Forecasting Hedge Fund Index Returns by Level and Classification: A Comparative Analysis of RBF Neural Network Topologies

By

Gordon H. Dash, Jr. *
Associate Professor of Finance and Insurance

Nina Kajiji **
Assistant Professor of Research, Education

Initial Printing: 31-MAR-03 (pre-release version for CBA presentation on Friday, 4-APR-03)
Second Printing: 25-Apr-03

JEL CATEGORY

C22 ECONOMETRIC METHODS: Time Series Models
C45 ECONOMETRIC AND STATISTICAL METHODS; Neural Networks
C53 ECONOMETRIC MODELING; Forecasting

Keywords: Neural Networks, radial basis function neural networks, alternative investments, hedge funds, return predictability

---

Submitted for presentation consideration at the 10th Annual International Conference on Forecasting Financial Markets, Paris, 4-6 June, 2003.
Please address all correspondence to: *Gordon H. Dash, Jr., The NKD Group, Inc., 777 Smith Street, Providence, RI, 02908. Fax: (401) 874 4312; Email: GHDash@nkd-group.com

**National Center on Public Education & Social Policy, University of Rhode Island, 80 Washington Street, Providence, RI 02903

© 2003 By Gordon H. Dash, Jr. and Nina Kajiji. All rights reserved. Explicit permission to quote is required for text quotes beyond two paragraphs. In all cases, full credit, including © notice is required.

The authors wish to acknowledge a research grant provided by The NKD Group, Inc. of Wilmington, Delaware; a financial engineering software company.

Abstract

Over the recent past, stylized facts have not yielded a synthesis regarding the predictability of returns for alternative investment assets such as hedge funds. Recent studies on alternative asset return predictability have added to the ambiguity. These studies suggest that classification prediction methods may dominate more traditional return-level prediction methodology. This paper examines the predictive accuracy of three alternate radial basis function neural networks when applied to the returns of thirteen Credit Swiss First Boston/Tremont (CSFB) hedge fund indices. We provide evidence that the Kajiji-4 RBF neural network dominates within the RBF topology in the modeling and prediction of hedge fund returns by both level and classification. The results also show that the Kajiji-4 method is capable of near perfect directional prediction.

Forecasting Hedge Fund Index Returns by Level and Classification: A Comparative Analysis of Neural Network Topologies

I. Introduction

Whether the investor's objective is to trade direction or maximize trading returns in a particular market, an optimal trading rule is necessary if the investor is to form an expectation of the future return. Recent comparisons of alternative return prediction methodologies offer a mixed view as to the comparative accuracy of classification methods versus return-level prediction approaches. Unlike return-level forecasts that attempt to predict a future return level, classification-based methods focus on the direction of the expected movement. However, the value of future return predictions depends solely upon the efficacy of the forecasting method. The determination of which prediction methodology is preferred has been subjected to a meaningful debate. So far, this debate has yielded support for methods that predict return levels of associated capital market instruments.

In a recent study on the predictability of three international capital market indices, Leung, et. al. (2000) present findings that challenge the contemporary view supporting the dominance of return-level prediction over classification prediction methods. Leung reported that classification-based prediction dominates return-level methods in the number of times a predicted observation was consistent with its actual outcome. Additionally, a threshold trading rule simulation found greater wealth creation from trading activity to be associated with a classification based approach. The probabilistic classification methods examined by Leung included linear discriminant analysis, logit- and probit-modeling along with a probabilistic neural network (PNN). The return-level forecasting methods were exponential smoothing, multivariate transfer function (ARIMA), vector autoregression with Kalman filter, and multilayered feedforward neural network (MLFN). In a comparison of predictive strength, Leung concludes that the artificial neural network architecture (MLFN) achieved superior within class performance.

If, as these findings report, that classification methods dominate traditional return-level forecasting strategies this would certainly provide an interesting challenge to some of the earliest

and most influential findings on predicting asset class returns as observed in the U.S. and international markets [see, for example, Keim and Stambaugh (1986), Campbell and Shiller (1989), Fama and French (1989), Ferson and Harvey (1991), Barberis (2000), Harasty and Roulet (2000), and Lynch (2000)]. We note, however, that the Leung analysis is based upon a software product (ThinkPro computer package) for which there is no active Internet site nor any other published academic evaluations. The absence of a comparative reference does not permit a certification of the modeling software nor does it help to position the efficiency of the ThinkPro computer package against more recognized ANN applications. Balci (2001) provides for an analytical framework for certifying modeling and simulating software applications. Other contemporary issues related to software compactness are described in Debray, et al (2000), Fraser and Wendt (1986), Hanson (1983), Lindvall, et.al (2003), Dyba (2000), Sheldon and Greiner (1999), and Mayrand, et.al (2000).

The purpose of this study is twofold. First, it is to reexamine and reconcile the findings on alternative hedge fund returns prediction provided by Leung on the one hand and Amenc, et. al. (2002) on the other. Second, it is to extend the modeling and forecasting of hedge fund indexes by applying the Kajiji-4 RBF ANN to the Credit Swiss First Boston/Tremont (CSFB/T) family of hedge fund index returns. The nonparametric Kajiji-4 RBF ANN algorithm has proven to be an efficient and dominant algorithmic tool when compared against the GARCH framework and a broad range of alternative ANN topologies. For example, in a direct comparison to both the generalized regression and backpropagation ANN algorithmic structures, Dash et. al. (2003) demonstrate the method's dominance when modeling high frequency volatility. Elsewhere, Dash and Kajiji (2002) provide additional evidence of algorithmic dominance in a comparison of the Kajiji-4 method against well-known RBF ANNs in an application of 1-hour FX volatility.

The paper proceeds as follows. In section 2 we present a discussion of the multivariate statistical method used to uncover and update existing findings regarding the predictability of hedge fund returns. Section 3 of the paper identifies the comparative RBF topologies that are tested for efficient prediction of the hedge fund returns. Results of the modeling experiment are presented in section 5. Section 6 presents the one-period ahead monthly forecast for each of the hedge fund indexes. Section 7 provides a summary and conclusion.

2. The Structure of Hedge Fund Returns

Exposition guidelines lead us to center the analysis on two of the thirteen hedge funds within the CSFB/T group. Throughout the paper we refer to the Dedicated Short Bias fund and the Equity Market Neutral fund as the focus indices. They are chosen for this role based on the level of their relative volatility (coefficient of variation). For the time period of this study, the Dedicated Short Bias is the most volatile of the indexes and the Equity Market Neutral index is the least volatile within the group.

2.1 Data

The data for this analysis consists of 108 monthly return observations from January 1994 to December 2002 on the group of hedge fund indexes published by CSFB/T. The 13 CSFB/T hedge fund indices range from a high volatility style (Dedicated Short Bias) to a much lower volatility style (Equity Market Neutral). Detailed descriptive characteristics of the fund indexes are reported in Amenc (2002). Performance characteristics on the CSFB/T indexes are provided by Lhabitant (July 2002). Because one of our objectives here is to model returns by tactical style for the purpose of obtaining accurate predictions, we augment the previously presented statistical findings on returns symmetry. The added information is necessary to fully achieve our objective, which is to compare performance differences among the alternative RBF topologies on a small monthly returns database.

