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Real Estate 'Value' Stocks and International Diversification[+].

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Abstract

In recent years there has been an increased interest in the extent to which managers can improve their property portfolio position through international diversification. Much of this research interest has centred around the use of various statistical/econometric tests of time varying correlations and long run equilibrium positions using whole of country property indices. In this article we effectively adopt a short-run 'tactical asset allocation' approach to securitised property only international diversification. Using neural network methodology we build a neural network model that `learns' well established rules of portfolio investment using a set of individual property companies across three of the most highly securitised property markets in the world viz. the United States, the United Kingdom and Australia. We ask the model to compare portfolios constructed purely from domestic assets with portfolios constructed from internationally held assets allowing for foreign exchange adjustments. When the foreign exchange risk is actively managed the outcomes from the analysis suggest that the gains from hedging are conditional on both the return to the unhedged position and the volatility of the underlying currency being hedged.

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Real Estate 'Value' Stocks and International Diversification.

1. INTRODUCTION

The potential to hold an internationally diversified portfolio of securitised property is a relatively recent phenomenon. Eichholtz and Koedijk (1996) point out that the combined market value of all listed real estate companies in the world was under $20 billion in the mid-1980's. This size was generally considered to be too small to construct a well-diversified international portfolio and be treated seriously by institutional investors. By the mid-1990's the combined market value had risen to about $240 billion and to $350 billion towards the end of the 1990's, making it possible to construct portfolios that were fine-tuned to exposure by region and type of real estate.

Despite the relative youth of this research area, Wilson and Zurbruegg (2003a) in their review of the literature on international diversification, argue that there were two very clear and opposing views on the benefits to be obtained from globalised holdings of property assets. While the majority view held that there are real benefits to be had from international diversification, these authors point to an emerging `school' of thought that is questioning the risk reduction benefits from diverse international holdings of real estate assets. This second 'school' essentially finds that the risk-adjusted returns may not be large, or at least not significantly more than the returns that could be obtained from other financial instruments. With the ever-increasing globalisation of financial markets the issue of diversification benefits tends to be at the forefront of investor's concerns – is it worthwhile holding property assets offshore? Analyses by various researchers such as Gordon, Canter and Webb (1998) and Seiler, Webb and Myer (1999) has indicated that adding real estate to a portfolio of stocks and bonds should improve the risk/return profile. While much has been written on the benefits to be gained from international diversification of real estate in portfolios containing other financial assets, there is much less research into the benefits to be gained from diversifying single asset property holdings across several countries [1]. The present article seeks to further extend our knowledge on this issue and hopefully put one more piece of the puzzle into place. The approach will be to use a neural network model with a non-linear transfer function to adjust portfolio holdings of real estate assets across three countries with the world's most highly developed securitised property markets viz. the US, the UK and Australia. A distinct advantage of this neural network approach is that it is capable of picking heretofore unrecognized non-linear relationships between inputs (factors that determine the portfolio composition) and outputs (the risk adjusted returns to the portfolio). In contrast to Wilson and Zurbruegg (2003b) who adopt a long-run approach, this article effectively adopts a short-run tactical asset allocation approach to securitized property. Essentially we extend the approach of Ellis and Wilson (2005) to an international context. These authors find neural network constructed domestic real estate portfolios outperformed a general securitised property market benchmark captured by both the ASX 300 property market index and a property market index constructed by Datastream International. The remainder of the article is set out as follows: Section 2 briefly reviews and updates the literature on international diversification of real estate assets; section 3 sketches the neural network and Black-Scholes methodologies; section 4 presents the portfolio outcomes while the final section offers some conclusions.

[1] For example Liu and Mei (1998) analyse the possible integration of real estate markets and stock markets across a number of countries. The researchers find there are diversification benefits, but these benefits are primarily driven by unanticipated returns that, in turn, are partially driven by changes in exchange rate risk. They find that from a US investor's viewpoint, investing in international real estate securities provided additional diversification benefits over and above that associated with holding international stocks.

2. LITERATURE REVIEW

(a) International diversification

The extant literature on the question of diversification benefits from international holdings of property can be neatly dichotomized into that associated with direct property and that associated with securitised real estate assets. Since the portfolios constructed in the current article only contain securitised property the literature on direct property will not be reviewed. Ibbotson and Fall (1979), along with Hartzell, Hekmand and Miles (1986), were among the first researchers to examine the issue of diversification in real estate. Their work prompted further inquiry into the potential benefits of international diversification in securitised real estate holdings, with most of this research being supportive of the concept. For instance, in a study on the role of indirect property holdings in a mixed asset portfolio over the 1980-1988 period Asabere, Kleiman and McGowan (1991) demonstrate there are benefits to diversification. These researchers find low positive correlations between US REITs and international real estate equities, suggesting that the addition of international real estate should improve portfolio performance. Hudson-Wilson and Stimpson (1996) examine the inclusion of US securitised real estate assets in Canadian property portfolios over the period 1980-1994. While they find the currency risk component to be substantial their results indicate that Canadian investors would have benefited by the inclusion of US real estate in their portfolios. Addae-Dapaah and Kion (1996) take the viewpoint of a Singaporean investor holding property stocks in seven countries between 1977 and 1992. Conventional mean-variance analysis is used to construct optimum portfolios and these researchers find the potential gain from international diversification to be substantial, finding no significant differences between exchange adjusted and unadjusted performance. However these researchers did warn that temporal instability of correlation coefficients may be cause for concern.

Eichholtz (1996a) undertakes a comparative study on the international diversification benefits of real estate evaluated against stocks and bonds, finding significantly lower cross-country correlations for real estate returns than for either common stock or bond returns, thereby asserting that international diversification improves the efficiency of the real estate portfolio more so than for equity or bonds. Returns in Eichholtz's analysis are in the local-currency, therefore automatically assuming a perfectly hedged currency exposure. In a finding that is highly relevant to the present study Eichholtz shows that, compared with a single-country holding of property securities, an internationally diversified portfolio has higher expected returns at lower risk.

Ling and Naranjo (2002) undertake a broad international investigation that incorporates more than 600 companies across 28 countries over the period 1984 through 1999. These researchers find that property securities may provide international diversification benefits. While the study detects little evidence of abnormal, risk-adjusted returns at the country level, the researchers did find evidence of a strong world wide-factor in international real estate returns. More recently Bond, Karolyi and Sanders (2003), in a study across 14 countries comprising nearly 300 publicly traded real estate companies over the period 1991 to 2001 find that while there are benefits to international diversification of real estate assets, the process is more complex than previously thought. The authors find a regional pattern in country specific risk factors viz. country specific risk is more significant in the Asia-Pacific region than in Europe or North America, a pattern that previous studies have not uncovered.

A smaller group of researchers are less inclined to unequivocally accept the benefits of international diversification. For example Mull and Soenen (1997), using mean-variance analysis find that in exchange adjusted (US dollar) terms, the inclusion of US REITs in mixed asset foreign portfolios does not significantly increase risk-adjusted returns between 1985 and 1994. This is in contrast with the results from Asabere *et al* (1991) over a similar time length, but different time period. In addition Stevenson (2000) examines the potential benefits of international property diversification on both a hedged and unhedged basis, using securitised property data across ten countries from 1978 to 1997. In contrast to the findings of Eichholtz (1996a), Stevenson does not find evidence to support the view that international diversification in real estate stocks provided enhanced benefits in a mixed asset portfolio.

