ex. U.K. ($). This is a float-adjusted market capitalization index containing the equities of 22 developed markets. The problem with this index is that it is very heavily weighted towards the U.S. (perhaps a market that is closely linked to the U.K.). At present there could be an argument to include an emerging market index as well in order to further diversify and represent a growing area of equity investment.

For fixed income investments I will include two different indices one to represent those bonds to which credit risk is considered to be a minor factor and one to represent fixed income issues were the returns are generally higher because varying degrees of credit risk are accepted by the investor (this follows a similar logic to, for example; Bond et al 2008). The indices I have used are from Barclays Capital (formally the Lehman Brothers Indices); to represent domestic sovereign bonds I have selected the U.K. Gilt All Maturities. To represent bonds with credit risk I have used the Sterling Credit Ex Sov/Supra All Maturities. The credit index is mostly corporate bonds and all bonds within it must still be investment grade. I would have also liked to have included an emerging markets or non-U.K. bond index although I did not have access to a suitable one.

I have included both direct real estate measure and a listed real estate measure. The IPD U.K. all property total return index is used to represent direct investment. IPD Property indices are valuation based rather than transaction based. This means that the indices are made up from professional appraiser's estimates. These tend to use market information like comparable transactions and fundamental variables to produce values; this tends not to produce accurate prices (Geltner et al. 2003, Key and Marcato (2007). The index value thus suffers from a smoothing bias and thus I have carried out a desmoothing process in order to give a more realistic risk/ return profile for this index. I tested several methods (Key and Marcato 2007) but none produced significantly better results than the basic first order auto-regressive filter (Gelter 1993). In my analysis I have also still used the original IPD index in as a comparison.

In some of the articles on asset allocation with real estate REITs or listed real estate is used as a proxy for directly owned real estate (e.g. Schneeweis, Vassilios, and Georgiev 2002). Although it is clear that the return profiles of direct real estate and of listed real estate do vary, especially in the short term (Geltner et al.2007). There are several reasons for these including liquidity premiums (Clayton and MacKinnon 2003) and the general tendency for information to take longer to transfer in the direct market (Barkham, and Geltner 1995). Unlike some articles, I do not think that listed real estate companies or REITs should be used as a proxy for direct real estate. They offer different return profiles and as such are considered here along with direct property. I have used the FTSE/ NAREIT UK total return index, with is an index based on the real estate companies listed on the FTSE.

There are many ways for an investor to invest in different commodities including purchasing physical commodities (my include storage and related cost as well as other costs) and investing in the returns of commodity producing companies. However; perhaps the most popular way is to do it though investing in commodities futures contracts. An easy way to do this is to buy an investable commodity futures index. These are also useful as a more general proxies and benchmarks for all commodity returns in general, although their return profile will be different (frequently significantly) from those of the spot price. This is because of roll yields, which are the costs that results as the futures which the index tracks are rolled over. If the futures curve is in contango (upward slopping) then this roll yield is negative. In order to give a 'fair' picture of commodities returns I use the total return series of 3 different indices. The total return indices incorporate this roll yield (in rough terms the total return less the roll yield is the spot return). There are a few widely used indices but the one that appears to be used the most in academic literature is the S&P Goldman Sachs Commodity Index [GSCI] (used in Bond et al. 2007; Schneeweis et al 2002). This index comprises of 24 different commodities split into 5 sub-asset classes of which energy is by far the biggest; currently making up 72% of the index (Goldman

Sachs 2010), although this has almost been as high as 80% in the past 3 years. I will use this index in my analysis but because of the high energy weighting of the index I also have included a second commodity index to represent a wider commodity exposure. Thus I have included the Thomson Reuters/Jefferies CRB total return index. It comprises of 19 different commodities of which 39% can currently be described as energy, the index rebalances monthly to its fixed target weightings. Although it is also part of the two indices above (less than 3% in the S&P GCSI and 6% in the Thomson Reuters/Jefferies CRB) I think it is important to include gold as an asset class. Gold has been discussed extensively during the financial crises and has become increasingly popular as an investment. As with the indices above a total return futures index is considered rather than the spot price; the S&P GSCI Gold index is used, which is a sub-index of the index discussed above.

As a proxy for holding a diversified portfolio of hedge funds a hedge fund index will be used in the analysis. There are a number of hedge fund indices including those by MSCI and S&P although the two main ones that are used in academic literature are the HFR and Credit Suisse/ Tremont indices as they are regarded as the most transparent and comprehensive (Fung and Hsieh 2002). Both of these indices and hedge fund returns in general do suffer from various statistical problems and in built biases. These include Hedge fund indices do tend to contain survivorship bias and related affects (e.g. Agarwal and Naik 2000a) Also selection bias also has an effect on the returns of hedge fund indices compared with the performance of the whole universe of hedge funds (e.g. Fung and Hsieh 2002), also related to this is backfill bias. For the hedge fund index I have used the HFRI Fund Weighted Composite (e.g. Agarwal and Naik 2000a), this contains less survivorship bias than the Credit Suisse/ Tremont index although it is likely to contain back fill bias. Although the risks are likely to be higher in terms of possible larger losses and that there is a definite case to adjust returns for the purpose of this paper I have not. The HFRI Fund Weighted Composite Index is an equally weighted performance index encompassing over 2000 funds which is used by numerous hedge fund managers as a benchmark for their own hedge funds.

3.2 Data descriptive statistics

Exhibit 1 shows the characteristics of the data of the 11 indices that are used to represent different asset classes. As one might expect, the average monthly returns are substantially different across the different asset classes with the maximum one being HFRI at 0.99% a month and the lowest one being the Reuters/ Jefferies CRB index with a figure of 0.20%. The mean returns for the FTSE 100 and the MSCI ex. U.K. are quite similar at 0.61% and 0. 51% respectively. Both fixed income proxies (U.K. Gilts and U.K. Credit) have similar means returning on average 0.66% a month. This highlights the historically high levels of total returns that have been attainable for investing in sovereign debt over the last 10 or so years. Furthermore the two commodity indices have close returns (0. 20% and 0. 25%), although gold (0. 43%), significantly outperformed both of these. Since the mean returns only tell us part of the story, we also need to look at the variation asset returns over time. Fixed income assets produced high levels of variation in their total returns over time; gilts had a standard deviation of 0.169% and a range of 0.135. Hedge funds only showed a low level of monthly volatility with a standard deviation of 0.020% and a range of 0.016. The asset with the most volatility was listed real estate, the FTSE EPRA/ NAREIT index had a standard deviation of 0.668% (with a range of 0.5666), and it also had the highest monthly return of 0.31 and the lowest of -0.255. One must be careful with regard of the distributions of these assets; all but the gilt index fail the Jarque-Bera test for normality at both 95% and 90% confidence levels, whilst the gilt index only passes at 90%. Many of the indices are leptokurtic, particularly the two IPD (original and unsmoothed) versions and the Reuters/ Jefferies index. On the other hand the FTSE 100 and gilts indices are extremely platykurtic. All of the indices except the S&P Gold index have varying levels of negative skewness of which the most extreme is the MSCI World ex. U.K.

[INSERT EXHIBIT 1 HERE]

3.3 Static correlations

In order to get an overall view of the diversifying powers of each asset we can refer to Exhibit 2, which displays the overall static correlations between the asset classes. We will then move on to consider dynamic correlations in the next section. The first thing to note are those asset classes which are very highly correlated. The two assets that have the highest correlation coefficient are the two commodity indices at just over 0.80. One interesting point is that the S&P GSCI which is heavily weighted towards energy (Goldman Sacs 2009) is less correlated with the other asset classes than the Reuters/ Jefferies-CRB index. This could possibility be expanded due to the fact that energy may be a cost to many firms and thus low energy prices may help equities and related classes. The S&P GSCI has an average correlation of 0.20 with the other 9 asset classes (excluding the original IPD data), while the Reuters/ Jefferies-CRB index – which is more diversified across a range of commodities – has an average correlation of 0.245. As expected, two very highly correlated asset classes are U.K. Gilts and U.K. credit (0.774),as they both represent fixed income securities and are thus driven by similar underlying factors, including interest rates. Another two highly correlated asset classes (0.774) are domestic equity and overseas equity, supported by relevant literature on co-movement in international equity markets, starting from Kaplanis (1988). The FTSE 100 and the Barclays UK Credit indices are also quite highly correlated with a coefficient of 0.42, suggesting that the Credit index may have a high proportion of U.K. corporate bonds. Companies issuing these bonds may be part of FTSE 100 index and so there should be a correlation between the share price and credit risk. Finally another high correlation is between hedge funds and equities, both domestic (0.64) and overseas (0.75). This is the likely due to the fact that a large number of hedge funds in the index are involved in equity rated strategies (Dor, Dynkin and Gould 2006) and hedge funds are also likely to be U.S. centric and thus are large holders of US equities; this may explain the greater link with overseas equities.