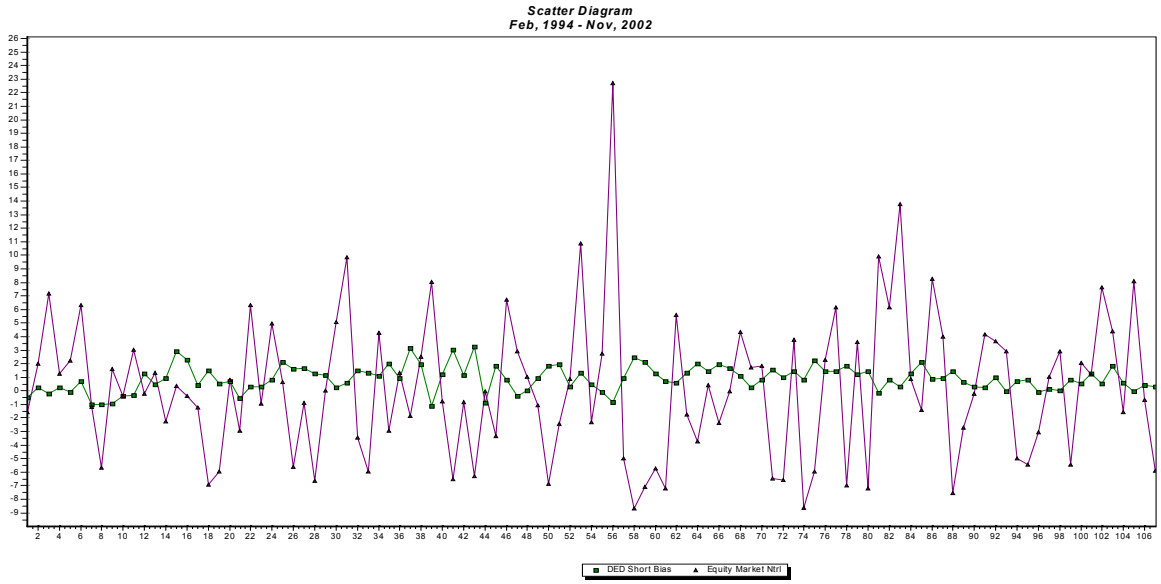
2.2 Hedge Fund Returns

This section has two focal points. In the first section we focus on a descriptive analysis of the historical time series of returns. In addition to providing a graphical view of monthly returns, a solution from the linear factor-analysis is provided to help uncover the latent relationship among the thirteen indexes under study.

2.2.1 Observable Variability within a Latent Structure

We turn to figure 1 to view a cross-scatter chart of the monthly returns for the two focus hedge funds. This display is complemented by the descriptive statistics presented in table 1. The table corroborates and extends the returns analysis of Amenc by reporting skewness and kurtosis distributional characteristics. The table also presents the results of applying the small sample Shapiro-Wilk test for normality (W-Statistic).

Figure 1: Scatter Diagram of DED Short Bias v/s Equity Market Neutral Fund



The latent dimensions that alternatively characterize the distributions are extracted by the application of a linear principal components analysis (PCA). As a purely linear projection method, we recognize that PCA may not be able to capture non-linear relations among the data. However, because our objective here is to re-examine the findings and conclusions of earlier studies, we do not attempt to extend the study beyond the well-known and widely implemented PCA method with a Varimax rotation. See Demartines & Herault (1997) for a curvilinear component analysis that is better able to consider non-linear relations.

Table 1. Descriptive Statistics

	Mean	STD	Variance	CV	Skewness	Kurtosis	W:Normal
CSFB/T Hedge Fund Index	0.879	2.569	6.599	2.924	0.110	1.238	0.889
Convertible Arbitrage	0.825	1.405	1.973	1.704	-1.602	3.877	0.826
Dedicated Short Bias	0.203	5.310	28.201	26.177	0.825	1.819	0.802
Emerging Markets	0.547	5.361	28.739	9.795	-0.477	2.999	0.895
Equity Market Neutral	0.882	0.922	0.849	1.045	0.126	-0.006	0.919
Event Driven	0.851	1.813	3.288	2.132	-3.272	20.153	0.773
Distressed	0.983	2.092	4.375	2.127	-2.609	14.281	0.821
E.D. Multi Strategy	0.783	1.919	3.684	2.452	-2.499	14.522	0.807
Risk Arbitrage	0.680	1.326	1.758	1.949	-1.345	5.775	0.874
Fixed Income Arbitrage	0.547	1.184	1.402	2.165	-3.155	14.930	0.734
Global Macro	1.172	3.668	13.453	3.129	-0.018	1.459	0.907
Long / Short	0.973	3.325	11.055	3.417	0.236	2.717	0.859
Managed Funds	0.571	3.463	11.993	6.062	0.042	0.743	0.913

Table 2. Varimax Analysis of Hedge Fund Index Returns

	Factor 1	Factor 2	Factor 3	Row %
Dedicated Short Bias	-0.8673	.	.	76.69%
Long/Short	0.8322	.	.	76.44%
Event Driven	0.8234	0.4776	.	91.51%
Distressed	0.7814	.	.	75.01%
E.D. Multi-Strategy	0.7434	0.5511	.	86.06%
Emerging Markets	0.6906	.	.	58.96%
Risk Arbitrage	0.6886	.	.	60.06%
CSFB/Tremont Hedge Fund Index	0.6302	0.4651	-0.5537	92.01%
Equity Market Neutral	0.5278	.	.	33.34%
Convertible Arbitrage	.	0.7591	.	69.77%
Global Macro	.	0.5140	-0.7246	85.55%
Managed Funds	.	.	-0.7710	70.05%
Fixed Income Arbitrage	.	0.8646	.	76.42%
Eigenvalue	**5.1028**	**2.6988**	**1.7172**	
Cum. Variance Explained	**39.25%**	**60.01%**	**73.22%**	

Table 2 presents the three factors with eigenvalues of at least 1.0 produced by the application of PCA methods. For exposition purposes, factor loadings below the absolute value of 0.40 are replaced with a period. Factor one is defined by indexes that feature a short-trading or incorporate a short-trading investment style. Factor two is defined by fixed income investing (and multi-strategy funds). Factor three is defined by broad-based global investment strategies. Interestingly, but as expected, the CSFB/Tremont index loads across all three dominant factors. Taken together, these first three factors account for just over 73% of the variation in the hedge fund returns. Despite our concerns about the observed non-linearity in hedge fund returns, the Varimax procedure was able to differentiate among the various trading styles. In the next section we examine the distributional properties of the hedge fund return vectors.

2.2.2 Gaussian Properties

In a manner that is consistent with prior findings we test the Gaussian properties of the index returns (see, Fung and Hsieh (1999) and Kat and Lu (2002) for detailed reviews on hedge fund Gaussanity). As shown in table 1, the *p*-values extracted from the application of the Shapiro-Wilk test support the conventional wisdom that hedge fund returns are not characteristic of a normal distribution. Additionally, we find strong and significant evidence that the CSFB/T returns are leptokurtic (fat-tailed). Specifically, we find only one fund (Equity Market Neutral) with a kurtosis measure that is close to zero (-0,006). The skewness measure for this one index is also very small and positive (we expected a negative value). This finding cannot be generalized to seven of the thirteen indexes. Within this subgroup of seven indexes, the kurtosis measure is measurably different from zero and, in some cases, quite high. At the low end in this group is the Emerging Markets index with a kurtosis value of 2.999. The Event Driven index tops this subgroup with a measure of 20.153. The returns distributions for this group all display negative skewness coefficients. This leads us to conclude that the distributions within this subgroup are asymmetrical. The implication for the risk-averse investor is not a promising one. That is, these findings suggest the potential for extreme negative returns; a finding that negates the application of traditional mean-variance diversification. As we look ahead to the forecasting simulation, it will be interesting to focus on the ability of the various algorithmic methods to treat the observable asymmetries.