There is also some concern among researchers over both the temporal instability of correlation coefficients as a guide to asset selection, and the degree of market integration - with its obvious implications for diversification. For instance a study by Forbes and Rigobon (2002) shows that conventional cross-correlation coefficients of several markets can be biased upwards during periods of increased volatility in just one market. This implies that portfolios that appeared well diversified when correlations are low may later appear sub-optimal - thereby implying far less diversification benefits than originally anticipated. Property researchers have been aware of this issue for some time. For example, Eichholtz (1996b) points out that the international covariance structure of real estate returns is temporally unstable, implying that Markowitz models used to allocated real estate assets across countries will yield sub-optimal results. In a study on the return distributions of property shares in emerging markets over the period 1973 to 1998, Lu and Mei (1999) find that correlations are higher during times of market volatility (when ideally the opposite is desired) thereby casting some doubt on the benefits from international diversification. More recently Wilson and Zurbruegg (2004) consider whether the 1997 downturn in the Thai property market led to a contagion effect across other Asia-Pacific property markets by examining both conditional and unconditional correlation coefficients. The authors find no contagion effect, implying continuing interdependence across the group of property markets studied.

(b) Neural network models in property analysis

There has been relatively little work done on the application of neural network models in property market research. Those studies undertaken have largely been confined to direct property markets in the context of property appraisals, and there is a moderate literature on this [2]. One of the few pieces of research available on the application of neural network models in securitised property markets is that by Brooks and Tsolacos (2003). In a study on the comparative performance of statistical models and commonly used financial indicators for forecasting securitised real estate returns, these authors suggest that analysts should exploit the potential of neural networks and assess more fully their forecast performance against more traditional models - although the researchers indicate there is limited potential for neural network models in policy analysis. More recently Ellis and Wilson (2005) analyse the performance of portfolios consisting of Australian securitised property companies on both a risk adjusted and unadjusted basis. The outcome of that study indicates neural network selected portfolios are capable of outperforming both a benchmark property index and randomly selected portfolios of property companies.

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[2] Interested readers could see Borst (1991), Tay and Ho (1992), Do and Grudnitski (1992), Worzala, Lenk and Silva (1995), McGreal *et al* (1998), Connellan and James (1998), Wilson *et al* (2002).

3. DATA and METHODOLOGY

(a) Data

Property companies across three countries - the US, the UK and Australia - are used for portfolio construction. The countries chosen are the most highly securitised property markets in the world, and certainly address the issues of market size (for instance, are the markets large enough to absorb substantial amounts of capital?) and liquidity (for instance, can assets be sold quickly when there is a need to do so?) raised by Eichholtz, Op't and Vestbirk (1999). Monthly data over the period January 1990 through February 2004 is used in the present analysis, which is undertaken in both local currency and GBP exchange adjusted terms, with all analysis nominal. In addition output is shown both with no transaction costs, and with round trip transaction costs of 0.5% and 1%.

For consistency all data is taken from the Datastream International real estate indices for each country [3]. In all, there are 101 property companies across the three countries during the study period, comprising 46 for the US, 31 for the UK, and 24 for Australia. For each company in the sample the following data has been obtained: closing price (P), market capitalisation (MV), dividend yield (DY), price-to-cashflow (PC), price-earnings (PE), and price-to-book-value (PTBV). Closing prices and the dividend yield for each company are used to calculate the total return index for each stock as follows:

$$RI_t = RI_{t-1} \times \frac{P_t}{P_{t-1}} \times \left(1 + \frac{DY_t}{100} \times \frac{1}{12}\right) \qquad (1)$$

[3] A Datastream calculated Index, the 'Real Estate' series is based on the FTSE classification and includes the following sub-sectors: Real Estate Development, Property Agencies, and Real Estate Investment Trusts.

where P_t and DY_t are the price and dividend yield at time t respectively, and RI_t is the total return index. This formulation for the total return is identical to that used by Datastream to estimate the Return Index, and adjusts the total return for the monthly frequency used in this article [4]. Total return is then calculated as the log difference of the total return index:

$$R_t = \log RI_t - \log RI_{t-1} \tag{2}$$

(b) US, UK and Australian property markets

The property companies within the US, UK and Australian markets have different characteristics and are subject to different tax regimes. This may act to increase the attractiveness of diversification to the portfolio manager. In the US a real estate investment trust (REIT) is a property company structured under the Rules of the Estate Investment Trust Act of 1960 (cf. Corgel, Ling and Smith (2001)). Provided certain criteria are met a REIT is *not* taxed at company level. To qualify as a tax-free intermediary a REIT must: have at least 75% of its assets invested in real estate, real estate equities, mortgages or government securities; distribute at least 90% of net annual income to shareholders; have at least 75% gross income derived from real estate assets; and not hold property primarily for the purpose of sale. There are also certain restrictions to ensure diversified ownership. Three types of REIT exist viz. Equity, Mortgage and Hybrid. Equity REITs invest in and operate income-producing properties. Mortgage REITs purchase mortgage obligations (thereby becoming real estate lenders), and Hybrid REITs hold both properties and mortgages.

In Australia securitised property companies that trade on the Australian Stock Exchange are known as Listed Property Trusts (LPTs). The Australian LPT sector now represents nearly

[4] Equation (1) in this article differs from the Datastream model for total return only in that the Datastream model is based on a daily frequency and uses 260, rather than 12, in the denominator.

10% of the world's listed real estate assets [5]. LPTs are popular investment vehicles due partly to their ability to access tax concessions such as capital depreciation allowances and to partial deferral of tax associated with the rental income earned by the LPT. The tax-deferred component of the dividend - generally between 15% and 100% of the total dividend - is passed through to investors such that investors do not pay tax on this portion of the dividend until the trust is sold. This reduces the cost base and capital gains are based on the new cost base, which can lead to attractive results net of tax. So, like their REIT counterparts, there are distinct tax advantages associated with Australian LPTs.

Over the study period there was no REIT-like or LPT-like structure in the UK[6]. For securitised property the property company earnings are taxed at source, which can lead to remarkable differences in some areas of behaviour. For example, due to the differences in tax regimes compared with either the US or Australia, UK real estate companies are more likely to borrow money as a tax effective means of raising capital. With higher degrees of leverage the impact from interest rate changes will undoubtedly be more noticeable in the UK market (cf. Stevenson et. al (2005)).

(c) The neural network modelling process

The underlying notion of a neural network (NN) model is to emulate the parallel processing power of the human brain. Ellis and Wilson (2005) outline the basics of a neural network model as follows. Lets suppose there are several input variables x_i, $i = 1, \ldots, n$ each with a corresponding weight w_{ij} attached. These inputs effectively represent signals that a neuron in the human brain might receive from the units to which it is connected, and the weights

[5] This data and the remainder of the paragraph is a summary of the information available at http://www.asx.com.au/investor/

[6] A REIT like structure is now in place in the UK, but the vehicle is outside the study period.

attempt to simulate the synaptic strengths in a natural neuron [7]. The subscript *j* in the weight is the index of a given neuron or processing node.

The weighted signal is passed through a transfer function, *f( )*, that activates the process and produces an output. In the first instance these weights are randomly assigned and in later iterations are adjusted for relative importance. Occasionally there may be an externally applied bias - roughly equivalent to an intercept in a regression model - which has the effect of lowering or increasing the net input. The output that is produced is sometimes called the *potential* or the *net* of the neuron and is given by Giudici (2003) as:

$$P_j = \sum_{i=1}^{n} x_i w_{ij} = net_j \tag{3}$$

The abovementioned transfer function *f( )*, which exists in what is called a *hidden layer* is then applied to net_j to produce the output

$$y_j = f(P_j) = \sum_{i=1}^{n} x_i w_{ij} \tag{4}$$

Within the hidden layer there may be numerous neurons all working on the same problem (i.e. parallel processing). A schematic representation of a typical network architecture is provided by Ellis and Wilson (2005).