Assets with the lowest correlations should in theory be of most use to offer diversification in a portfolio context. Above we have already seen that commodities, particularly for S&P GSCI, appear to offer low correlation to other assets. The S&P GSCI has an average correlation coefficient with other asset classes of 0.20 and a correlation with U.K. equity of 0.16. However, the two asset classes that, on average, show the smallest correlations are Gilts and gold. UK Gilts have an average correlation with the 9 other assets of 0.052, with 4 coefficients being negative and 2 below 0.050. However, the correlation with UK equities is 0.145; this is still very low although far from negative. It still shows that the classic split of fixed income and equities still has significant risk reducing power, especially if the majority of the fixed income exposure is though government bonds. Recently gold has had a lot of attention for being a safe haven asset in times of financial distress (Greely and Currie 2009). Thus the inclusion of gold in the overall investors' portfolio is likely to add further diversifying powers. In fact gold has a negative average correlation of -0.036 with the 9 other assets and one of -0.217 with domestic equities. It also has tiny negative correlation with both commodity indices of which it will be a very small part of. U.K. Gilts and gold also only have a very small correlation of 0.074.

If we now consider the diversifying power of real estate, firstly the IPD desmoothed index shows a very low average correlation with other asset classes (0.101). It is has fairly low correlations with most of the asset classes including 0.097 and 0.110 for domestic and overseas equities respectively and 0.113 with UK credit. Its highest correlation, except that with real estate equities, was with hedge funds of 0.189. The correlations with listed real estate (i.e. real estate companies, represented by the FTSE EPRA/NAREIT UK index) have a slightly higher average correlation (0.169). The coefficients with credit (0.156) and hedge funds (0.258) were also slightly higher. Interestingly the correlation between listed real estate companies and U.K. equities is about the same as with hedge funds at 0.252. A lot of evidence points to the fact that in the short term listed real estate companies tend to be highly correlated with the general equity market and thus may not offer that much diversification. However; longer term they become to follow the direct real estate market more closely and thus over time offer diversifying powers away from the general equity market. The correlation coefficient between listed and the direct real estate market is 0.294. This supports the argument that listed real estate equities do act differently in the overall portfolio than direct real estate and thus should not perhaps be considered a proxy for direct real estate in an investor's portfolio.

[INSERT EXHIBIT 2 HERE]

4. Rolling correlations

As mentioned above, a basic way of showing that correlations are dynamic and thus change over time is to look at rolling correlations. Rolling correlations are correlation coefficients that are calculated over defined moving windows (e.g. in a 6 month rolling window one would calculate the correlation from month 1 to month 6 to give the first coefficient; returns from month 2 to month 7 would then give the second coefficient and so on). I have used 36 month rolling windows as in Ziering, Liang and McIntosh (1999) and Solnik, Boucrelle and Le Fur (1996). In their article Ziering, Liang and McIntosh (1999) comment on the problems in choosing rolling window lengths, they mention twice that a longer window may display a considerable amount of inertia while using too short periods may lead to results that are susceptible to large idiosyncratic fluctuations.

A table that summarises the mean, standard deviation and range (maximum minus minimum value) is shown below. From the means; we can see that the average rolling coefficients are similar to the static ones although they tend to be generally lower. For example the average rolling correlation coefficient for the correlation between the two equity indices is 0.728 (slight below the static correlation of 0.774). The two commodity indices had a static correlation of 0.770, compared with an average rolling correlation 0.677. Although this is the general case, the correlation coefficient between U.K. Gilts and U.K. credit is 0.774 if we use a static approach and of 0.886 if we average figures computed with rolling windows.

The most interesting aspect of this first set of results is not represented by the value of their means but by their trend over time. The amount of variability over time can be determined from their standard deviation and range which are displayed in exhibit 3. The standard deviation and range show that all of the correlations display an assortment of results. Thus we can conclude that, at least anecdotally correlations between assets do vary over time. Since values range over time depending on at what point a correlation value is calculated, the result can give a very different picture of the relationship between the two assets. For example some of the assets may appear to have very little levels of correlation when based on their mean (e.g. 0.091 between sovereign debt and U.K. equities). However; their standard deviation is significant (0.411) and so is their range (1.23, from a maximum of 0.760 to a minimum of -0.480).

[INSERT EXHIBIT 3 HERE]

5. Stastisical testing of Correlation Matrices

5.1 Model and methodology

Already we have looked at rolling correlations to establish that correlations do change over time and then we also will go on to address this issue from a different perspective using the technique of semicorrelation. Although both these methodologies are useful they suffer from the problem of not having any statistical power (Schindler 2009).

Thus it is worthwhile to include statistical tests for the stability of the correlation matrices and covariance matrices, these be tested over time using the a test developed by Jennrich (1970) and another one first presented in Box (1970). Both of these tests allow the length of the data series used to calculate the correlations to be considered. Therefore; correlations that are derived from longer data series are considered to be more reliable by the tests. Lee (2006) tests different lengths of sub-periods to consider this point.

Kaplanis (1998) uses both the Jennrich test and the Box M test on the sub-periods of the covariance matrices of his returns. However; he only uses the Jennrich test on correlations of his returns as originally the Box test was only used for covariance testing. Like Tang (1995) and also Lee (2006) I also use the Box test on the correlation matrix . This is made possible by first adjusting the raw data in order to turn it into standard scores for each sub-period (see the appendix of Tang 1995 for a proof) .

The Jennrich (1970) test

The test statistic for the testing of correlation matrices is shown below:

$$\chi^2 = \frac{1}{2} tr(Z^2) - diag'(Z)S^{-1}diag(Z)$$

Within the above equation:

$$Z = c^{\frac{1}{2}}R^{-1}(R_1 - R_2)$$

in which

$$R = \frac{n_1 R_1 + n_2 R_2}{n_1 + n_2}$$

and

$$c = \frac{n_1 n_2}{n_1 + n_2}$$

With $\mathbf{R_1}$ and $\mathbf{R_2}$ are the correlation matrices to be compared and are the number of observation upon each are based.

Also

$$S = \left(\delta_{ij} + r_{ij} r^{ij}\right)$$

Where δ_{ij} is the Kronecker delta, r_{ij} is the elements of R, while r^{ij} is the elements of R^{-1}.

The Jennrich test χ^2 test statistics has p(p-1)/2 degrees of freedom.

In order to calculate the Jennrich chi-squared statistic for use on two covariance matrices, the term after the minus sign is omitted from the equation above. Also in this case the statistic has p(p+1)/2 degrees of freedom.

Box M test (1949)

This test is similar to the Jennrich test, although it was originally created for use on the covariance matrix only. I am including both tests for comparison purposes.

$$M = n \ln |\mathbf{C}| - \sum_{i=1}^{T} n_1 |C_i|$$

$$C = \frac{1}{n \sum_{i=1}^{T} n_i C_i}$$

Above; $\mathbf{C_i}$ is the variance-covariance matrix which is calculated from the sample period i. While T is the total number of sub-periods where the equality of matrices is tested.

In Box (1949) it is shown that either a chi-square statistic or an F statistic can be used to approximate the M statistic . Lee (2006) uses the F statistic following on from the findings of

Pearson (1969) that the F statistic is more accurate and from Morrison (1990) that it is more appropriate to use when there are more than 5 variables.

In order to perform the tests we will first look at the correlations of the of the assets but split into 4 equal groups of 4 years and 7 months (55 months) each. These are split chronologically and in order to keep them simple and equal I have not used the last 2 months of the data. Although since you can adjust the sample size within both of the tests this was not mandatory. Thus I am left with the following 4 time periods: Jan 1991 to July 1995, August 1995 to February 2000, March 2000 to September 2004 and October 2004 to April 2009.