2.3 Hedge Fund Predictors

We propose the calibration of an ANN model by reducing redundancy in predictor variable variation. Following Burgess (1995), Refenes (1997) and, for parsimony with model evolution within the arbitrage pricing framework as reviewed by Han (2002), we propose the use of a linear reduction method. More importantly, in the absence of daily (or greater) observations we are not able to invoke a dynamic factor multivariate stochastic volatility test. Our reliance on monthly data also rules out the ability to invoke the Bollerslev (1986) multivariate GARCH model or the multivariate stochastic volatility of Chib, et. al. (2001). We proceed in the following manner. First we identify the commonly used predictor variables in forecasting and modeling returns by ANN methods. Next, we employ factor analytic methods to reduce the collinear structure of these subjectively chosen predictor variables.

2.3.1 Predictor Variables

Since one objective of this paper is to re-examine earlier modeling and prediction efforts, we create a set of predictor variables from those examined by Leung, et. al. (2000) and Amenc (2002). The variable(s) used to proxy each dimension is listed below the dimension identifier in table 3. It is well known that many of the predictor proxies listed below exhibit collinear structure. This condition can lead to over-fitting that, in turn, leads to poor out-of-sample performance. Unless specifically adapted, ANN algorithms require predictor variables to maintain statistical independence. Some ANN methods, like the Kajiji-4 algorithm, resolve collinearity structure. Nevertheless, where possible statistical independence is desired. As an alternative to exhaustive testing of alternative model specifications, we employ the well-known multivariate principal component analysis (PCA) with Varimax rotation to reduce dimensionality and to uncover the latent uncorrelated factor structure among the economic proxies.

2.3.2 Varimax Rotation

The results of applying the Varimax rotational technique to the predictor variables are presented in table 4. The factor analysis results produced eight factors with eigenvalues of at least 1.0. These factors explain slightly more than 76 percent of the total variation in the predictor variables.

Table 3. Contemporary Predictor Variables

Economic Dimension	Pneumonic(s)	Proxy-a	Proxy-b
Short Term Interest Rates	3TBYld; 1D3TBYld	Yield on the 3-month T-bill rate for the US	First difference of yield on 3-month US T-bill rate
Long Term Interest Rates	1D20TB	First difference of the 20 year government bond rate for the US	
Consumer Price Index (CPI)	1DCPI	First difference US CPI	
Industrial Production Level	1DIP	First difference of US industrial production index	
Dividend Yield	S&PdivYld	Dividend yield on the S&P stocks	
Default Spread	MBaaMAAA	Difference between the yield on Moody's long term Baa bonds and the yield on Moody's long term AAA bonds	
Term Spread	10TB-3TB	Difference between the yield on 10-year T-bond and 3-month T-bill	
Implicit Volatility	ΔVIX	Change in the average intra-month values of the VIX	
Market Volume	ΔNYSE	Change in the market value on the NYSE	
Events	MLHBF; MLHBFCC	Merrill Lynch High Yield Bond Fund	Log-differenced returns on the Merrill Lynch High Yield Bond Fund
Oil Price	WTXOIL; WTXOILlag	Average price of west Texas intermediate crude	Lag price of west Texas intermediate crude
US Equity Factor	S&PlagCC; S&PCC	One period lag of the log-differenced returns of the S&P500 Index.	Log-differenced returns of the S&P500 Index
World Equity Factor	MSCIlagCC	Log-differenced returns on the MSCI World Index excluding US	
Currency Factor	1DCRB; USDTW	First difference in the Bridge Commodity Research Bureau Currencies Index	Trade-weighted Exchange Value of USD
Futures Index	CRBF; 1DCRBF	CRB Futures Index	First difference CRB Futures Index

Table 4: Varimax Rotated Factor Loading

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Row %
MLHBF	-0.946	.	.	.	.	.	.	.	94.9%
S&PdivYld	0.928	.	.	.	.	.	.	.	96.7%
USDTW	-0.834	.	.	.	.	.	.	.	90.2%
CRBF	0.805	.	.	.	.	.	.	.	80.0%
MBaaMAAA	-0.466	0.744	.	.	.	.	.	.	82.1%
1D3TBYld	.	.	.	.	.	-0.660	.	.	63.0%
3TBYld	.	-0.907	.	.	.	.	.	.	93.1%
10TB-3TB	.	0.886	.	.	.	.	.	.	88.7%
WTXOILlag	.	.	.	-0.915	.	.	.	.	92.7%
WTXOIL	.	.	.	-0.940	.	.	.	.	95.5%
1DCRBF	.	.	.	.	.	.	.	0.495	63.7%
1DCRB	.	.	.	.	.	0.522	.	.	54.5%
MLHBFCC	.	.	.	.	0.864	.	.	.	82.7%
S&PCC	.	.	0.936	.	.	.	.	.	92.3%
ΔVIX	.	.	-0.558	.	-0.595	.	.	.	80.0%
MSCIlagCC	.	.	0.951	.	.	.	.	.	94.4%
1DCPI	.	.	.	.	.	.	0.804	.	82.2%
1D20TB	.	.	.	.	.	-0.773	.	.	66.3%
S&PlagCC	.	.	.	.	0.833	.	.	.	78.9%
ΔNYSE	.	.	.	.	.	.	0.745	.	77.3%
1DIP	.	.	.	.	.	.	.	0.837	75.5%
Eigenvalue	**3.716**	**2.600**	**2.407**	**2.345**	**2.047**	**1.501**	**1.378**	**1.251**	
CumVariance Explained	**17.7%**	**30.1%**	**41.5%**	**52.7%**	**62.5%**	**69.6%**	**76.2%**	**82.1%**	

2.3.3 Latent Factor Descriptions

The latent factor dimensions are subjectively classified and presented in table 5.

Table 5: Latent Factor Classification

Factor	Domain Characteristic
F1	Yields on Equity and Risky Bonds with Currency and Futures Effects
F2	Default and Term Spread with Inverse 3-Tbill Effect
F3	Continuously compounded returns on domestic and world Equity markets with inverse effects of VIX
F4	Oil
F5	Continuously compounded returns on high yield bonds with lagged equity returns and inverse VIX
F6	First Differenced 20-year Tbond and 3-Tbill with inverse on differenced currency effect
F7	Effect of CPI and change in domestic market volume
F8	Change in industrial production

2.3.4 Factor Scores

Based on the extracted factors, we compute factor scores of each subject as a means of reducing the predictor variables down to eight latent variables that correspond to the rotated domains. We follow the method of Thomson (1951). If f_r is the score of the r^{th} factor corresponding to a response of **x**, then we estimate f_r by a linear combination of the x_i: $\hat{f}_r = a_r x$. We choose $\boldsymbol{a}_r$ such that $E\left[\left(\hat{f}_r - f_r\right)^2\right]$ is minimized. In vector notation $f' = \left(f_1, ..., f_k\right)$, and the solution is estimated by:

$$\hat{F} = \hat{\Lambda}' \hat{\Sigma} x, \qquad (1)$$

where Λ is the factor loading matrix, Σ the covariance matrix, and $\boldsymbol{x}$ the original data matrix. From each set of responses $\boldsymbol{x}$ we obtain the vector of factor scores $\boldsymbol{f}$.