Clearly a crucial aspect of the NN modelling process is represented by the transfer function that is applied in Equation (4). While various forms of activation function can be defined, the

[7] The synapse is the locus where a nervous impulse passes from the axon of one neuron to the dendrites of another.

four commonly applied types are linear, log-sigmoidal (logistic), hard limit (also known as stepwise or 'all or nothing') and hyperbolic tangent (tanh). The linear activation function may be expressed as

$$f(P_j) = \alpha + \beta P_j \tag{5}$$

Written in this form there is a clear similarity between a linear transfer function and linear regression. Guidici (2003) points out that a regression model can be seen as a simple type of neural network [8]. A sigmoidal activation function is given by

$$f(P_j) = \frac{1}{1+e^{-\beta P_j}} \tag{6}$$

where β is some positive parameter. A stepwise function is given by

$$f(P_j) = \begin{cases} 1 & if\ P_j \geq 0 \\ 0 & if\ P_j < 0 \end{cases} \tag{7}$$

Finally a hyperbolic tangent transfer (or tanh) function is given by

$$f(P_j) = \frac{e^{P_j} - e^{-P_j}}{e^{P_j} + e^{-P_j}} \tag{8}$$

The sigmoidal and hyperbolic tangent transfer functions are the most widely used as they are non-linear, easily differentiable and not unlike the smooth transition autoregressive processes

[8] In particular a regression model may be viewed as a neural network model without hidden layers and with a linear activation function (cf. Giudici, op.cit. p.114).

developed by Terasvirta (1994). An advantage of using a non-linear as opposed to a linear transfer function is that, since linear independence of the input patterns is not required, a wider range of problems can be tackled (Coakley and Brown, 2000).

In each layer of the NN there will be several neurons with different weights operating on the problem and there may be several layers. If there is more than one layer the output from each layer is passed through to the next layer and subjected to further weighting and activation functions. This is an example of a feedforward multi-layered perceptron. If the output from the final layer fails to meet some acceptable error the whole process re-calculates from the first layer. This is known as backpropagation learning, where 'backpropagation' is simply the technical term given to this error minimization process. Feedforward systems with backpropagation learning provide the basis for over 90% of commercial and industrial applications of artificial neural networks (Kantardzic, 2003) and over 80% of all problems are trained using backpropagation with three layers – input, hidden and output (Yu, 1999).

As in a conventional statistical sense, the error is the difference between the actual (expert) response and the predicted (neural network) response viz

$$e_j(n) = a_j(n) - y_j(n) \tag{9}$$

The j^{th} neuron produces output y_j and this is compared with the actual output, a_j, which is obtained (theoretically) from the same set of n inputs. The error functions normally employed are based on the maximum likelihood principle. If the error meets the desired goal (e.g. a one or five percent error) the final output is produced, if not then there is a closed feedback loop that sends small adjustments back to the weights and the system re-calculates. Iterations continue until either the error criteria are satisfied, or the number of iterations exceeds some pre-set limit.

Every component a_{ij} of the response vector is assumed to be the sum of a deterministic term and an error term. To extract more information the error terms are assumed normally distributed and Giudici (2003) shows that the error function for minimisation can be written as

$$E(w) = \sum_{i=1}^{n} \sum_{j=1}^{q} (a_{ij} - y_{ij})^2 \tag{10}$$

which is minimised using a gradient descent method.

(d) Portfolio construction

As noted earlier the current analysis seeks to extend the work of work of Ellis and Wilson (2005) to an international context and, in doing so, ascertain whether the concerns of Wilson and Zurbruegg (2003a, 2004) regarding the lack of benefit from international diversification is more a long run than a short run issue. The process of portfolio construction is simply one where the neural network model learns to recognize property stocks with certain desirable characteristics. The 'desirable' stocks are then added to the portfolio, while stocks already in the portfolio but failing to retain those same desirable characteristics as the portfolio is rolled forward, are removed. This becomes the neural net portfolio and, once identified, it is evaluated against the benchmark UK market index, as well as against randomly diversified portfolios comprising the same underlying assets from which the neural network portfolios are constructed. Portfolio performance relative to the market index is measured by the

Sharpe ratio (Sharpe, 1966) for risk-adjusted returns, and the Sortino procedure (Sortino and Forsey, 1996; Sortino *et al* 1997) for adjusting returns on a downside risk basis.

The procedure followed here is similar to that followed by Ellis and Wilson (2005). The desirable characteristics are those identified by O'Shaughnessy (1998) as being determinants of 'value', i.e. stocks whose market value is lower than their intrinsic or liquidating value. These characteristics include large stocks with: low Price/Earnings ratios; low Price/Book ratios; low Price/Cashflow ratios; low Price/Sales ratios; and, high Dividend Yields. 'Large' stocks are defined by O'Shaughnessy as those with a higher than average market capitalization. Given the lower volatility of large stocks relative to all stocks, value portfolios comprising large stocks are shown by O'Shaughnessy to typically outperform the market index by a sizeable margin in risk-adjusted terms. As per O'Shaughnessy (1998) and Eakins and Stansell (2003), low ratios are herein defined as those that are lower than the market average ratio and vice-versa.

Based on the characteristics that determine 'value', a set of NN models are developed and tested against the different benchmarks. The output from each model is a binary in that the tested property stock either belongs to the 'value' class (output = 1), or it does not (output = 0) [9]. For each NN model the transfer function was pre-set as a hyperbolic tangent since other research on evaluating the forecast performance of neural network models has shown that this transfer function has faster convergence than other transfer functions (Coakley and Brown, 2000) [10].

9 As well as binary node models, a set of linear node models are also tested. These showed no significant differences. As opposed to the 0/1 output of the binary model, the linear model develops an output set of discrete numbers between zero and one such that the output may represent the 'degree of value'.

10 The software used for the analysis is the Braincel Neural Network software version 3.62. Mr. Gideon Isaac, Technical Support Unit, Promised Land Technologies (Gideon@micro-net.com), confirms that the tanh transfer function is used in both input and hidden layers.

A total of 84 observations for each property company from January 1990 through December 1996 are used to train each neural network model. A further 86 observations for each company (January 1997 through February 2004) are then used to test the neural network output. Observations for all stocks are initially ranked by date. As not all stocks traded for the full length of the test period (1997 - 2004) this avoids problems associated with survivorship bias that may influence our results (cf. Brown *et al*, 1992). In order to avoid the effects of pattern bias during the training phase, observations for each stock are date scrambled using a random number generator. Since each stock is tested against the value criteria on a monthly basis, value stocks in one time period are not necessarily value stocks in the next period, or in subsequent periods. To avoid look-ahead bias associated with making investment decisions based on data which is not yet known, portfolios constructed at time t comprise stocks which are identified by the neural network as being value stocks at time t *-1*.

(e) Risk-adjusted returns

Neural network portfolio performance is analysed on both a nominal and risk-adjusted basis. For comparative purposes both the Sharpe ratio and Sortino downside risk ratio are calculated. The Sharpe ratio is calculated by dividing the risk premium for the portfolio by its standard deviation and measures the risk premium earned per unit of risk exposure:

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma(R_p)} \qquad (11)$$

The Sortino ratio is calculated as the difference between the portfolio return R_p and the minimum acceptable return *MAR*, divided by the downside deviation *DD* of the portfolio return versus the minimum acceptable return DD_{MAR}. Downside deviation is similar to the loss standard deviation with the exception that it (*DD*) only includes portfolio returns below the *MAR*, rather than portfolio returns below the mean. The basis of the Sortino ratio is that investors are more concerned with the risk of loss (downside risk), than the risk of gains (upside risk). Standard deviation as used by the Sharp Ratio considers both upside and downside risk. The Sortino ratio is given by

$$Sortino\ ratio = \frac{R_p - R_{MAR}}{DD_{MAR}} \tag{12}$$

$$DD_{MAR} = \sqrt{\frac{\sum_{i=1}^{N}(L_i)^2}{N}}$$

$$\begin{aligned} &L_i = (R_i - R_{MAR}) \quad if\ (R_i - R_{MAR}) < 0 \\ &\quad or \\ &L_i = 0 \quad if\ (R_i - R_{MAR}) > 0 \end{aligned}$$

The *MAR* for each portfolio is taken as the mean of the monthly 10-year domestic government bond rate for the test period [11].

4. RESULTS

(a) Descriptive statistics

Summary statistics pertaining to monthly returns for the Datastream Australian, US and UK Real Estate Indices and the GBP/AUD and GBP/USD exchange rates are provided in Table 1. The Datastream Australian Real Estate Price Index started the sample period (01/01/1990) at

[11] Source, OECD Main Economic Indicators. UK annual average equals 5.3%; US annual average equals 5.2%; Australian annual average equals 5.9%.