5.1 **Empirical Results**

In Exhibit 4 below the test statistics are shown for test of the correlation matrices over 6 different pairs of time periods. Both the Box M test and Jennrich test statistics are shown. Using the Jennrich (1970) test, the correlation matrices appear of be stabile over certain time periods; over the first and second, and first and third periods as well as the second and third. This test; however, finds that the matrices can not be deemed equivalent for 3 pairs at the 10 percent significance level. What is apparent about the pairs that failed the test are that they all feature the last time period; from October 2004 to April 2009. This is interesting as this period includes the recent financial crises during which there may be evidence that correlations between assets may have increased substantially. Looking at the Box test on the other hand we can see immediately that all of the 6 comparisons can be deemed to be not stabile at least at the 10% significance level. The first and second periods as well as the first and third are the only two that do not fail at the 1% level. The results therefore are comparable with the Jennrich test although obviously the Box test appears to reject the test of stability more easily. The only exception to this is test for the first and third periods; here it is stable using the Jennrich test while it fails at the 1% significance level when the Box M test is applied. Following the logic contained in Pearson (1969) and Lee (2006) an F statistic was also approximated for the Box M test this changed none of the significance levels of any results.

[INSERT EXHIBIT 4 HERE]

Both tests are also applied to the covariance matrices for the 6 different periods in Exhibit 5 below. One can immediately see that using both tests we can reject that the covariances are stable for all the 6 period parings at even the 1% level. Again using the F statistic with the box test have the same results. Thus we can conclude that the instability of the covariance matrix is substantially more significant to that of the correlation matrix especially when using the Jennrich test. This finding is supported by that of Schindler (2009) who gets similar results from testing correlation and covariance matrices of international listed property company indices using the Jennrich test. This paper in turn supported results from a previous study on national property company indices (Eichholtz 1996). Using the Box M test Lee (1996) also finds that the correlation matrix are more stable than covariance matrix (were all sub-periods failed the test) for U.K. direct real estate sub-sectors. In Kaplanis (1988) the correlation matrix for international equity markets is found to be stable across all periods compared while the covariance matrix is not stable across most periods compared.

[INSERT EXHIBIT 5 HERE]

6. Semicorrelation

6.1 Model and methodology

Semicorrelation is a useful methodology to use because these unlike the statistical tests above it considers all of the data either as one group or on a rolling basis. Therefore it does not just compare two periods at once. It also begins to consider the possibility that correlation may be higher during times when asset values tend to be falling.

So far there appear to be only four articles using semicorrelation - Erb, Harvey and Viskanta (1994), Newell and Acheampong (2001), Gabbi (2007) and Schindler (2009) – but this measure follows the same principles as semivariance which has been used extensively (see Harlow 1991 for an introduction). The general principle follows the insight of Markowitz (1959)

Semicorrelation is a method of calculating the correlation of returns in different market states, where the ex-post returns of an asset are separated between above and below average (i.e. up and down). This is calculated as an asset return compared with its mean in a given period. This leads to a measurement of correlation in 3 possible states of the world (actually 4 if we consider the up-down and down-up states as being separate):

1/ up-up (returns of both assets are above the mean)

2/ down-down (returns of both assets are below the mean)

3/out of phase or mixed (one asset's returns is above the mean while the other is below)

The out of phase correlations (up-down and down-up states) will generally be negative. Statistically there is no reason why the returns above the means (up-up state) should have different correlations to those below the mean (down-down state). Thus statistically the negative and positive semicorrelations should be indistinguishable from one another.

Notation:

This equation below shows how one calculates semicorrelation in the up-up state (positive semicorrelation). Where X and Y are two random variables with means $\mu\mathbf{x}$ and $\mu\mathbf{y}$ respectively then population semi-correlation is defined:

$$\rho_{X,Y} = \frac{COV^{++}[X,Y]}{V^{++}[X]V^{++}[Y]}$$

Where:

$$COV^{++}[X,Y] = \int_{\mu x}^{\infty}\int_{\mu y}^{\infty}(x - \mu x)(y - \mu y)f(x,y)dx\,dy$$

This may be consistently estimated by using:

$$\rho_{X,Y} = \frac{\Sigma[(x_i] - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma(x_i - \bar{x})^2 (y_i - \bar{y})^2}}$$

Where the summation is over values of $\mathbf{x_i}$ greater than $\bar{\mathbf{x}}$ and values of $\mathbf{y_i}$ greater than $\bar{\mathbf{y}}$. Down-down correlation is defined similarly and estimated by summing over values of $\mathbf{x_i} < \bar{\mathbf{x}}$ and values of $\mathbf{y_i}$ less than $\bar{\mathbf{y}}$. For mixed correlation the summations are over $\mathbf{x_i} > \bar{\mathbf{x}}$ and $\mathbf{y_i} < \bar{\mathbf{y}}$ or $\mathbf{x_i} < \bar{\mathbf{x}}$ and $\mathbf{y_i} > \bar{\mathbf{y}}$.

6.2 Empirical results

6.2.1 Static semicorrelations

In Exhibits 6 and 7one can quickly see by looking at the averages line (average of correlations with all other assets; in all cases excluding the original IPD index) that all average correlations are higher in down-down periods than up-up periods. The FTSE 100 average correlation almost doubles from 0.184 to 0.35 while the MSCI World ex. UK more than doubles from 0.205 to 0.434 Listed real estate companies average correlation increases by a greater amount from 0.116 to 0.366. One of the most significant results; however, is the average correlation with the direct real estate original data, which increases from 0.050 to 0.435, while the unsmoothed IPD index does not display the same magnitude of change, only increasing from 0.127 to 0.255. Both commodity indices display tiny negative average positive semicorrelations, whilst their average semicorrelations in the down-down state are quite high at 0.444 (GSCI) and 0.302 (CRB). Although sovereign fixed income (gilts) had a higher negative semicorrelation than positive semicorrelation the increase in correlation was by the least amount from 0.086 to 0.106This negative semicorrelation is the lowest one out of all assets and it shows that gilts still retain most of their diversifying power when it is needed most. The same can not be said of any other asset, even the more credit exposed fixed income. Although the credit benchmark had a lower positive semi-correlation than gilts at 0.009, this increased to 0.363 in a down-down state.

Looking beyond the average results, I find that many of the individual correlations obviously reflect the average trend. For the two equity indices which had an overall static correlation of 0.774, these had a much higher negative semicorrelation of 0.746 than positive semicorrelation of 0.507. A similar increase happens with the two commodity indices; which have a negative semicorrelation of 0.814 which is much greater than the positive semicorrelation of 0.606. Interestingly the correlation between the unsmoothed IPD index and the raw data index is one correlation where the positive semicorrelation (0.828) is greater than the negative semicorrelation (0.770), although only slightly. In theory this would imply that the link between the original and smoothed direct real estate indices is fairly stable over different market states. However; I suspect that this is a technical result of the filter used to create the unsmoothed index. As this removes the first order autocorrelation in the index- MORE!!! Real estate companies showed low positive semicorrelations with both U.K. (0.240) and overseas (0.323) equities and with the unsmoothed direct real estate index (0.083). These are considerably lower than the negative semicorrelations which are 0.284 with U.K. equities, 0.510 with overseas equities and 0.433 with unsmoothed direct real estate index This follows the results above between the two broad equities indices; overall equities tend to move much more closely together in the down-down state. This perhaps could be a function of their implied riskiness combined with their relative liquidity.

Direct (unsmoothed) real estate has some of the biggest correlation changes; for example its correlation with listed real estate companies increased from 0.083 (up-up) to 0.434 (down-down). Some of the biggest changes in the other assets were those of the two commodity indices. For example the R/J CRB index correlation with direct real estate increased from 0.062 (up-up) to 0.568 (down-down). Its correlation with both listed real estate and with domestic equities also changes dramatically from being negatively correlated (up-up) to being quite highly positively in down-down states. For listed real estate companies the correlation with the R/J CRB index moved from -0.107 (up-up) to 0.594 (down-down), while the correlation with domestic equities increased from -0.117 to 0.521. The trend was the same but not quite as large for the GSCI. Hedge funds were an asset class where most of the individual correlations increased approximately in line with the average, although the increase was slightly higher in the case of the correlation with direct real estate from -0.019 to 0.232 than any other. Except for Gilts, all the negative semicorrelations are substantially bigger than the positive ones for hedge funds with all other assets. Gold had the smallest increase from 0.116 to 0.166, while all other assets had increases of around 0.20 or more. Overall hedge funds appear to offer less diversification in stressful times.