3. The Kajiji-4 Benchmark Radial Basis Function

In this section we present the methodology supporting the use of the Kajiji-4 RBF as the control neural network against which the alternate neural network topologies are tested. Within the radial basis function class of neural networks we explicitly consider the RBF algorithms produced by StatSoft (2001) and SPSS (2001).[1]

The optimal weighting values used within the RBF network are generally extracted by applying a supervised least-squares method to a subset of the data series (the training set). The supervised learning function is stated as,

$$y = f(x) \tag{2}$$

where, y the output vector is a function of x the input vector with n number of inputs. Alternatively, the supervised learning function can be restated as the following linear model,

$$f(x_i) = \sum_{j=1}^{m} w_j h_j(x) \tag{3}$$

where, *m* is the number of basis functions (centers), *h* is the hidden units, *w* is the weight vectors, and *i = 1..k* output vectors (target variables). The flexibility of *f(x)* and its ability to model many different functions is inherited from the freedom to choose different values for the weights. Then applying the least-squares principle is similar to minimizing the sum of squared errors as represented by:

$$SSE = \sum_{i=1}^{p} \left(\hat{y}_i - f(x_i) \right)^2 \tag{4}$$

Kajiji (2001) presents the RBF mapping function as a modified Tikhonov regularization equation (1977). Tikhonov regularization adds a weight decay parameter to the error function to penalize mappings that are not smooth. If a weight penalty term is added to the SSE, the SSE can be restated as the following cost function

[1] Dash and Kajiji (2002) report seriously inconsistent performance characteristics for the Matlab RBF ANN. In addition to excessively long computation times vis-à-vis alternative RBF implementations, the Matlab RBF method was also prone to numerical under- and over-flow conditions that failed the program. These reasons force us to

$$C = \sum_{i=1}^{p} \left(\hat{y}_i - f(x_i) \right)^2 + \sum_{j=1}^{m} k_j w_j^2 \qquad (5)$$

where k_j are regularization parameters or weight decay parameters. Under this specification the function to minimize is:

$$\frac{\text{argmin}}{k} \left(\varsigma \sum_{i=1}^{p} (y_i - f(x_i \mid \bar{k}))^2 + \sum_{j=1}^{m} k_j w_j^2 \right) \qquad (6)$$

Iterative techniques are commonly employed to compute the weight decay parameter, k, or a vector of parameters $\bar{k}$. But, since the introduction of weight decay methods by Hoerl and Kennard (1970) and Hemmerle (1975) it is generally understood that iterative techniques are computationally burdensome and lack specificity [see, Orr (1996; 1997)]. Further, computational experience has established that iteration often leads to local minima or, in the case where the weight decay approaches infinity, inflated residual sums of squares. By contrast, the Kajiji RBF algorithm is a Bayesian regularization algorithm that derives a globally optimized regularization parameter based on a cross-population of recent extensions in optimal ridge regression parameter estimation by Crouse (1995). The Kajiji algorithm directly attacks the twin evils that deter efficient ANN modeling: the "*curse*" of dimensionality (over-parameterization) and inflated residual sum of squares (inefficient weight decay).

4. The Modeling Process

Let $r_t = (r_{it},\ldots,r_{pt})$ represent a vector of p returns observed at time t, $t = 1,\ldots,n$. Let $F_t = (F_{1t},\ldots, F_{kt})$ specify k latent factors with which there are corresponding maximum validity factor scores denoted by S_t for k latent factors. The following economic model is formulated for each of the m CSFB/T indexes, where $m = 1,\ldots,M$ for the 13 published indexes.

$$HFI_m = f(S_1,\ldots,S_k). \qquad (7)$$

---

defer including Matlab in this test of numerical efficiency.

HFI_m is the individual hedge fund that is subjected to the model comprised of the S_k factor scores.

4.1. Measurement Errors in Return Level Prediction

Comparative evaluation relies upon the computed residuals for the training, out-of-sample validation, and fitness (entire sample) data subsets. Specifically, model errors are computed as,

$$MSE_{training} = \sum_{i=1}^{t} \left(y_i - \hat{y}_i \right)^2 \Big/ t \qquad (8)$$

$$MSE_{validation} = \sum_{i=1}^{v} \left(y_i - \hat{y}_i \right)^2 \Big/ v \qquad (9)$$

$$MSE_{fitness} = \sum_{i=1}^{T} \left(y_i - \hat{y}_i \right)^2 \Big/ T \qquad (10)$$

where $MSE_{training}$ is local to the training sub-set (T_t) and the $MSE_{validation}$ measure captures the out-of-sample error component ($T_{t+1}..T_v$). The $MSE_{fitness}$ measure is computed over all (T) observations. For purposes of this paper, all algorithmic comparisons rely solely on the direct evaluation of the computed $MSE_{fitness}$.

4.2. Measurement Errors - Classification Prediction

Neural network classification topology generally relies upon an output function of probabilities to assign group membership. Leung preferred this approach. However, for return classification it is possible to use a direction measure to test the number of times a prediction neural network predicts the direction of the predicted return movement correctly. In this study in order to minimize the chance of introducing new specification errors by from the use of alternative neural network architecture we implement measurement errors that take into account the simultaneous behavior of trend and magnitude within the trend.

4.2.1. Direction Measure

Direction is defined as the number of times the prediction followed the up and down movement of the underlying index. The initial calculations were presented by Harvey, et. al. (2002) and later modified by Castiglione (2001) as shown below.

$$\zeta = \frac{1}{|T|} \sum_{i+1 \in T} HS\left(P_{i+1} G_{i+1}\right) + 1 - HS\left(\left|P_{i+1}\right| + \left|G_{i+1}\right|\right) \qquad (11)$$

where:

P_{i+1} = Index_{i+1} / Index_i is the percentage return on the index at time step $i+1 \in T$

G_{i+1} = the forecast percentage return on the index at time step $i+1 \in T$

T = the number of days in the validation period

HS = a modified Heavyside function where HS(x)=1 for x>0, and 0 otherwise.