449.37 points and finished on 01/02/2004 at 1109.1 points. The Datastream US Real Estate Price Index started at 484.57 points and finished at 1263.29 points, and the Datastream UK Real Estate Price Index started at 1892.89 points and finished at 2864.05. The mean monthly return to the Australian market index is approximately 1.02%. Mean returns for the US and UK market indices are 0.94% and 0.57% respectively. The GBP/AUD started at 0.4899 GBP per 1 AUD and finished at 0.4175 implying UK investors with a long position in AUD denominated assets would realize an exchange loss of about 0.0724 GBP per 1 AUD invested. The USD likewise depreciated versus the GBP from 0.6202 GBP per 1 USD on 01/01/1990 to 0.5497 for a loss of 0.0705 GBP per 1 USD invested. Depreciation of the AUD and USD against the GBP (appreciation of the GBP) and appreciation of the Australian, US and UK real estate indices is confirmed by the sum of monthly returns which should be equal to zero for a white noise process.

**** insert Table 1 about here ****

Partial autocorrelations, along with autocorrelations, are also calculated up to lag 30 for each series for various lags[12]. The partials and their associated *t*-statistics are also presented in Table 1. Tests for autocorrelation are conducted as one measure of the level of linear dependence in the index and foreign exchange returns series. The results show significant positive autocorrelation for the UK real estate index at lag 10 and lag 20, but no significant autocorrelations beyond lag 1 for the Australian real estate index and the GBP/USD exchange rate. The correlation of monthly index and foreign exchange returns in Table 2 shows significant positive correlation between the indices and the between the GBP/AUD and GBP/USD.

[12] For space conservation reasons the autocorrelations are not shown but are available on request.

**** insert Table 2 about here ****

(b) Neural network value portfolios of real estate stocks

The performance of each of the neural network value portfolios of real estate stocks relative to the Datastream UK Real Estate Index is shown in a series of tables. Table 3 describes the performance of the Australian (AUS) and United States (US) value portfolios of real estate stocks, and Table 4 the performance of United Kingdom (UK) value portfolios. The performance of diversified portfolios of foreign real estate value stocks (i.e. Australian and US value stocks only) and of foreign plus domestic real estate value stocks is described in Table 5. Finally, Table 6 shows mean statistics for 100 randomly constructed portfolios of all Australia, US and UK real estate stocks, plus randomly diversified portfolios thereof. The use of randomly constructed portfolios in this article provides an alternative performance benchmark to the Datastream UK Real Estate Index. Initially, all returns are calculated in GBP and so are inclusive of any foreign exchange gains or losses to UK investors holding AUD and/or USD denominated real estate stocks. By way of example, the effective rate of return to a UK investor from a position in AUD denominated assets is calculated as

$$R_{GBP} = [(1 + R_{AUD}) * (1 + \Delta S_{GBP/AUD})] - 1 \tag{13}$$

where R_{AUD} is the AUD denominated total return, R_{GBP} is the GBP denominated return, and $\Delta S_{AUD/GBP}$ is the change in the spot British Pound/Australian Dollar exchange rate. The effective rate of return to a UK investor from a position in USD denominated assets is similarly calculated by replacing the terms R_{AUD} and $\Delta S_{AUD/GBP}$ in Equation (13) with their USD equivalents. Returns to AUD denominated value portfolios in Tables 1 – 5 are inclusive of a 0.113% GBP mean loss per month. USD denominated portfolios in the tables include a 0.067% GBP mean loss.

Figures in the tables for the number of companies allocated to each of the value portfolios are indicative of the number of individual companies which satisfy the aforementioned value criteria. Expressed as a percentage of the total number of companies in each market over the test period (see section 3 (a) above), the values may be used to gain information on the relationship between value portfolio size and excess return.

*** *insert Table 3 about here* ***

Monthly average (excess) returns for each neural network value portfolio in Table 3 represent the mean of the neural network value portfolio in GBP less the mean return to the Datastream UK Real Estate Index (0.56%) for the period 01/01/1997 – 01/02/2004. Positive values for the neural network value portfolios indicate that the strategy outperformed the market index, and negative values underperformance. Despite the foreign exchange loss to UK investors holding USD denominated assets, all USD denominated value portfolios in Table 3 outperformed the UK market index on a nominal (non-risk adjusted) basis. Except for the MV value portfolio, all other AUD denominated values portfolios underperformed the UK market index. The result is consistent with the lower mean depreciation of the USD versus the GBP and the observed higher maximum monthly gains relative to maximum monthly losses for USD denominated value portfolios and lower maximum monthly gains relative to maximum monthly losses for AUD denominated value portfolios. An analysis of z scores and p-values for the difference between the UK market index and random mean returns in Table 6 to the neural networks value portfolios however reveals that the difference in nominal performance levels for both US and Australian value portfolios is not statistically significant[13].

Cumulative returns for most Australian value portfolios are lower than the cumulative UK index return (47.68%) and the Australian random mean cumulative return from Table 6 of 33.66%. Except for the market capitalisation value portfolio (MV) cumulative returns to all US value portfolios exceed both the cumulative UK index return and the US random cumulative return (96.24%). Cumulative returns in this article are calculated as the sum of monthly portfolio returns and do not include the effects of monthly compound interest. Compound returns - the percentage return to £1 invested at the beginning of the test period and subsequently reinvested at each period's monthly rate of return - are also calculated, and are discussed separately in part (c) of this section.

Risk-adjusted returns in this study are calculated using the Sharpe ratio and the Sortino ratio as outlined above. The (excess) Sharpe and Sortino ratios in the tables are defined as the ratio for the neural network value portfolio less the UK market ratio of 0.9088 and 0.0332 respectively. Risk-adjusted returns to all US and Australian value portfolios are shown to be significantly lower - indicating underperformance - than both the UK market index and the random mean according to the (excess) Sharpe ratio. However (excess) Sortino ratios for all US value portfolios indicate significant levels of over performance when compared to either the UK market index or the random mean, thus confirming the superior performance of USD denominated value portfolios over the UK market index.

[13] Value portfolio z scores and p-values are available from the author's by request.

Results pertaining to the performance of UK neural network value portfolios are presented in Table 4. Values in the table represent the returns available by applying the ‘value’ rule set to UK domestic real estate stocks and as such do not include an exchange rate component.

**** insert Table 4 about here ****

Except the market capitalization portfolio, all of the real estate value portfolios in Table 4 outperformed both the UK market index and the UK mean random portfolio (0.21% average excess return in Table 6), although as per the findings for the Australian and US markets the average excess returns are not significantly different from zero. Consistent also with prior findings, the UK value portfolios significantly underperformed on a risk-adjusted basis when the Sharpe measure is used, yet the majority significantly outperformed the market index when the Sortino measure is used instead. Overall these findings have important implications for how investors and mangers alike interpret risk, specifically whether the potential for higher than expected gains – as per the standard deviation measure – indeed constitutes a ‘risk’.

To this point we have considered the performance of value portfolios in individual markets only. We now consider the diversified portfolios of Australian plus US real estate value stocks (foreign only) and Australian plus US and UK real estate value stocks (foreign plus domestic). The performance of diversified portfolios of foreign real estate value stocks is presented in the upper panel of Table 5, and of foreign plus domestic real estate value stocks in the lower panel of Table 5.