The only asset with correlation coefficients actually decreasing from up-up to down-down states is that of Gilts, (i.e. it has 7 negative correlations with other assets in the down-down state). Domestic equities correlation with gilts decreased from 0.352 (up-up) to 0.040 (down-down), while real estate equities decreased from 0.344 (up-up) to -0.135 (down-down). Also the negative semicorrelation for gilts and hedge funds was -0.242, a large decrease when compared to a positive semicorrelation of 0.012. In fact the only asset which still had a high negative semicorrelation with gilts was credit (0.590) which was still lower than the positive semicorrelation of 0.710. An explanation of this may be found in the fact that in very extreme falling markets there may be a 'flight to safety' effect that will drive up the price of certain Gilts.

Overall my findings at a multi-asset class portfolio level can be compared with the ones of Erb, Harvey and Viskanta (1994) and Gabbi (2007), with increased correlations in down-down markets. The magnitude of the changes in correlation between up-up and down-down states is much more comparable with Erb, Harvey and Viskanta (1994) than Gabbi (2007) , although Gabbi used a rolling method.

[INSERT EXHIBIT 6 HERE]

[INSERT EXHIBIT 7 HERE]

6.2.1 Rolling semicorrelations

As in Gabbi (2007), I have also looked at the semicorrelations between assets on a rolling basis, I have used 36 month long window, rolled forward one month at time, while he used a six month long rolling of rolling returns window that is moved two weeks at time. This is useful as it can help further support the findings above.

In Exhibits 6,7 and 8 we present the positive and negative rolling semicorrelations as well as a summary of the differences between them. In the positive and negative tables both the mean of rolling semicorrelation coefficients and their standard deviations are shown. Firstly both the positive and negative coefficients have reasonability high stand deviations with a minimum of approximately 0.2 and a high of 0.49, which was the negative semicorrelation of the unsmoothed IPD index and gold (it had a mean of 0.67). In general the standard deviations of the negative rolling semicorrelations are greater than those of the rolling positive semicorrelations this is the same in as in Gabbi (2007) were they tend to be slightly higher.

When compared to the static semicorrelation analysis the results here were more mixed but are very interesting. Only 32 of the average coefficients were more than 0.10 greater in their down-down stages than in their up-up states. These included the two equity indices which had a difference of 0.205, which resulted from a negative semicorrelation of 0.551 and a positive one of 0.345. The biggest increase in absolute terms was with the semicorrelation between the UK equities and the Reuters/ Jefferies- CRB index which have a negative semicorrelation of -0.217 and a positive one of 0.145. There was also a large reduction of the diversifying power of hedge funds along with UK equities and overseas equities. With the FTSE they increased from a positive semicorrelation of 0.201 to 0.447 and with the MSCI World they almost doubled from 0.316 to 0.617. Listed real estate has notability higher negative semicorrelations with 5 other assets: UK equities, hedge funds, gold and the two diversified commodity indices. It is one of the assets that appears to lose its diversifying power the most in down-down markets along with hedge funds and the Reuters/ Jefferies- CRB.

Another asset that has a lot of negative semicorrelation coefficients which are substantially higher than the positives ones is the Reuters/ Jefferies- CRB index which has large semicorrelation increases with UK equities, overseas equities, real estate equities, the 'original' IPD index, credit and hedge funds. Despite these increases; however, it still has diversifying properties as even the down-down states semicorrelations are not that high. The large differences results from the fact that the in up-up markets the index is negatively correlated with all the other assets except the GSCI and hedge funds. The results for the GCSI index are similar but not as extreme in terms of the size of the move in the semicorrelations, in the down-down states it remains as a good diversifier for most of the other assets.

Perhaps the most interesting discovery in terms of the direct real estate indices is that the positive semicorrelation between the 'raw' IPD index and the unsmoothed version is, at 0.554 significantly higher than that of the negative of (0.162).This leads to the discovery that for 6 correlation pairs that the positive semicorrelation with the raw IPD index is actually lower than the negative ones. This would imply good diversifying power including -0.086 with the FTSE 100 in down-down states. The unsmoothed index also has not had many substantial increases in semicorrelation, this implies that its correlations are reasonably stable across the two types of markets It also remains a good diversifying asset in down-down states with its maximum negative semicorrelation being 0.173 with hedge funds.

Gold is one asset were there is no overall pattern that seems to arise in the results; it has 2 positive differences (negative less positive semicorrelation) which are with real estate equities and the GSCI. Meanwhile it also has two large negative differences where the positive semicorrelations between it and UK equities and the Reuters/ Jefferies are negative. Overall however it appears to have diversifying powers with most assets, except with real estate. Credit also provided mixed results it has positive differences with both the equity indices and Gold, although only that with overseas equities seems significant. Which the other assets it had a slight increase in value from positive semicorrelation to negative semicorrelation but nothing substantial.

As with the static semicorrelation analysis it is clear again that gilts tend to have more diversifying power in down-down states than in up-up states. In the case of 8 of the other assets their negative semicorrelation with gilts was higher than their positive semicorrelation. The difference was particularly big with the two types of equity; Gilts average positive semicorrelation with U.K. equities was 0.265 while their negative one was efficiently uncorrelated at 0.008. With overseas equities the change was even greater, the average positive semicorrelation was 0.247 while the negative one was -0.216. Also the semicorrelation with the GSCI index displayed a big change with an average semicorrelation of 0.01 moving to an average negative semicorrelation of -0.273. The power of gilt's diversifying power in down-down markets is clearly displayed here. Out of the 10 pairings, the only one that does not have a negative semicorrelation that is either close to 0 or a negative semicorrelation with a negative value is the correlation with credit in the down-down state which increased slightly to 0.769.

[INSERT EXHIBIT 8 HERE]

[INSERT EXHIBIT 9 HERE]

[INSERT EXHIBIT 10 HERE]

7. Conclusions

This study has firstly proven that the correlations between a number of different asset class proxies are not stable over time. We looked at the variation between the asset classes' rolling correlations and then applied some statistical testing. This testing proved that the covariance matrix was not stable over time. Using the Jennrich test the correlation matrix was sometimes found to be stable but tended to be less likely to be stable over the last quarter of the data set when compared to the rest. When the Box M test was used the correlation matrix was found to be even more unstable over time. The fact that the last quarter of the correlation data seemed to suggest a statically significant change in correlation gives us some evidence that during the 'credit crunch' correlations may have changed greatly. The semicorrelation analysis displays that the negative semicorrelation is generally higher than the positive one, thus the overall correlation is changing over time as asset values rise and fall.

Following on from this the study shows that in most cases that correlations tend to move up in down markets. The use of semicorrelation shows that in many cases the correlation between assets is higher when both assets are falling. This means that a lot of assets diversifying powers are lowest when in an overall portfolio context they are needed the most. This also confirmed findings by for example Erb et al. (1994) and Longin and Solnik (2001), that in general asset correlations are highest in bear markets.

In my opinion the most important conclusion from the semicorrelation analysis is that of the role of sovereign debt within a portfolio. This asset was the only one that tended not to have a big positive difference between the negative and positive semicorrelations. In fact in many cases this difference was negative. On a rolling basis all but 2 of gilt's semicorrelations actually decreased from up-up to down-down states and there was only one pairing that does not have a negative semicorrelation that is either close to 0 or a have a negative value semicorrelation. On an average basis against all the other main assets ,in general almost all the assets excluding gilts lost diversifying powers in the down-down states.

Meanwhile although they tended to be fairly uncorrelated between other assets in the up-up states commodities tended to be more correlated to other assets in the down-down states. Gold appears to retain some diversifying power in the short term in down-down markets although it does not seem to give the same 'safe haven' asset effect that gilts do. Hedge funds also do not provide the same degree of diversification in the negative semicorrelation state, especially with equities. Therefore this study supports the anecdotal evidence that during the credit crises that alternative assets fell with other assets and that sovereign debt was a safe haven asset and thus remained a portfolio diversifier.