4.2.2. Modified Direction Measure

A more robust method of direction was presented by Merton (1981) and named modified direction:

Modified Direction = *((# of correct up predictions / # of times index up) +*
(# of correct down predictions / # times index down)) – 1 *(12)*

4.2.3 Time Dependent Directional Profit

The two direction measures each provide a summary of how well the predicted time-series and the actual time-series move together at any given point in time. We introduce the Yao (Access Year: 2003) time dependent directional profit measurement error (TDDP) as a means by which to capture the simultaneous effects of time and profit in the forecast simulation. Under this method incorrectly predicted directional moves are penalized more heavily than are correct predictions. The weights are then adjusted based on the amount of change from one forecast point to the next. In essence, a large adjustment to the weights is made given a wrong directional forecast, which is accompanied by a large change in the underlying values. Conversely, a small

adjustment to the weights is signaled by a correct directional forecast for a correspondingly large change in the underlying. The TDDP error measure is defined as,

$$E_{TDP} = \frac{1}{2N}\sum_{p=1}^{N} f_{TDP}(p)(t_p - o_p)^2 \qquad (13)$$

where $f_{TDP} = f_{DP}(p) * w(p)$, and the vectors *t* and *o* capture the target-prediction and observed values over the *p* prediction periods. Changes in the underlying and direction as described above are determined by $f_{DP} = F(|t_p - t_{p-1}|, sign(\Delta t_p, \Delta o_p))$. At prediction point *p*, the directional profit adjustment factor is determined according to

$$f_{DP}(p) = \begin{cases} a_1 & if\ \Delta t_p * \Delta o_p > 0 and\ |\Delta t_p| \le \sigma \\ a_2 & if\ \Delta t_p * \Delta o_p > 0 and\ |\Delta t_p| > \sigma \\ a_3 & if\ \Delta t_p * \Delta o_p < 0 and\ |\Delta t_p| \le \sigma \\ a_4 & if\ \Delta t_p * \Delta o_p < 0 and\ |\Delta t_p| > \sigma \end{cases} \qquad (14)$$

where σ is the standard deviation of the target variable over all *N* observations (training and validations observations). Simulation results for the monthly time scale lead us to the following parameter values: $a_1 = 0.5$; $a_2 = 0.8$; $a_3 = 1.2$; and, $a_4 = 1.5$. We caution, however, that there is insufficient evidence to recommend the extrapolation of these settings to other time scales such as daily or higher frequencies.

5. Modeling Characteristics

In this section we present the results of applying the sample data to each one of the three test algorithms. The hardware configuration for this experiment consisted of a 2ghz Pentium-4 CPU with 512 MB of random access memory. All program executions were made under the Microsoft XP Professional operating system. Algorithmic differences in solution execution times were measurable but small. Solutions times ranged from about 4 seconds (Kajiji-4) to just under 8 seconds (SPSS). While this difference is negligible for the relatively small monthly dataset used in this study, it is an issue that may require renewed attention under tests involving

large-scale datasets consisting of thousands of high frequency observations. Despite the similar model solving times, other similarities and substantial differences arise when comparing the relative modeling efficiency of the three RBF ANNs. Specific modeling results for the Kajiji-4 method are presented next. This is followed by the presentation of results for the solutions generated by SPSS and StatSoft algorithms, respectively.

5.1 Kajiji-4

The analysis of algorithmic efficiency begins with a review of the MSE fitness measures are presented in table 6. The fitness error is just over 0.40 for the Dedicated Short Bias index and is about the same for the Equity Market Neutral hedge fund index. We note that the Global Macro index fund achieved a low fitness error measure (0.00) of near zero. As we extend the analysis to uncover overall algorithmic efficiency, we observe that the two low fitness-MSE models also have correspondingly low skewness and kurtosis measures. This finding suggests that model efficiency improves as the effects of skewness and kurtosis diminish. When the third- and fourth-moment characteristics are considered the algorithmic results reported for the Equity Market Neutral index appear interestingly efficient. At the other end of the modeling spectrum is the model applied to the Event Driven index. This model produced fitness MSE (0.221) that is approximately twice that of the Dedicated Short Bias index. This result yields an interesting insight into the algorithmic performance when applied to monthly hedge fund returns. We note that the Event Driven index has the highest absolute skewness coefficient (-3.272) and the highest kurtosis measure (20.153). These results add to our earlier observations about the importance of understanding the role of distributional symmetry in hedge fund returns. In the former case, low values for skewness and kurtosis were associated with low fitness MSE results. In this latter case, relatively high skewness and kurtosis measures are associated with deterioration in modeling accuracy as measured by the fitness MSE. The reported modeling efficiency is buttressed by the cross-plot of the observed and target observations. Figures 2 and 3 provide a visual validation that the error deviation within the validation set is small for the two indices of interest.

Next, we assess the ability of the Kajiji-4 algorithm to correctly predict the directional change of hedge fund returns. Both the direction and modified direction measures report

identical results across all model applications. The direction measure solves at 0.988 and the modified direction measure is constant at its maximum value of 1.0. The modified direction measurement of 1.0 does not necessarily imply that the prediction is perfect. A more conservative interpretation of the result allows us to conclude that the target variable correctly attempts to model the peaks and troughs found in the observed dataset. Take together, these two measures provide strong evidence that the Kajiji-4 algorithm when applied to monthly return data for alternative assets can achieve near perfect results in forecasting directional changes in the returns data.

The strong performance of the directional measures does not address the profit incentive held by investors. The profit-enhanced TDDP measure presents a very clear picture of modeling efficiency.

Table 6: Kajiji-4 Model Results

	SFB / Tremont Hedge Fund	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Distressed	E.D. Multi-Strategy	Risk Arbitrage	Fixed Income Arbitrage	Global Macro	Long / Short	Managed Funds
Lambda	1.051	1.129	1.165	1.912	46.713	0.238	0.195	0.469	0.792	0.154	9.764	1.530	1.982
Return-level Error Measures													
Training Error	1.271	1.107	1.019	1.248	1.189	1.136	1.079	1.186	1.040	1.165	1.295	1.212	0.853
Validation Error	0.143	0.531	0.757	0.227	0.400	0.191	0.219	0.207	0.508	0.132	0.111	0.309	1.095
Fitness Error	0.022	0.021	0.401	0.046	0.000	0.221	0.425	0.111	0.065	0.098	0.000	0.035	0.233
Classification Error Measure													
Direction	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988
M. Direction	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
TDDP	0.0054	0.0052	0.1418	0.0114	0.0001	0.0718	0.1374	0.0361	0.0229	0.0308	0.0001	0.0087	0.0802