**** insert Table 5 about here ****

**** insert Table 6 about here ****

Although calculated independently of the already presented findings, nominal and risk-adjusted returns for the diversified portfolios in the table correspond closely to the weighted mean of the individual country returns where the weights are the mean number of companies allocated to the respective value portfolios in each country (see Table 3 and Table 4). As such, given the relative underperformance of Australian value portfolios to the UK market index, diversified portfolios including Australian stocks tend to be dragged down by the inclusion. Relative to US value portfolios in Table 3, the risk-adjusted performance of diversified portfolios of Australian and US value assets in Table 5 is significantly lower at the 0.05 level, such is the contribution of underperforming Australian value stocks. However relative to AUD value portfolios, the risk-adjusted performance of diversified portfolios of Australian and US value assets in Table 5 is significantly higher at the 0.05 level owing to the inclusion of overperforming US value stocks. The mean size of the foreign stock diversified value portfolios in Table 5 is 40 stocks, while the foreign plus domestic diversified value portfolios is 52 stocks.

The major implication drawn from this result is that whilst diversification of the international real estate portfolio has reduced the risk - standard and downside deviation – to the UK investor from holding foreign currency denominated stocks by 1% – 2%, risk adjusted returns to the diversified portfolio are only greater if value stocks in *all* markets invested in are performing at similar levels. This general conclusion is supported when we include UK real estate stocks to the existing portfolio to create a diversified portfolio of foreign and domestic value stocks. In line with the relatively high excess returns earned by the GBP denominated price-to-cashflow (PC), price-earnings (PE), and price-to-book-value (PTBV) value portfolios in Table 4, risk-adjusted returns to these portfolios in Table 5 are significantly higher when the UK stocks are included in the diversified portfolio. Likewise the relative underperformance of the UK market capitalization (MV) portfolio in Table 4 means this portfolio suffers significantly lower risk-adjusted returns in Table 5 when UK market capitalization value stocks are included.

The impact of transaction costs on foreign plus domestic diversified value portfolio returns from Table 5 is considered in Table 7 and in Figure 1 for round trip transaction costs of 0.5% and 1.0%. Value portfolios in this article it will be remembered are rebalanced each month during the test period.

**** insert Table 7 about here ****

The deduction of a 0.5% round trip transaction cost in Table 7 reduces diversified portfolio risk-adjusted mean returns by between 0.68% to 0.11% and for a 1.0% round trip transaction cost, risk-adjusted returns are 0.14% to 0.22% lower than in Table 5. Relative to a buy-hold strategy on the UK market index, all diversified value portfolios except the market-capitalisation portfolio continue to outperform the UK market index on a risk-adjusted basis when a 0.5% round trip transaction cost is deducted. When a 1.0% round trip transaction cost is deducted, only the price-to-cashflow diversified value portfolio outperforms the UK market index on a risk-adjusted basis. The break-even round trip transaction cost is calculated to be approximately 0.79%.

Figure 1 plots the return to an initial £1 invested in a diversified value portfolio of Australian, US and UK real estate stocks, the mean monthly return for which is equal to the average of the five diversified value portfolio (MV, DY, PC, PE and PTBV) mean monthly returns in Table 5.

**** insert Figure 1 about here ****

For round trip transaction costs of 0.5% the end-of-period value for the diversified portfolio is £1.70 and for costs of 1.0% is £1.38. A buy-hold strategy in the UK market index returns £1.44 and £1.45 given round trip transaction costs of 0.5% and 1.0% respectively.

(c) Hedging foreign exchange exposure

UK investors with open positions in foreign currency denominated assets face two questions viz: what is the contribution of exchange gains or losses to overall portfolio performance?; and should the underlying exchange rate risk be actively managed? Appreciation of the foreign currency (AUD or USD in the present case) will increase the domestic currency value of foreign currency denominated assets, and depreciation will decrease the value of foreign currency denominated assets. As previously discussed, results presented in Table 3 and Table 5 include both a property stock gain (loss) component and an exchange rate gain (loss) component, i.e. the effective rate of return to a UK investor. To consider the impact of currency variability on portfolio returns in Table 3, Table 8 provides comparative returns for the cases where: (i) the GBP/AUD and GBP/USD exchange rates are fixed; and (ii) the exchange risk is fully, but costlessly hedged.

**** insert Table 8 about here ****

The fixed exchange rate scenario in the upper panel of Table 8 assumes that the GBP/AUD and GBP/USD exchange rates are at par for the entire test period such that the change in the exchange rate in Equation (5) above is zero. Compared to diversified portfolios of Australian, US and UK real estate value stocks in the lower panel of Table 5, nominal, cumulative and risk-adjusted returns to all portfolios in Table 8 are higher when the GBP/AUD and GBP/USD exchange rates are assumed to be fixed. Furthermore the analysis of z scores and p-values for the difference between the risk-adjusted returns in Table 5 and Table 8 shows that the exchange rate effect (appreciation of the GBP versus both the AUD and USD) is significant at the 0.05 level for all portfolios. Given the degree of exchange losses on the foreign currency denominated component of the diversified portfolio, it would seem obvious that a UK investor would be better off hedging their exchange rate exposure than not.

It will be recalled from prior discussion that neural networks value portfolios purchased at time *t* use all available information up to the previous period, *t-1*. The recognition of look-ahead bias however requires that the investor bears the risk of depreciation of the foreign currency between *t* and *t-1*, which will result in exchange rate losses. To manage exchange rate risk between time *t-1* and *t* the hedge in the lower panel of Table 8 is constructed along the following lines: at time *t-1* the investor purchases a GBP/AUD (GBP/USD) foreign exchange put option with an exercise value equal to the then current spot exchange rate. The option maturity is the next period, time *t*. If the AUD (USD) depreciates between time *t-1* and *t*, the option is exercised and the portfolio effective rate of return is calculated on the change in the GBP/AUD (GBP/USD) to time *t-1*. Else if the AUD (USD) appreciates between time *t-1* and *t* then the put expires worthless and the portfolio effective rate of return is calculated on the change in the AUD/GBP to time *t*. This calculation of the effective rate of return replicates the payoff achieved by selling the AUD (USD) at the higher GBP rate when exercising the put option. The hedge strategy is similar to that employed by Ziobrowski and Ziobrowski (1993) in research into the benefits to US investors of hedging long-term positions in British Pound and Japanese Yen denominated real estate stocks with foreign exchange options, with the exception that the foreign exchange option premium is assumed - as least initially - to be zero.

Under the initial assumption that the above described hedge is costless, results for the *Costless hedging* real estate value portfolios in Table 8 show a significant degree of outperformance relative not only to the UK market index, but to all other portfolios with mean excess returns as high as 1.57% per month and cumulative returns over all 86 months as high as 180.83%. Relative to mean monthly excess returns presented in Table 5, the additional mean excess return of approximately 1.03% to 1.11% per month implies a potentially substantial benefit from hedging foreign exchange risk.

Under the assumption of costless hedging with currency options, fully hedged returns in Table 8 have already been shown to be significantly greater than their unhedged values. To determine the impact of the cost of the option premium on portfolio returns, Figure 2 plots the return to an initial £1 investment, reinvested each period for Australian, US and UK real estate value portfolios, and for the UK market given the cases where: (a) the exchange rate risk is unhedged; (b) the exchange risk is fixed; (c) the exchange risk is costlessly hedged; and (d) the real cost of the option premium is deducted from each period's reinvested value [14]. Unhedged portfolio returns in Figure 2(a) correspond to the mean of the individual value portfolio returns presented in Table 3 for the Australian and US markets, and to Table 4 for

[14] The *Hedged (Net)* beginning period value for Australian value portfolios is £0.9452 and for the US £0.9766. these amounts are calculated as the £1 initial investment less the initial option premium expressed in GBP.

the UK market. Fixed exchange rate and costlessly hedged portfolio returns in Figure 2(b) and Figure 2(c) respectively are calculated as the mean return to all portfolios of Australian, US and UK real estate value stocks.