References

Adrian, T. (2007), " Measuring Risk in the Hedge Fund Sector", *Current Issues in Economics and Finance*, 13(3), pp. 1-9

Agarwal, V., and Naik, N.Y. (2000a), "Multi-Period Performance Persistence Analysis of Hedge Funds", *The Journal of Financial and Quantitative Analysis*, 35 (3), pp. 327-342.

Agarwal, V., and Naik, N.Y. (2000b), "On Taking the 'Alternative' Route: Risks, Rewards and Performance Persistence of Hedge Funds", *Journal of Alternative Investments*, 2(4),pp. 6-23.

Ang A., and G., Bekaert, (2002) "International Asset Allocation with Regime Shifts", *Review of Financial Studies*, 15, pp. 1137-1187.

Barkham, R. and Geltner, D. (1995), "Price Discovery in American and British Property Markets", *Real Estate Economics*, 23 (1), pp. 21-44.

Bracker, K., and Koch, P.D., 1999. Economic Determinants of the Correlation Structure Across International. Equity Markets, *Journal of Economics and Business,* 51, pp. 443-471.

Bond, S.A., Hwang, S., Mitchell, M. and Satchell, S.E. (2007), "Will Private Equity and Hedge Funds Replace Real Estate in Mixed-Asset Portfolios?", *The Journal of Portfolio Management*, Special Real Estate Issue, pp. 74-84.

Box, G.E.P. (1949), "A general distribution theory for a class of likelihood criteria", *Biometrika*, 36, pp. 317-46.

Clayton, J. and MacKinnon, G. (2003)," The Relative Importance of Stock, Bond and Real Estate Factors in Explaining REIT Returns", *Journal of Real Estate Finance and Economics,* 27 (1)

Dor, B.A., Dynkin, D., and Gould, A (2006), "Style Analysis and Classification of Hedge Funds", *Journal of Alternative Investments*, Fall*,* 9(2), pp. 10-29.

Eichholtz, P.M.A. (1996), "The stability of covariances of international property share returns", *The Journal of Real Estate Research*, 11(2) pp. 149-58.

Engle, R., (2002), "Dynamic Conditional Correlation - a Simple Class of Multivariate GARCH Models", *Journal of Business and Economic Statistics,* 20, pp. 339-350.

Erb, C. B., Campbell, R. H. and Tadas, E. V. (1994) "Forecasting international equity correlations", *Financial Analysts Journal*, 6, pp. 32–45.

Fung, W., and Hsieh, D. (2002), "Benchmarks of hedge fund performance: information content and measurement biases", *Financial Analyst Journal*, 58, pp. 22-34.

Gabbi, G, "Semi-correlations as a Tool for Geographical and Sector Asset Allocation", *The European Journal of Finance*, Vol. 11 (3) , 271-281.

Geltner, D. (1993), "Estimating Market Values from Appraised Values Without Assuming an Efficient Market", *Journal of Real Estate Research*, 8(3), pp. 325–46.

Geltner, D., MacGregor, B.D. and Schwann, G.M. (2003), "Appraisal Smoothing and Price Discovery in Real Estate Markets", *Urban Studies*, 40(5), pp. 1047–64.

Geltner, D. Miller, N., Clayton, J and Eichholtz (2007), *Commercial Real Estate Analysis and Investments*, Thomson

Goldstein, M.A. and Nelling, E.F. (1999), "REIT return behaviour in advancing and declining stock markets", Real Estate Finance, 15(4), pp. 68-77.

Greely, D and Currie, J (2009), " Forecasting Gold as a Commodity Global Economics", *Goldman Sachs*, Paper No: 183

Harlow,W. V. (1991) "Asset allocation in a downside risk framework", *Financial Analysts Journal*, 47, pp. 28–40.

Jennrich, R. I., (1970), "An Asymptotic Chiq- squared Test for the Equality of Two Correlation Matrices", *Journal of theAmerican Statistical Association*, 65, pp. 904–1

Kaplanis, E. C. (1988), " Stability and forecasting of the comovement measures of international stock market return", *Journal of International Money and Finance*, 7, pp. 63–76.

Kat, Harry M. (2003), "10 Things that Investors Should Know about Hedge Funds", *The. Journal of Wealth Management*, 5(4), pp. 72–81.

Key, T., and Marcato, G. (2007), "Index Smoothing and the Volatility of UK Commercial Property", Report to the Investment Property Forum.

Lee, S.(2006), "The stability of the co-movements between real estate returns in the UK", *Journal of Property Investment and Finance*, 24(5), pp. 434-442.

Longin, F. and B. Solnik (1995), 'Is the International Correlation of Equity Returns Constant: 1960-1990?' *Journal of International Money and Finance*, February, pp. 3-26.

Longin, F. and Solnik, B. (2001) Extreme correlation of international equity markets, *The Journal of Finance*, 56, pp. 3–26.

Markowitz, H.M. (1952), "Portfolio selection", The Journal of Finance, 7(1), pp. 77-91.

Morrison, D.F. (1990), Multivariate Statistical Methods, McGraw-Hill, New York, NY.

Newell, G. and Acheampong, P. (2001), "The dynamics of the Australian property market risk and correlation profile", *Pacific Rim Property Research Journal*, 7(4), pp. 259-70.

Pearson, E.S. (1969), "Some comments on the accuracy of Box's approximations to the distribution of M", *Biometrika*, 56, pp. 219-20.

Peyton, M., and F. Lotito. (2007), "Real Estate: The Classic Diversifying Asset." *PREA Quarterly*, Winter 2007, pp. 54-60.

Schindler, f. (2009), "Correlation structure of real estate markets over time", *Journal of Property Investment & Finance*; 27(6), pp. 579-92

Schneeweis, T., Karavas, V. N. and Georgiev, G. (2002), "Alternative Investments in the Institutional Portfolio", *Alternative Investment Management Association (AIMA)*.

Sebastian, S, and Sturm, M. (2007),"Correlations of Property Stocks with other Asset Classes - Broadening the Investor Base Study", European Public Real Estate Association.

Eliminato: ¶

Eliminato:

Eliminato: ¶

Solnik, B.H., Boucrelle, C. and Le Fur, Y. (1996), “International market correlation and volatility”, *Financial Analysts Journal*, 52(5), pp. 17-34.

Terhaar, K., R. Staub, and B. Singer. "Appropriate Policy Allocation for Alternative Investments." *The Journal of Portfolio Management,* 29(3) pp. 101-110.

Exhibits

Exhibit 1: Descriptive Statistics.

	FTSE 100	*MSCI WORLD EX UK*	*FTSE EPRA/NAREIT*	*IPD*	*IPD Unsmoothed*	*UK Gilts*	*UK Credit*	*S&P GSCI*	*Reuters/ Jefferies*	*S&P GSCI Gold*	*HFRI Composite*
Mean	0.0061	0.0051	0.0031	0.0057	0.0059	0.0067	0.0066	0.0025	0.0020	0.0043	0.0099
Standard Error	0.0028	0.0030	0.0045	0.0008	0.0027	0.0011	0.0011	0.0042	0.0025	0.0031	0.0014
Median	0.0099	0.0106	0.0050	0.0074	0.0069	0.0075	0.0080	0.0057	0.0043	-0.0008	0.0123
Standard Deviation	0.0419	0.0443	0.0668	0.0115	0.0406	0.0157	0.0169	0.0627	0.0378	0.0467	0.0206
Kurtosis	0.9094	2.7349	3.6479	7.9907	6.7012	0.8126	3.6682	3.2961	9.5083	3.0438	2.8871
Skewness	-0.6973	-1.0745	-0.1576	-2.1759	-0.6896	-0.1494	-0.8424	-0.7355	-1.3794	0.4751	-0.7593
Range	0.2419	0.3159	0.5666	0.0895	0.3880	0.1007	0.1349	0.5108	0.3812	0.3716	0.1635
Minimum	-0.1377	-0.2099	-0.2549	-0.0541	-0.1932	-0.0484	-0.0859	-0.3313	-0.2519	-0.1469	-0.0870
Maximum	0.1042	0.1060	0.3117	0.0354	0.1948	0.0523	0.0489	0.1795	0.1293	0.2247	0.0765
Jarque-Bera test (5%)	24.63*	106.94*	116.78*	733.4*	411.1*	6.26*	143.08*	114.2*	864.09*	88.67*	93.33*
Jarque-Bera test (10%)	24.63*	106.94*	116.78*	733.4*	411.1*	6.26	143.08*	114.2*	864.09*	88.67*	93.33*

Notes: This table summarises the basic descriptive statistics for the log returns of the data. The length of the data series was from January 1991 to June 2009.