Figure 2: Actual and Predicted Using Kajiji-4 RBF on Dedicated Short Bias Fund

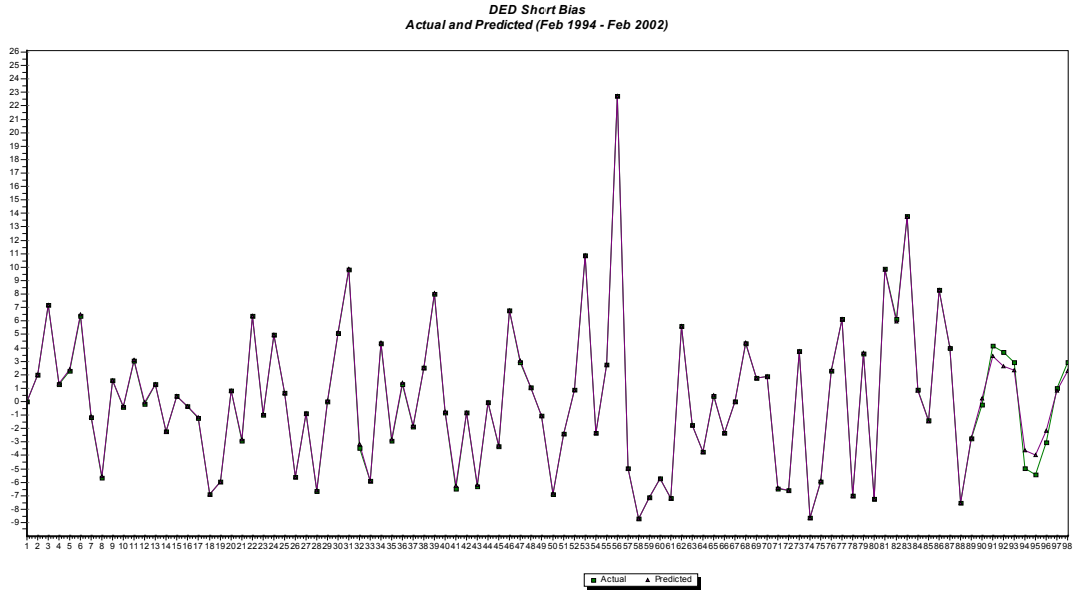
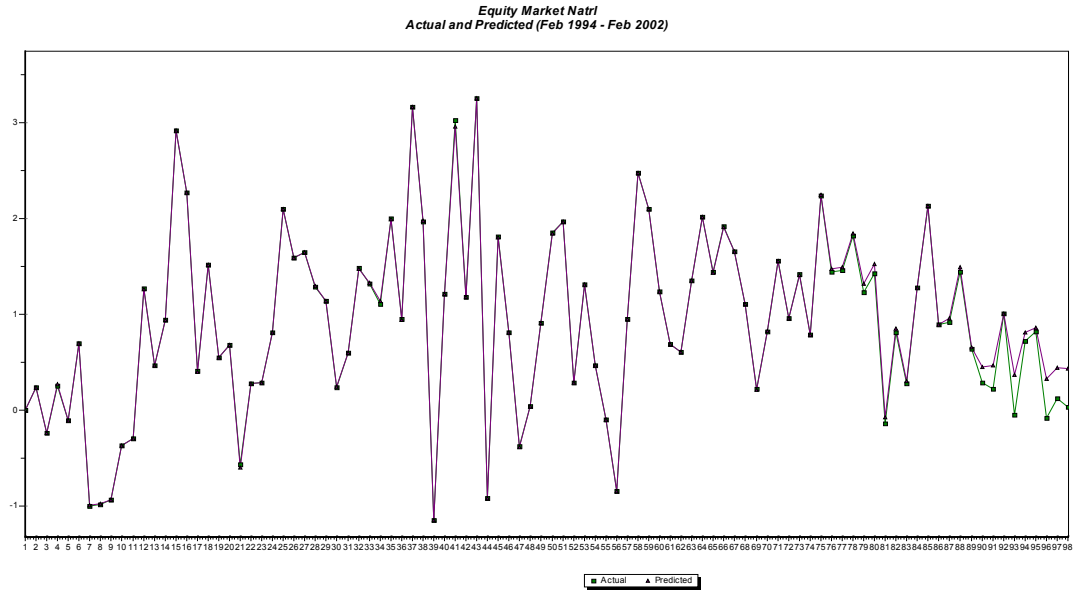


Figure 3: Actual and Predicted Using Kajiji-4 RBF on Equity Market Neutral Fund



5.2 SPSS's Neural Connection

The SPSS RBF results, presented in table 7, differ markedly from those produced by the Kajiji-4 algorithm. Based on a comparison of within algorithmic MSE results, the SPSS RBF modeling experiment achieves the lowest error value when modeling the Equity Market Neutral index. This is one of the two focus indices. However, at 1.370447 the SPSS reported error measure is more than one-thousand times larger than that produced by the Kajiji-4 simulation. For the other focus index, Dedicated Short Bias, the SPSS fitness MSE is more than 1,975 times higher than that produced by the Kajiji-4 counterpart. This is also the largest MSE reported by the application of the SPSS procedure. Returning to our examination of how RBF algorithms perform under conditions of distributional asymmetry we note that except for one case (the Fixed Income Arbitrage index), the SPSS algorithm generates a consistent performance ratio for hedge fund indices with absolute skewness levels above 3.00 and kurtosis measures greater than 14.0. Within the subgroup defined by the Event Driven, Distressed, and E.D. Multi-Strategy indices, the reported fitness MSE measures ranged from 3.172028 to 3.642675. By comparison, the Kajiji-4 algorithm also performed consistently across this same subgroup; but the reported MSE measures were decidedly lower under Kajiji-4 achieving levels that ranged from 0.425 to 0.111. In summary, the SPSS RBF algorithm demonstrated the ability to produce consistent performance across monthly return indices with high absolute skewness and high kurtosis measures. Unfortunately, asymmetry issues aside, the performance of the algorithm dissipate as the level of relative variation (CV) increases. A graphical display of the two focus indexes is provided in figures 4 and 5, respectively.

Table 7. SPSS Model Results

	SFB / Tremont Hedge Fund	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Distressed	E.D. Multi-Strategy	Risk Arbitrage	Fixed Income Arbitrage	Global Macro	Long / Short	Managed Funds
Return-level Error Measures													
Training Error	1.074746	0.998806	1.018551	1.073490	0.948484	0.98785	0.464553	0.91175	0.860569	0.522714	0.70402	1.01266	0.939322
Validation Error	0.279682	0.827859	0.868138	0.503276	0.544275	0.75957	0.899311	0.63094	0.671334	0.788974	0.22464	0.33472	1.210085
Fitness Error	6.999264	2.468697	27.655226	28.473214	1.370447	3.64267	3.127028	3.49122	1.698769	0.767644	10.93985	10.94859	12.05949
Classification Error Measure													
Direction	0.5046	0.6697	0.4404	0.5138	0.5780	0.5596	0.5688	0.5963	0.6055	0.6514	0.6789	0.5229	0.5413
M. Direction	0.3425	0.3080	0.1521	0.2103	0.3271	0.2917	0.5255	0.3644	0.2735	0.4862	0.4496	0.3112	-0.0137
TDDP	1.6879	0.8222	7.8533	5.3780	0.2697	0.8478	0.6223	1.0244	0.4540	0.1597	1.7682	3.4983	3.5241