**** insert Figure 2 about here ****

Real option premiums each period are calculated using the Garman and Kohlhagen (1983) modified Black-Scholes model for valuing foreign currency options:

$$P = Xe^{-rt}N(-d_2) - Se^{-rft}N(-d_1)$$

$$d_1 = \frac{\ln\left(\frac{S}{X}\right) + \left(r - r_f + \frac{1}{2}\sigma^2\right)t}{\sigma\sqrt{t}} \qquad (14)$$

$$d_2 = d_1 - \sigma\sqrt{t}$$

where P is the put option premium, $S = X$ are the spot GBP/AUD exchange rate at time t-1 and option exercise respectively, r is the mean of the monthly UK 10-year Commonwealth bond rate for the period, r_f is the mean of the monthly Australian 10-year Commonwealth bond rate (US 10-year Treasury bond rate), and σ is the annualized standard deviation of GBP/AUD (GBP/USD) monthly returns from January 1990 to December 1996. The average and total option premium paid over the test period is 0.0351AUD and 3.0168AUD respectively for GBP/AUD put options, and 0.0139USD and 1.1938USD respectively for GBP/USD puts.

Consistent with mean excess returns in Table 3 and Table 4, the mean return to £1 invested in Australian value portfolios is less than that earned by investment in the UK market index, and for US and UK value portfolios is greater than the market return on £1 invested when the foreign exchange risk is unhedged (Figure 2(a)). When the GBP/AUD and GBP/USD exchange rates are fixed (Figure 2(b)), all the value portfolios however return more than the UK market index. This latter result is again consistent with the devaluing effect of GBP appreciation on the return to UK investors from foreign investments. Also as per results presented in Table 8, end-of-period values to both the Australian and US value portfolios are significantly greater than either of those for the UK value portfolio or the UK market index, the returns to both of which of course remain unchanged by varying assumptions about the foreign exchange rate.

As is expected from results for the costlessly hedged portfolios in Table 8, end-of-period values for Australian and US value portfolios are greatest in Figure 2(c). When UK investors can hedge the underlying exchange exposure at zero cost by selling the underlying currency at the higher of S_{t-1} or S_t, the exchange component in Equation (13) is maximised. On a compound basis the additional mean excess return of approximately 1.03% to 1.11% per month earned by costless hedging adds £6.33 to the Australian unhedged end-of-period value and £4.77 to the US unhedged end-of-period value in Figure 2(a).

A different picture emerges however when the actual cost of hedging is considered. As illustrated by Figure 2(d) Australian hedged net returns are negative when each month's option premium is subtracted from the value portfolio return. This result can be seen to be due to the cumulative impact of the premium on the future value of reinvested returns. Despite the fact that the Australian hedged gross end-of-period value in Figure 2(c) minus the total premium paid exceeds the unhedged end-of-period value in Figure 2(a) and the UK market index end-of-period value, the subtraction of a premium each period reduces the value reinvested in the next period. This effect is cumulative over time resulting in much lower future values (compound returns) for the portfolio. The finding is consistent with those of Ziobrowski and Ziobrowski (1993) for US investors and confirms for the GBP/AUD exchange rate at least the incapacity of long-term hedged positions to return a yield in excess of the compound value of the option premium. The result may not preclude however the viability of a short-term hedge strategy where, for instance a derivatives position is taken only when there is a forecast likelihood of foreign currency depreciation every period.

Contrary to Ziobrowski and Ziobrowski (1993) however the US hedged net end-of-period value in Figure 2(d) exceeds both the unhedged and fixed exchange rate end-of-period values. At first surprising, we find this result to be due to a number of contributing factors: the relatively lower standard deviation of the GBP/USD exchange rate; the resulting lower GBP/USD option premiums; the smaller depreciation of the USD against the GBP relative to the AUD; and the higher mean return to US value portfolios. Taken together these individual impacts enable UK investors to earn a hedged return from US value portfolios that more than compensates for the cost of hedge. As such we find that our original conclusion, and that of Ziobrowski and Ziobrowski (1993) with respect to long-term hedged positions is not absolute, but rather is conditional on such key factors as those we have identified as contributing to the cost of hedging versus the hedged return.

5. CONCLUSIONS

This article has set out to ascertain whether the non-linear, parallel processing power of a neural network is capable of producing property portfolios that would outperform the UK property market on a regular basis with short horizon (monthly) asset re-allocations. We ask the model to compare portfolios from a single domestic market to diversified portfolios of foreign assets only and domestic and foreign assets. A number of interesting conclusions arise from our analysis. First we note that the use of a neural network model is capable of beating the general UK property market index as well as randomly selected portfolios using select criteria on a risk adjusted basis, although the primary source of the outperformance is the foreign exchange component.

Perhaps the crucial findings in the article are those pertaining to the potential benefits of international diversification and the long-term benefits of hedging foreign exchange fluctuations. With respect to international diversification we find that, while this may in fact reduce the overall risk of a portfolio, risk adjusted returns are maximized only if stocks are performing at similar levels in all markets. When faced with the added foreign exchange risk investors may, in fact, be no worse off by holding a well diversified portfolio of domestic value stocks. In broad agreement with the findings of Ziobrowski and Ziobrowski (1993) we find no long-term benefit to UK investors through hedging exposure to fluctuations in the GBP/AUD exchange rate owing to the continuous impact of the premium on compounded returns. Contrary to Ziobrowski and Ziobrowski we do find, however, that UK investors can successfully use a long-term hedge strategy to manage the risk of USD denominated value stocks. A number of key factors are identified in support of our finding.

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Table 1.
Summary statistics of index and foreign exchange monthly returns 1990 - 2004.

	AUS	*US*	*UK*	*GBP/AUD*	*GBP/USD*
Mean	0.0102	0.0094	0.0057	-0.0003	-0.0003
lower 98%	0.0037	0.0003	-0.0040	-0.0070	-0.0055
upper 98%	0.0166	0.0185	0.0155	0.0064	0.0048
Standard Deviation	0.0357	0.0504	0.0540	0.0371	0.0284
Skewness	0.0703	-0.4546	-0.3430	0.3615	1.5696
Kurtosis	0.1130	1.6256	0.1259	1.0109	6.7597
Minimum	-0.0852	-0.1769	-0.1500	-0.0885	-0.0577
Maximum	0.1219	0.1462	0.1480	0.1449	0.1500
Sum	1.7221	1.5873	0.9677	-0.0452	-0.0545
Partial ACF					
lag 1	-0.223	0.134	0.123	-0.052	0.159
t-statistic	2.898†	1.737	1.593	0.672	2.063†
lag 2	0.096	0.075	0.066	-0.133	-0.151
t-statistic	1.250	0.976	0.854	1.723	1.957
lag 5	0.019	-0.042	0.033	0.005	-0.059
t-statistic	0.249	0.548	0.430	0.062	0.761
lag 10	-0.005	-0.120	-0.183	-0.098	-0.109
t-statistic	0.060	1.563	2.373†	1.268	1.417
lag 20	0.031	-0.098	-0.167	0.020	-0.026
t-statistic	0.404	1.274	2.172†	0.254	0.337
lag 30	0.055	-0.072	0.002	0.030	0.017
t-statistic	0.716	0.932	0.026	0.389	0.223

† *significant at the 0.05 level*

Table 2.
Correlation of monthly index and foreign exchange returns 1990 - 2004.

	AUS	*US*	*GBP/AUD*
US	0.252		
p-value	0.001		
UK	0.281	0.369	
p-value	0.000	0.000	
GBP/USD			0.642
p-value			0.000

Table 3.
AUS and US value portfolios versus the UK real estate index 1997 - 2004.