* The asset fails the Jarque-Bera test at this level

Exhibit 2 - Static correlations

	FTSE 100	*MSCI WORLD EX UK*	*FTSE EPRA/NAREIT*	*IPD*	*IPD Unsmoothed*	*UK Gilts*	*UK Credit*	*S&P GSCI*	*Reuters/ Jefferies*	*S&P GSCI Gold*	*HFRI Composite*
FTSE 100	1.0000										
MSCI WORLD EX UK	0.7741	1.0000									
FTSE EPRA/NAREIT	0.2520	0.2772	1.0000								
IPD	0.1452	0.2180	0.3311	1.0000							
IPD Unsmoothed	0.0976	0.1102	0.2945	0.4742	1.0000						
UK Gilts	0.1831	0.0062	-0.0339	-0.1708	-0.1361	1.0000					
UK Credit	0.4231	0.2615	0.1562	0.0766	0.1135	0.7741	1.0000				
S&P GSCI	0.1597	0.2623	0.1579	0.1996	0.0655	-0.0806	0.1039	1.0000			
Reuters/ Jefferies	0.2374	0.3894	0.2118	0.2360	0.1744	-0.1229	0.1161	0.8044	1.0000		
S&P GSCI Gold	-0.2170	-0.1163	-0.0536	-0.0370	-0.0027	0.0745	0.0701	-0.0140	-0.0236	1.0000	
HFRI Composite	0.6432	0.7535	0.2576	0.1894	0.1892	0.0247	0.3030	0.3389	0.4164	-0.0414	1.0000

Notes: This table shows the overall correlations for the log returns of the data. The length of the data series was from January 1991 to June 2009.

Exhibit 3 - Rolling correlations (36 month)

		FTSE 100	*MSCI WORLD EX UK*	*FTSE EPRA/NAREIT*	*IPD*	*IPD Unsmoothed*	*UK Gilts*	*UK Credit*	*S&P GSCI*	*Reuters/ Jefferies*	*S&P GSCI Gold*	*HFRI Composite*
FTSE 100	Mean	1.000	0.728	0.204	0.046	0.064	0.091	0.275	0.067	0.135	-0.210	0.627
	SD	0.000	0.154	0.170	0.194	0.186	0.406	0.305	0.143	0.150	0.118	0.088
	Range	0.000	0.556	0.737	1.042	0.791	1.233	0.959	0.645	0.653	0.600	0.438
MSCI WORLD EX UK	Mean	0.728	1.000	0.205	0.068	0.016	-0.031	0.125	0.151	0.274	-0.100	0.755
	SD	0.154	0.000	0.182	0.200	0.259	0.243	0.196	0.210	0.120	0.105	0.121
	Range	0.556	0.000	0.727	0.899	0.932	0.937	0.867	0.892	0.593	0.477	0.464
FTSE EPRA/NAREIT	Mean	0.204	0.205	1.000	0.077	0.124	0.030	0.122	0.059	0.127	0.063	0.280
	SD	0.170	0.182	0.000	0.203	0.126	0.179	0.181	0.146	0.144	0.257	0.268
	Range	0.737	0.727	0.000	0.930	0.587	0.697	0.606	0.614	0.610	0.941	1.039
IPD	Mean	0.046	0.068	0.077	1.000	0.525	-0.074	-0.052	-0.050	0.069	-0.059	0.033
	SD	0.194	0.200	0.203	0.000	0.107	0.194	0.191	0.216	0.212	0.140	0.212
	Range	1.042	0.899	0.930	0.000	0.912	0.940	0.900	0.916	0.938	0.639	1.001
IPD Unsmoothed	Mean	0.064	0.016	0.124	0.525	1.000	-0.033	0.027	-0.127	0.006	-0.051	0.100
	SD	0.186	0.259	0.126	0.107	0.000	0.206	0.176	0.248	0.117	0.227	0.128
	Range	0.791	0.932	0.587	0.912	0.000	0.825	0.687	0.915	0.558	0.784	0.588
UK Gilts	Mean	0.091	-0.031	0.030	-0.074	-0.033	1.000	0.886	-0.003	-0.056	0.127	0.009
	SD	0.406	0.243	0.179	0.194	0.206	0.000	0.136	0.130	0.131	0.215	0.263
	Range	1.233	0.937	0.697	0.940	0.825	0.000	0.658	0.684	0.563	0.823	0.950
UK Credit	Mean	0.275	0.125	0.122	-0.052	0.027	0.886	1.000	-0.003	-0.048	0.078	0.174
	SD	0.305	0.196	0.181	0.191	0.176	0.136	0.000	0.143	0.144	0.204	0.198
	Range	0.305	0.196	0.181	0.191	0.176	0.136	0.000	0.143	0.144	0.204	0.198
S&P GSCI	Mean	0.067	0.151	0.059	-0.050	-0.127	-0.003	-0.003	1.000	0.677	0.012	0.199
	SD	0.143	0.210	0.146	0.216	0.248	0.130	0.143	0.000	0.143	0.206	0.168
	Range	0.645	0.892	0.614	0.916	0.915	0.684	0.673	0.000	0.586	1.004	0.846
Reuters/ Jefferies	Mean	0.135	0.274	0.127	0.069	0.006	-0.056	-0.048	0.677	1.000	0.000	0.302
	SD	0.150	0.120	0.144	0.212	0.117	0.131	0.144	0.143	0.000	0.156	0.165
	Range	0.653	0.593	0.610	0.938	0.558	0.563	0.623	0.586	0.000	0.737	0.755
S&P GSCI Gold	Mean	-0.210	-0.100	0.063	-0.059	-0.051	0.127	0.078	0.012	0.000	1.000	-0.008
	SD	0.118	0.105	0.257	0.140	0.227	0.215	0.204	0.206	0.156	0.000	0.079
	Range	0.600	0.477	0.941	0.639	0.784	0.823	0.793	1.004	0.737	0.000	0.447
HFRI Composite	Mean	0.627	0.755	0.280	0.033	0.100	0.009	0.174	0.199	0.302	-0.008	1.000
	SD	0.088	0.121	0.268	0.212	0.128	0.263	0.198	0.168	0.165	0.079	0.000
	Range	0.438	0.464	1.039	1.001	0.588	0.950	0.726	0.846	0.755	0.447	0.000

Notes: This table summarises the 36 month rolling correlations for the data. Range is the maximum rolling correlation coefficient minus the maximum value of correlation coefficient.

Eliminato: ¶

Exhibit 4 - Stability of Correlation Matrices

Periods Compared		Jennrich	Box
I	II	Chi-square	Chi-square
Jan 1991 to July 1995	Aug 1995 to Feb 2000	50.88	132.21**
Aug 1995 to Feb 2000	March 2000 to Sept 2004	52	94.37*
March 2000 to Sept 2004	Oct 2004 to April 2009	94.91***	174.09***
Jan 1991 to July 1995	March 2000 to Sept 2004	61.37	222.30***
Jan 1991 to July 1995	Oct 2004 to April 2009	74**	300.56***
Aug 1995 to Feb 2000	Oct 2004 to April 2009	69*	180.45***

Notes: This table show the results of testing 6 different combinations of time periods correlation matrices. The chi-square values for both the Jennrich and Box M test arte shown

*, **, *** denote rejection of the null hypothesis at the 10%, 5%, 1% levels of significance.