Figure 4. Actual and Predicted Using SPSS RBF on the Dedicated Short Bias Fund

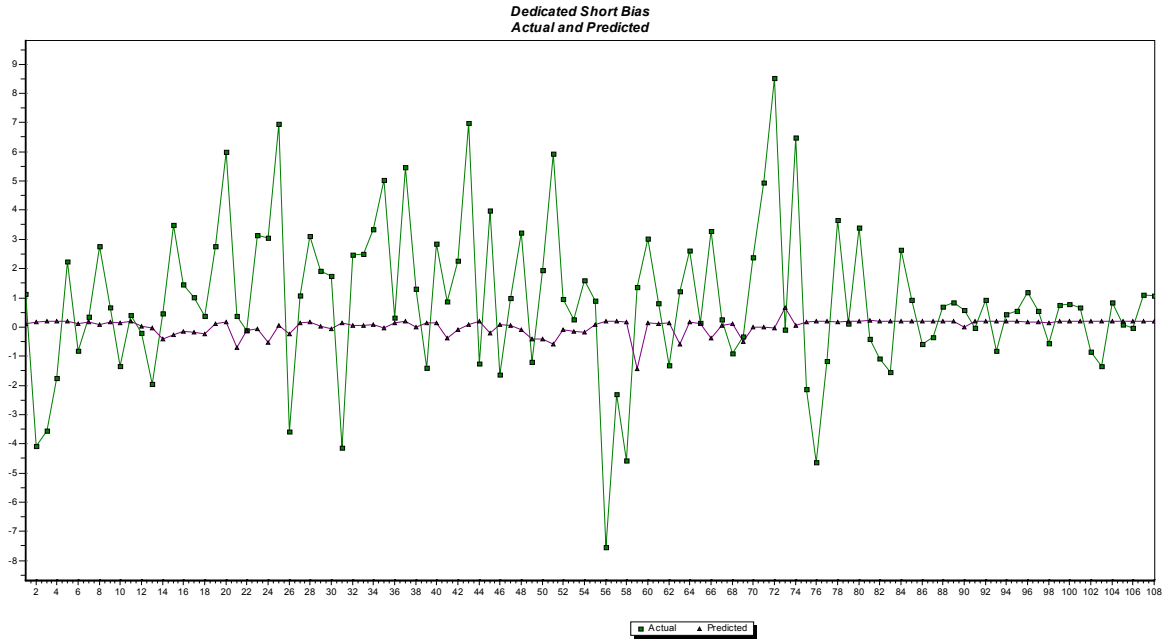
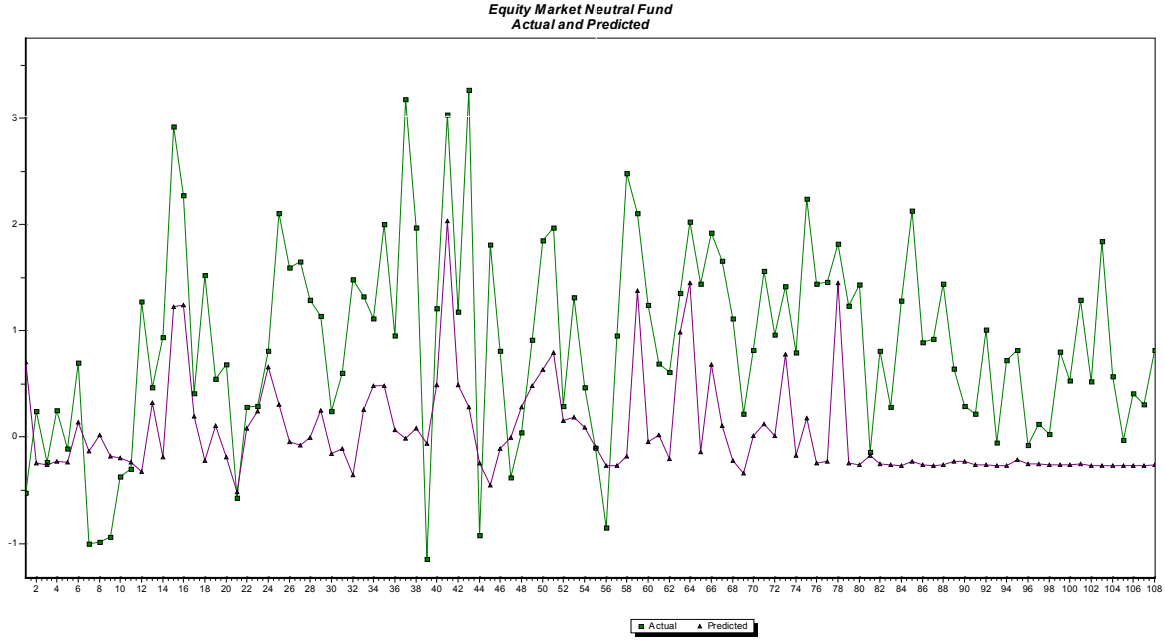


Figure 5. Actual and Predicted Using SPSS on Equity Market Neutral Fund



5.3 StatSoft's Statistica

On average, the results produced upon the application of the StatSoft RBF algorithm to the modeling problem fall in between those produced by the other two RBF algorithmic methods. Before presenting the details as provided in table 8, we wish to note that the user interface of the StatSoft algorithm differs considerably from that presented by either the Kajiji-4 or SPSS methods. For the StatSoft-based experiment, where possible, optional parameter settings were set to levels specified as default levels under the Kajiji-4 method. We then undertook a manual optimization process with the goal of identifying parameter settings that would produce best (if not optimal) solution results for the sample data. Stated differently, while we were able to apply default settings without modification under the Kajiji-4 and SPSS experiments, that was not possible in this case.

Like the Kajiji-4 algorithm, the StatSoft method reported the lowest fitness MSE for the Equity Market Neutral index model. The MSE reported by the StatSoft method is over 1,000 times larger than that achieved by application of the Kajiji-4 network. For the other focus index, Dedicated Short Bias, at 23.051 the fitness MSE is the highest recorded across all test models. This result is more than 57 times that achieved for the same index under the Kajiji-4 method. Figure 6 and 7 provide a graphical view of the algorithm's predictive ability for the Dedicated Short Bias and Equity Neutral fund returns. It is clear from this view that the target variable achieves reasonable directional performance but falls short in its ability to replicate the magnitude of the changes. We observe that the StatSoft method performs best when modeling monthly hedge fund returns with relatively low coefficients of variation. The algorithm's predictive ability dissipates noticeably as relative variation (CV) increases. How, if at all, this deterioration is impacted by distributional asymmetry is not immediately clear from the results generated by this experiment.

Table 8. Staistica-4 Model Results

	SFB / Tremont Hedge Fund	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Dis-tressed	E.D. Multi-Strategy	Risk Arbitrage	Fixed Income Arbitrage	Global Macro	Long / Short	Managed Funds
Return-level Error Measures													
Training Error	0.3647	0.5030	0.1663	0.1280	0.9018	0.4456	0.3509	0.4142	0.6886	0.6328	0.1994	0.2182	0.2826
Validation Error	0.4937	0.5097	0.1747	0.1227	0.5999	0.5693	0.4590	0.4475	0.6107	0.6829	0.2747	0.1314	0.4146
Fitness Error	5.0695	1.0008	23.0509	16.0618	0.7297	3.2304	3.2736	3.4262	1.4754	1.1334	15.0169	7.1130	10.8056
Classification Error Measure													
Direction	0.6330	0.8532	0.6055	0.6422	0.7523	0.7431	0.6422	0.6055	0.7248	0.6881	0.5963	0.5596	0.5229
M. Direction	0.1901	0.5861	0.3245	0.5216	0.0556	0.5211	0.4792	0.2315	0.2890	0.0415	0.0659	0.4142	0.2421
TDDP	1.0963	0.3143	6.4969	3.0278	0.1067	1.1203	0.8245	1.1080	0.4369	0.3822	4.3435	2.1328	3.0088

Figure 6. Actual and Predicted Using the StatSoft ANN on Dedicated Short Bias Fund