	UK Index	*MV*	*DY*	*PC*	*PE*	*PTBV*
				AUS		
Average (excess) return	0.56%	0.03%	-0.12%	-0.02%	-0.13%	-0.20%
Companies allocated to NN:						
Mean		23.8%	57.1%	61.9%	71.4%	76.2%
Max		33.3%	85.7%	85.7%	90.5%	90.5%
Min		19.0%	33.3%	33.3%	47.6%	57.1%
Std dev of returns	0.0485	0.0567	0.0478	0.0463	0.0465	0.0460
Down dev of returns	0.0362	0.0407	0.0357	0.0347	0.0354	0.0351
Max monthly gain	13.40%	15.52%	12.38%	11.55%	10.36%	11.06%
Max monthly loss	-11.95%	-16.01%	-12.65%	-12.67%	-13.00%	-11.18%
Cumulative return	47.68%	50.61%	37.53%	46.08%	36.59%	30.87%
(excess) Sharpe ratio	0.9088	-0.8817†*	-0.9089†	-0.8872†*	-0.9113†	-0.9259†
(excess) Sortino ratio	0.0332	0.0048†*	-0.0330†	-0.0040†*	-0.0361†	-0.0553†
				US		
Average (excess) return	0.56%	0.33%	0.72%	0.66%	0.62%	0.58%
Companies allocated to NN:						
Mean		33.3%	47.6%	61.9%	76.2%	64.3%
Max		40.5%	71.4%	92.9%	92.9%	83.3%
Min		21.4%	23.8%	26.2%	50.0%	47.6%
Std dev of returns	0.0485	0.0420	0.0395	0.0404	0.0390	0.0387
Down dev of returns	0.0359	0.0281	0.0242	0.0260	0.0242	0.0242
Max monthly gain	13.40%	11.72%	12.57%	12.75%	13.17%	12.59%
Max monthly loss	-11.95%	-10.43%	-9.18%	-9.71%	-9.18%	-9.26%
Cumulative return	47.68%	75.82%	108.90%	103.87%	100.32%	97.33%
(excess) Sharpe ratio	0.9088	-0.8016†*	-0.6964†*	-0.7156†*	-0.7194†*	-0.7271†
(excess) Sortino ratio	0.0332	0.1270†*	0.3134†*	0.2669†*	0.2723†*	0.2569†*

† indicates significantly different to the UK market index at the 0.05 level
* indicates significantly different to the random mean at the 0.05 level

Table 4.
UK value portfolios versus the UK real estate index 1997 - 2004.

	UK Index	*MV*	*DY*	*PC*	*PE*	*PTBV*
Average (excess) return	0.56%	-0.49%	0.31%	0.51%	0.36%	0.79%
Companies allocated to NN:						
Mean		23.3%	43.3%	66.7%	70.0%	63.3%
Max		30.0%	56.7%	86.7%	83.3%	86.7%
Min		20.0%	30.0%	40.0%	40.0%	23.3%
Std dev of returns	0.0485	0.0541	0.0466	0.0456	0.0448	0.0455
Down dev of returns	0.0359	0.0431	0.0345	0.0329	0.0331	0.0310
Max monthly gain	13.40%	12.72%	10.63%	11.32%	10.10%	13.98%
Max monthly loss	-11.95%	-15.36%	-15.67%	-11.14%	-12.06%	-10.34%
Cumulative return	47.68%	5.98%	74.15%	91.09%	78.36%	114.74%
(excess) Sharpe ratio	0.9088	-0.9774†*	-0.8165†*	-0.7707†*	-0.8016†*	-0.7090†*
(excess) Sortino ratio	0.0332	-0.1193†*	0.0918†*	0.1581†*	0.1119†*	0.2597†*

† indicates significantly different to the UK market index at the 0.05 level
* indicates significantly different to the random mean at the 0.05 level

Table 5.
Diversified portfolios of AUS, US and UK values assets versus the UK real estate index 1997 - 2004.

	UK Index	*MV*	*DY*	*PC*	*PE*	*PTBV*
				AUS + US		
Average (excess) return	0.56%	0.22%	0.45%	0.48%	0.36%	0.29%
Companies allocated to NN:						
Mean		30.2%	50.8%	61.9%	74.6%	68.3%
Max		38.1%	68.3%	87.3%	90.5%	81.0%
Min		20.6%	33.3%	34.9%	50.8%	52.4%
Std dev of returns	0.0485	0.0391	0.0351	0.0376	0.0348	0.0347
Down dev of returns	0.0359	0.0278	0.0240	0.0257	0.0240	0.0242
Max monthly gain	13.40%	10.10%	7.90%	9.27%	8.49%	7.83%
Max monthly loss	-11.95%	-11.00%	-9.86%	-10.79%	-9.65%	-9.93%
Cumulative return	47.68%	66.56%	86.27%	88.22%	78.58%	72.18%
(excess) Sharpe ratio	0.9088	-0.8215†*	-0.7456†*	-0.7502†*	-0.7700†*	-0.7915†
(excess) Sortino ratio	0.0332	0.0897†*	0.2061†*	0.1986†*	0.1680†*	0.1351†*
				AUS + US + UK		
Average (excess) return	0.56%	0.06%	0.45%	0.54%	0.38%	0.44%
Companies allocated to NN:						
Mean		25.7%	44.6%	59.4%	66.3%	61.4%
Max		30.7%	57.4%	78.2%	81.2%	73.3%
Min		17.8%	35.6%	38.6%	52.5%	42.6%
Std dev of returns	0.0485	0.0366	0.0334	0.0345	0.0334	0.0331
Down dev of returns	0.0359	0.0266	0.0233	0.0235	0.0235	0.0231
Max monthly gain	13.40%	8.98%	6.58%	7.61%	7.07%	7.90%
Max monthly loss	-11.95%	-8.72%	-9.89%	-10.20%	-9.60%	-10.06%
Cumulative return	47.68%	52.75%	85.58%	93.95%	80.21%	84.82%
(excess) Sharpe ratio	0.9088	-0.8600†*	-0.7397†*	-0.7164†*	-0.7585†*	-0.7406†*
(excess) Sortino ratio	0.0332	0.0341†*	0.2096†*	0.2491†*	0.1807†*	0.2072†*

† indicates significantly different to the UK market index at the 0.05 level
* indicates significantly different to the random mean at the 0.05 level

Table 6.
Randomly diversified portfolios of all AUS, US and UK assets 1997 - 2004.

	UK Index	*AUS*	*US*	*UK*	*AUS + US*	*AUS + US + UK*
Average (excess) return	0.56%	-0.16%	0.57%	0.21%	0.33%	0.30%
Companies allocated to NN:						
Mean		44.5%	46.7%	47.1%	46.0%	46.4%
Max		74.0%	66.7%	70.7%	63.4%	61.2%
Min		18.9%	27.6%	26.2%	28.8%	32.5%
Std dev of returns	0.0485	0.0486	0.0394	0.0488	0.0358	0.0344
Down dev of returns	0.0359	0.0366	0.0250	0.0367	0.0250	0.0249
Max monthly gain	13.40%	12.25%	12.29%	12.47%	8.22%	7.59%
Max monthly loss	-11.95%	-12.97%	-9.44%	-14.23%	-10.16%	-10.49%
Cumulative return	47.68%	33.66%	96.24%	65.88%	75.39%	73.06%
(excess) Sharpe ratio	0.9088	-0.9184	-0.7336	-0.8400	-0.7845	-0.7874
(excess) Sortino ratio	0.0332	-0.0452	0.2444	0.0604	0.1460	0.1355

Table 7.
Diversified portfolios of AUS, US and UK values assets versus UK market index: *Impact of transaction costs 1997 - 2004.*

	UK Index	*MV*	*DY*	*PC*	*PE*	*PTBV*
		0.5% round trip				
Average (excess) return	0.56%	-0.18%	0.20%	0.30%	0.14%	0.19%
Std dev of returns	0.0484	0.0366	0.0334	0.0345	0.0334	0.0331
Down dev of returns	0.0359	0.0279	0.0244	0.0247	0.0247	0.0243
Max monthly gain	13.40%	8.73%	6.33%	7.36%	6.82%	7.65%
Max monthly loss	-11.95%	-8.97%	-10.14%	-10.46%	-9.85%	-10.32%
Cumulative return	47.18%	31.48%	64.30%	72.67%	58.94%	63.54%
(excess) Sharpe ratio	0.9088	-0.9283†*	-0.8146†*	-0.7890†	-0.8334†*	-0.8163†*
(excess) Sortino ratio	0.0315	-0.0571†*	0.0972†*	0.1359†	0.0705†*	0.0942†*
		1% round trip				
Average (excess) return	0.55%	-0.43%	-0.04%	0.05%	-0.11%	-0.05%
Std dev of returns	0.0484	0.0366	0.0334	0.0345	0.0334	0.0331
Down dev of returns	0.0360	0.0292	0.0257	0.0259	0.0259	0.0256
Max monthly gain	13.40%	8.48%	6.08%	7.11%	6.57%	7.40%
Max monthly loss	-11.95%	-9.22%	-10.39%	-10.71%	-10.10%	-10.57%
Cumulative return	46.68%	10.15%	42.97%	51.34%	37.61%	42.21%
(excess) Sharpe ratio	0.9088	-0.9968†*	-0.8897†*	-0.8617†*	-0.9086†*	-0.8922†*
(excess) Sortino ratio	0.0299	-0.1402†*	-0.0050*	0.0328†*	-0.0290†*	-0.0084†*

† indicates significantly different to the UK market index at the 0.05 level
* indicates significantly different to the random mean at the 0.05 level

Table 8.
Diversified portfolios of AUS, US and UK values assets versus UK market index: Impact of the exchange rate 1997 - 2004.