Exhibit 5 - Stability of Covariance Matrices

Periods Compared		Jennrich	Box
I	II	Chi-square	Chi-square
Jan 1991 to July 1995	Aug 1995 to Feb 2000	157.04***	192.00***
Aug 1995 to Feb 2000	March 2000 to Sept 2004	105.91***	109.23***
March 2000 to Sept 2004	Oct 2004 to April 2009	236.33***	374.89***
Jan 1991 to July 1995	March 2000 to Sept 2004	209.02***	273.74***
Jan 1991 to July 1995	Oct 2004 to April 2009	219.02***	334.53***
Aug 1995 to Feb 2000	Oct 2004 to April 2009	224.28***	364.32***

Notes: This table show the results of testing 6 different combinations of time periods covariance matrices. The chi-square values for both the Jennrich and Box M test arte shown

*, **, *** denote rejection of the null hypothesis at the 10%, 5%, 1% levels of significance.

Exhibit 6- Static semicorrelations in up-up markets

	FTSE 100	*MSCI WORLD EX UK*	*FTSE EPRA/NAREIT*	*IPD*	*IPD Unsmoothed*	*UK Gilts*	*UK Credit*	*S&P GSCI*	*Reuters/ Jefferies*	*S&P GSCI Gold*	*HFRI Composite*
FTSE 100	1.0000	0.5076	0.2397	0.0616	0.0620	0.3520	0.3586	-0.0985	-0.1170	0.0383	0.3144
MSCI WORLD EX UK	0.5076	1.0000	0.3232	-0.0164	0.0264	0.1533	0.2368	0.1507	0.0217	0.0405	0.3868
FTSE EPRA/NAREIT	0.2397	0.3232	1.0000	0.2181	0.0825	0.3444	0.3290	-0.0855	-0.1071	-0.1786	0.0927
IPD	0.0616	-0.0164	0.2181	1.0000	0.8281	0.1957	0.2572	-0.1710	-0.0891	0.0163	0.0709
IPD Unsmoothed	0.0620	0.0264	0.0825	0.8281	1.0000	0.1243	0.1187	0.0196	0.0627	0.1171	-0.0185
UK Gilts	0.3520	0.1533	0.3444	0.1957	0.1243	1.0000	0.7096	-0.1486	-0.1995	-0.0175	0.0166
UK Credit	0.3586	0.2368	0.3290	0.2572	0.1187	0.7096	1.0000	-0.0487	0.1554	-0.0096	0.0885
S&P GSCI	-0.0985	0.1507	-0.0855	-0.1710	0.0196	-0.1486	-0.0487	1.0000	0.6061	0.0066	0.1758
Reuters/ Jefferies	-0.1170	0.0217	-0.1071	-0.0891	0.0627	-0.1995	0.1554	0.6061	1.0000	0.3549	-0.0356
S&P GSCI Gold	0.0383	0.0405	-0.1786	0.0163	0.1171	-0.0175	-0.0096	0.0066	0.3549	1.0000	0.1156
HFRI Composite	0.3144	0.3868	0.0927	0.0709	-0.0185	0.0166	0.0885	0.1758	-0.0356	0.1156	1.0000
Average v 9	0.1841	0.2052	0.1156	0.0501	0.1277	0.0868	0.0090	-0.0101	-0.0048	0.1276	0.1262

Notes: Semicorrelation in up-up markets show (positive semicorrelations)

Eliminato: ¶

Exhibit 7 - Static semicorrelations in down-down markets

Eliminato: ¶

	FTSE 100	MSCI WORLD EX UK	FTSE EPRA/NAREIT	IPD	IPD Unsmoothed	UK Gilts	UK Credit	S&P GSCI	Reuters/ Jefferies	S&P GSCI Gold	HFRI Composite
FTSE 100	1.0000	0.7467	0.2842	0.3274	0.2195	0.0406	0.4588	0.2835	0.5213	0.1181	0.5075
MSCI WORLD EX UK	0.7467	1.0000	0.5094	0.4992	0.3612	-0.0988	0.4000	0.5335	0.6315	0.1428	0.6819
FTSE EPRA/NAREIT	0.2842	0.5094	1.0000	0.6471	0.4338	-0.1354	0.2723	0.5638	0.5942	0.4182	0.3551
IPD	0.3274	0.4992	0.6471	1.0000	0.7724	0.1255	0.5128	0.6016	0.6179	0.6462	0.4042
IPD Unsmoothed	0.2195	0.3612	0.4338	0.7724	1.0000	-0.1143	0.2986	0.5113	0.5384	0.5676	0.3225
UK Gilts	0.0406	-0.0988	-0.1354	0.1255	-0.1143	1.0000	0.5896	-0.1768	-0.0389	-0.1238	-0.2421
UK Credit	0.4588	0.4000	0.2723	0.5128	0.2986	0.5896	1.0000	0.2741	0.5250	0.2670	0.4003
S&P GSCI	0.2835	0.5335	0.5638	0.6016	0.5113	-0.1768	0.2741	1.0000	0.8147	0.4100	0.3756
Reuters/ Jefferies	0.5213	0.6315	0.5942	0.6179	0.5384	-0.0389	0.5250	0.8147	1.0000	0.5113	0.6205
S&P GSCI Gold	0.1181	0.1428	0.4182	0.6462	0.5676	-0.1238	0.2670	0.4100	0.5113	1.0000	0.1596
HFRI Composite	0.5075	0.6819	0.3551	0.4042	0.3225	-0.2421	0.4003	0.3756	0.6205	0.1596	1.0000
Average v 9	0.3534	0.4342	0.3662	0.4359	0.2556	0.1060	0.3635	0.4446	0.3025	0.3777	0.3625

Notes: Semicorrelation in down-down markets show (negative semicorrelations)

Exhibit 8- Rolling 36 month semicorrelations in up-up markets

UP UP	*FTSE 100*	*MSCI WORLD EX UK*	*FTSE EPRA/NAREIT*	*IPD*	*IPD Unsmoothed*	*UK Gilts*	*UK Credit*	*S&P GSCI*	*Reuters/ Jefferies*	*S&P GSCI Gold*	*HFRI Composite*
FTSE 100	1.0000	0.3447	-0.0595	0.2571	0.0538	0.2649	0.2314	-0.1099	-0.2174	0.1230	0.2016
	0.0000	*0.4033*	*0.3380*	*0.3716*	*0.4100*	*0.2133*	*0.2776*	*0.2985*	*0.2118*	*0.3749*	*0.2229*
MSCI WORLD EX UK	0.3447	1.0000	0.1716	0.0129	0.0538	0.2467	0.2020	0.0846	-0.1152	-0.0693	0.3160
	0.4033	*0.0000*	*0.3715*	*0.3410*	*0.2234*	*0.3019*	*0.3114*	*0.3122*	*0.2593*	*0.3367*	*0.2934*
FTSE EPRA/NAREIT	-0.0595	0.1716	1.0000	0.1299	0.1557	0.1339	0.1783	0.0869	-0.1307	-0.0102	0.0992
	0.3380	*0.3715*	*0.0000*	*0.3219*	*0.2906*	*0.4148*	*0.3555*	*0.3340*	*0.3575*	*0.3787*	*0.2852*
IPD	0.2571	0.0129	0.1299	1.0000	0.5536	0.1046	0.0857	-0.0229	-0.2747	0.1124	0.1879
	0.3716	*0.3410*	*0.3219*	*0.0000*	*0.3586*	*0.3690*	*0.3131*	*0.4437*	*0.4034*	*0.4059*	*0.3377*
IPD Unsmoothed	0.0538	0.0538	0.1557	0.5536	1.0000	0.0296	-0.0283	-0.2399	-0.0961	-0.0139	0.0442
	0.4100	*0.2234*	*0.2906*	*0.3586*	*0.0000*	*0.3340*	*0.2655*	*0.3296*	*0.2907*	*0.3510*	*0.3877*
UK Gilts	0.2649	0.2467	0.1339	0.1046	0.0296	1.0000	0.7302	0.0133	-0.0841	0.0775	0.0304
	0.3097	*0.3318*	*0.3117*	*0.0000*	*0.3236*	*0.3720*	*0.3229*	*0.4677*	*0.3818*	*0.3487*	*0.3654*
UK Credit	0.2314	0.2020	0.1783	0.0857	-0.0283	0.7302	1.0000	0.0091	-0.1748	0.0104	0.0141
	0.2776	*0.3114*	*0.3555*	*0.3131*	*0.2655*	*0.2226*	*0.0000*	*0.2766*	*0.2513*	*0.2348*	*0.2896*
S&P GSCI	-0.1099	0.0846	0.0869	-0.0229	-0.2399	0.0133	0.0091	1.0000	0.4471	-0.1266	0.0020
	0.2985	*0.3122*	*0.3340*	*0.4437*	*0.3296*	*0.2766*	*0.2766*	*0.0000*	*0.2862*	*0.2988*	*0.2714*
Reuters/ Jefferies	-0.2174	-0.1152	-0.1307	-0.2747	-0.0961	-0.0841	-0.1748	0.4471	1.0000	0.2134	-0.0499
	0.2118	0.2593	0.3575	0.4034	0.2907	0.2414	0.2513	0.2862	0.0000	0.4544	0.3120
S&P GSCI Gold	0.1230	-0.0693	-0.0102	0.1124	-0.0139	0.0775	0.0104	-0.1266	0.2134	1.0000	-0.0433
	0.3749	*0.3367*	*0.3787*	*0.4059*	*0.3510*	*0.2695*	*0.2348*	*0.2988*	*0.4544*	*0.0000*	*0.2670*
HFRI Composite	0.2016	0.3160	0.0992	0.1879	0.0442	0.0304	0.0141	0.0020	-0.0499	-0.0433	1.0000
	0.2229	0.2934	0.2852	0.3377	0.3877	0.3366	0.2896	0.2714	0.3120	0.2670	0.0000

Notes: Semicorrelation in up-up markets show (positive semicorrelations) . First value is the mean of the coefficients, the figure underneath of their standard deviation.

Exhibit 9 - Rolling 36 month semicorrelations in down-down markets

Down down	FTSE 100	*MSCI WORLD EX UK*	*FTSE EPRA/NAREIT*	*IPD*	*IPD Unsmoothed*	*UK Gilts*	*UK Credit*	*S&P GSCI*	*Reuters/ Jefferies*	*S&P GSCI Gold*	*HFRI Composite*
FTSE 100	1.0000	0.5497	0.1496	-0.0857	0.0846	0.0077	0.2120	-0.0750	0.1451	-0.1436	0.4465
	0.0000	*0.3157*	*0.3243*	*0.3097*	*0.2889*	*0.3821*	*0.3067*	*0.3378*	*0.4433*	*0.2966*	*0.2900*
MSCI WORLD EX UK	0.5497	1.0000	0.1991	0.0201	0.0596	-0.2155	-0.0849	0.1531	0.1754	-0.0987	0.6165
	0.3157	*0.0000*	*0.3470*	*0.3318*	*0.3745*	*0.3185*	*0.3403*	*0.3551*	*0.4163*	*0.2875*	*0.1931*
FTSE EPRA/NAREIT	0.1496	0.1991	1.0000	0.0857	0.1034	-0.0504	0.0580	0.2548	0.0912	0.2529	0.2285
	0.3243	*0.3470*	*0.0000*	*0.3117*	*0.3641*	*0.2885*	*0.3545*	*0.3261*	*0.3373*	*0.3477*	*0.2803*
IPD	-0.0857	0.0201	0.0857	1.0000	0.1623	0.0302	0.0931	0.0335	0.0127	0.0105	0.0546
	0.3097	*0.3318*	*0.3117*	*0.0000*	*0.3236*	*0.3720*	*0.3229*	*0.4677*	*0.3818*	*0.3487*	*0.3654*
IPD Unsmoothed	0.0846	0.0596	0.1034	0.1623	1.0000	-0.0411	0.0694	-0.0226	-0.0008	0.0693	0.1733
	0.2889	*0.3745*	*0.3641*	*0.3236*	*0.0000*	*0.4409*	*0.3891*	*0.2833*	*0.2440*	*0.4867*	*0.3463*
UK Gilts	0.0077	-0.2155	-0.0504	0.0302	-0.0411	1.0000	0.7688	-0.2730	-0.0022	-0.1220	-0.0997
	0.3821	*0.3185*	*0.2885*	*0.3720*	*0.4409*	*0.0000*	*0.2973*	*0.3603*	*0.3384*	*0.2903*	*0.4027*
UK Credit	0.2120	-0.0849	0.0580	0.0931	0.0694	0.7688	1.0000	-0.1329	0.0325	-0.0848	0.0958
	0.3067	*0.3403*	*0.3545*	*0.3229*	*0.3891*	*0.2973*	*0.0000*	*0.3653*	*0.3343*	*0.4225*	*0.3523*
S&P GSCI	-0.0750	0.1531	0.2548	0.0335	-0.0226	-0.2730	-0.1329	1.0000	0.5300	0.0506	0.0376
	0.3378	*0.3551*	*0.3261*	*0.4677*	*0.2833*	*0.3603*	*0.3653*	*0.0000*	*0.2279*	*0.3258*	*0.3213*
Reuters/ Jefferies	0.1451	0.1754	0.0912	0.0127	-0.0008	-0.0022	0.0325	0.5300	1.0000	-0.1654	0.2750
	0.4433	*0.4163*	*0.3373*	*0.3818*	*0.2440*	*0.3384*	*0.3343*	*0.2279*	*0.0000*	*0.3255*	*0.3440*
S&P GSCI Gold	-0.1436	-0.0987	0.2529	0.0105	0.0693	-0.1220	-0.0848	0.0506	-0.1654	1.0000	-0.0092
	0.2966	*0.2875*	*0.3477*	*0.3487*	*0.4867*	*0.2903*	*0.4225*	*0.3258*	*0.3255*	*0.0000*	*0.3657*
HFRI Composite	0.4465	0.6165	0.2285	0.0546	0.1733	-0.0997	0.0958	0.0376	0.2750	-0.0092	1.0000
	0.2900	*0.1931*	*0.2803*	*0.3654*	*0.3463*	*0.4027*	*0.3523*	*0.3213*	*0.3440*	*0.3657*	*0.0000*

Notes: Semicorrelation in down-down markets show (negative semicorrelations). First value is the mean of the coefficients, the figure underneath of their standard deviation.

Eliminato: ¶

Exhibit 10 - The differences between rolling 36 month semicorrelations in down-down markets and up-up markets

Difference	*FTSE 100*	*MSCI WORLD EX UK*	*FTSE EPRA/NAREIT*	*IPD*	*IPD Unsmoothed*	*UK Gilts*	*UK Credit*	*S&P GSCI*	*Reuters/ Jefferies*	*S&P GSCI Gold*	*HFRI Composite*

FTSE 100	0.0000	0.2050	0.2090	-0.3428	0.0308	-0.2572	-0.0194	0.0349	0.3625	-0.2666	0.2450
MSCI WORLD EX UK	0.2050	0.0000	0.0275	0.0072	0.0058	-0.4623	-0.2869	0.0685	0.2906	-0.0294	0.3005
FTSE EPRA/NAREIT	0.2090	0.0275	0.0000	-0.0443	-0.0523	-0.1843	-0.1203	0.1679	0.2219	0.2631	0.1293
IPD	-0.3428	0.0072	-0.0443	0.0000	-0.3913	-0.0744	0.0074	0.0565	0.2874	-0.1019	-0.1333
IPD Unsmoothed	0.0308	0.0058	-0.0523	-0.3913	0.0000	-0.0707	0.0977	0.2173	0.0954	0.0832	0.1291
UK Gilts	-0.2572	-0.4623	-0.1843	-0.0744	-0.0707	0.0000	0.0386	-0.2863	0.0819	-0.1995	-0.1302
UK Credit	-0.0194	-0.2869	-0.1203	0.0074	0.0977	0.0386	0.0000	-0.1419	0.2073	-0.0952	0.0817
S&P GSCI	0.0349	0.0685	0.1679	0.0565	0.2173	-0.2863	-0.1419	0.0000	0.0830	0.1772	0.0356
Reuters/ Jefferies	0.3625	0.2906	0.2219	0.2874	0.0954	0.0819	0.2073	0.0830	0.0000	-0.3787	0.3249
S&P GSCI Gold	-0.2666	-0.0294	0.2631	-0.1019	0.0832	-0.1995	-0.0952	0.1772	-0.3787	0.0000	0.0341
HFRI Composite	0.2450	0.3005	0.1293	-0.1333	0.1291	-0.1302	0.0817	0.0356	0.3249	0.0341	0.0000

Notes: Semicorrelation differences in mean (means in Exhibit 9 minus those in figure 8).