	MV	*DY*	*PC*	*PE*	*PTBV*
	Fixed exchange rate				
Average (excess) return	0.08%	0.46%	0.57%	0.44%	0.51%
Std dev of returns	0.0308	0.0261	0.0276	0.0265	0.0255
Down dev of returns	0.0211	0.0169	0.0174	0.0171	0.0162
Max monthly gain	9.13%	6.47%	6.81%	6.67%	7.85%
Max monthly loss	-6.51%	-7.13%	-7.33%	-6.85%	-7.26%
Cumulative return	54.61%	87.03%	96.15%	85.08%	91.01%
(excess) Sharpe ratio	-0.8437	-0.6859	-0.6588	-0.6975	-0.6624
(excess) Sortino ratio	0.0621	0.3107	0.3625	0.2942	0.3553
	Costless hedging				
Average (excess) return	1.14%	1.55%	1.57%	1.45%	1.55%
Std dev of returns	0.0344	0.0307	0.0319	0.0304	0.0299
Down dev of returns	0.0193	0.0163	0.0169	0.0163	0.0158
Max monthly gain	10.11%	7.16%	8.11%	7.32%	7.90%
Max monthly loss	-8.16%	-6.44%	-6.78%	-6.12%	-6.87%
Cumulative return	144.68%	179.25%	180.83%	171.14%	179.03%
(excess) Sharpe ratio	-0.5424	-0.3652	-0.3812	-0.3924	-0.3521
(excess) Sortino ratio	0.6199	0.9889	0.9627	0.9321	1.0225

Figure 1.
Nominal return from £1 invested less transaction costs 1997 - 2004.

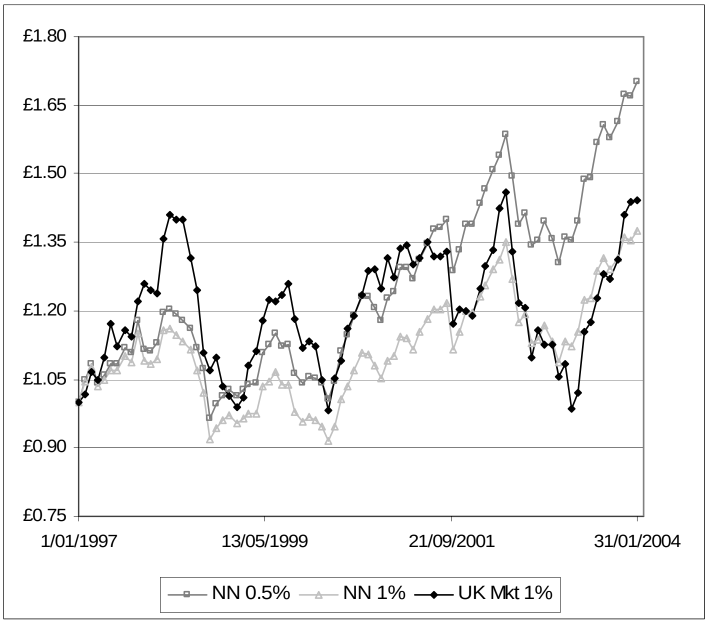
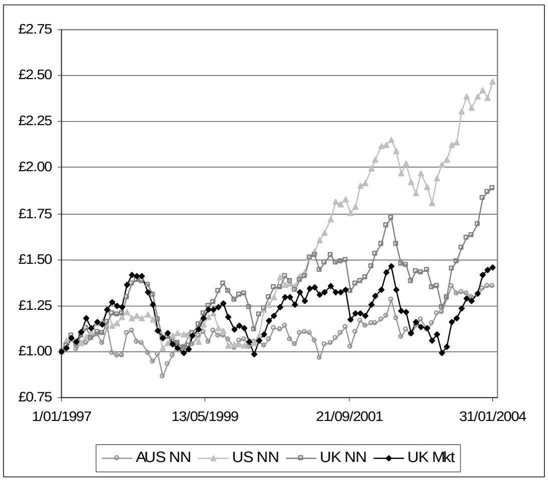
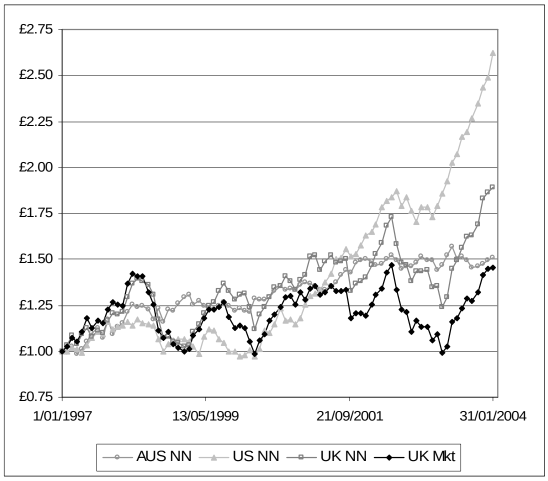


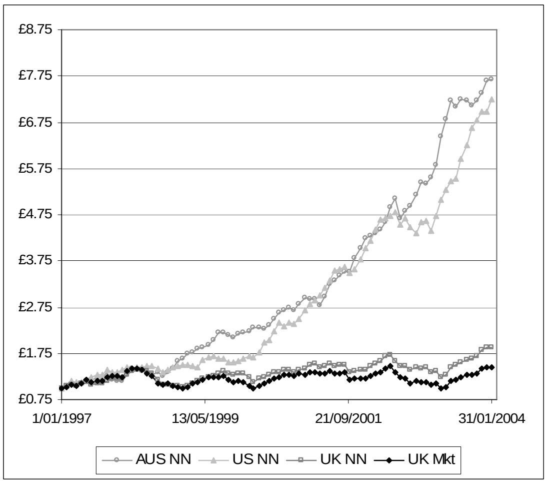
Figure 2.
Return from £1 invested 1997 - 2004.



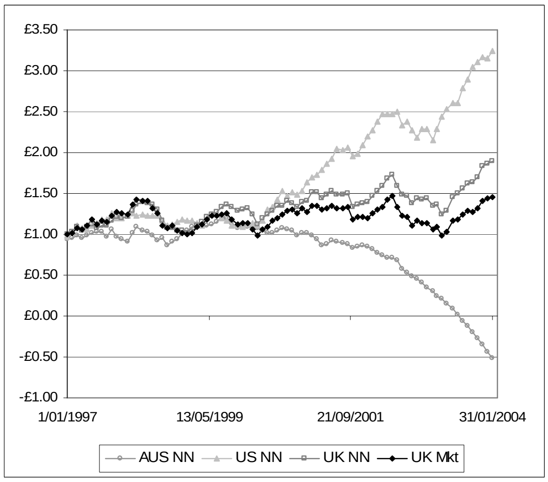
(a) Nominal GBP



(b) Fixed exchange rate



(c) Hedged (Gross)



(d) Hedged (Net)