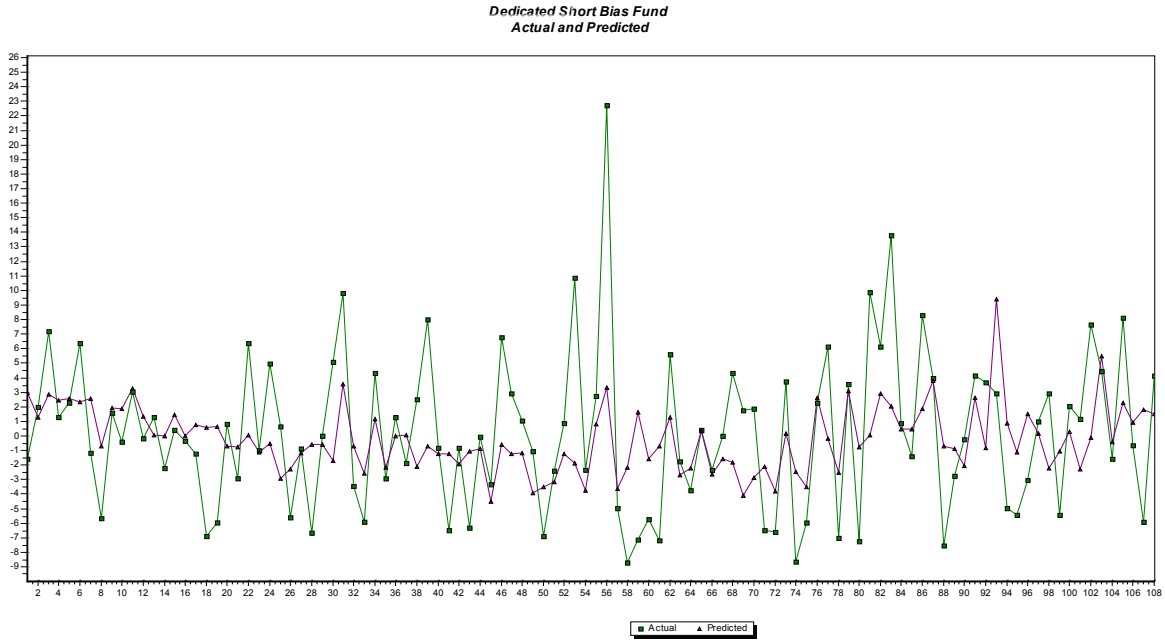
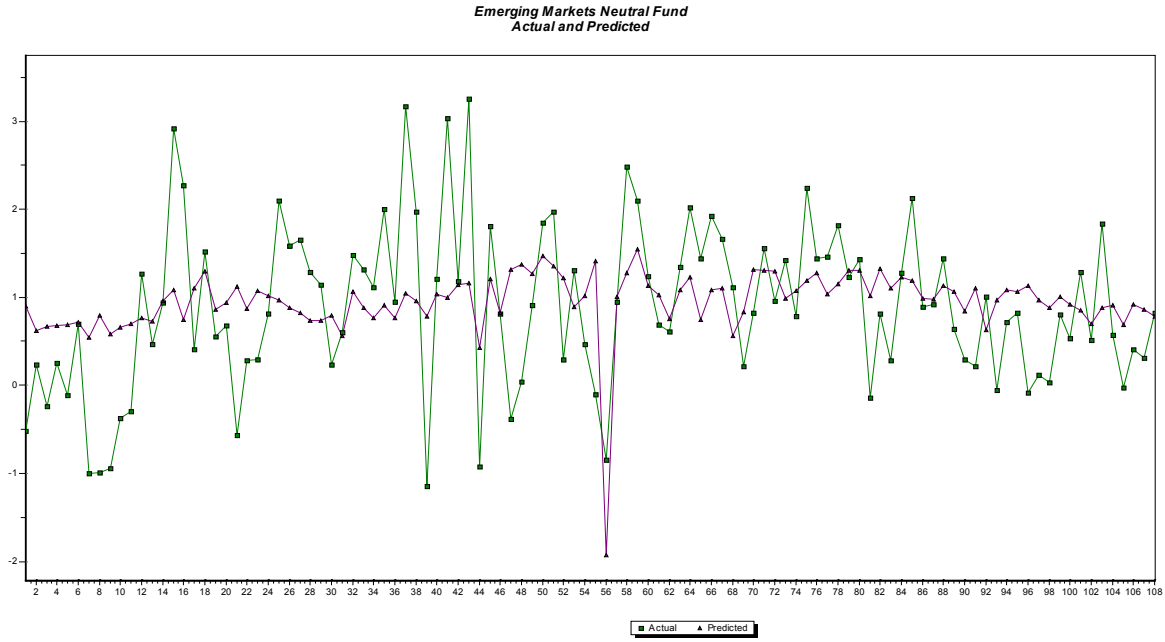


Figure 7. Actual and Predicted Using the StatSoft ANN on Equity Market Neutral Fund



5.4 Efficient Model Selection

A comparative analysis of the three RBF algorithms points to the role of CV and distributional asymmetry as factors that measurably impact modeling accuracy. Table 9 provides a concentrated view of the underlying statistical properties by algorithm. We focus our view on the role of third- and fourth-moment characteristics as factors that influence the behavioral characteristics of the models with the lowest fitness MSE. In this context, it becomes apparent that model solutions produced by the SPSS and StatSoft algorithms choose the indices with the thirteenth ranked CV and the thirteenth ranked kurtosis. These indices also exhibit low skewness (tenth ranked). From these results it is apparent that the SPSS and StatSoft algorithms perform best under conditions where the time series is least disturbed by third- and fourth-moment asymmetries. By contrast, the Kajiji-4 algorithm was at its best whenever relative dispersion was at its highest. Although the Kajiji-4 algorithm was the dominant modeling method under the presence of moderate levels of skewness and kurtosis, it too performed more accurately as asymmetry measures diminished. But, it is interesting to observe that the highest MSE produced by the Kajiji-4 method occurred only when the index exhibited high(est) skewness and kurtosis measures. Under SPSS and StatSoft the highest MSE was not necessarily influenced by distributional asymmetry.

Table 9. Relative Dispersion Comparison

	Kajiji-4	SPSS	StatSoft
Lowest Validation MSE	Dedicated Short Bias [1,7,9]; and Global Macro [5,13,10]	Equity Market Neutral [13,10,13]	Equity Market Neutral [13,10,13]
Highest Validation MSE	Event Driven [9,1,1]	Dedicated Short Bias [1,7,9]	Dedicated Short Bias [1,7,9]

Rankings for CV, Skewness, Kurtosis are in parentheses

5.5 Directional Efficiency

Table 10 provides a comparison of directional forecasting accuracy. Results are reported by algorithmic method in order to show which forecast produced the minimum and maximum for

each directional error measure. We note that the results generated by application of the Kajiji-4 method are at the theoretical maximum of 0.988 and constant across all tested models. The same is true for the modified direction measure (all 1.0). Tables 11 and 12 present an augmented comparative analysis of the results achieved by the application of the SPSS and StatSoft algorithms. These tables rank the performance based on the direction measure. What is most obvious is the lack of a ranking consistency. Except for a weak argument to the benefit of the Managed Funds index, there is no overlap in the rankings achieved across the remaining two algorithms. Despite this lack of consistency, it does appear that the StatSoft algorithm maintains an efficiency edge over the SPSS algorithm in directional accuracy.

Table 10. Summary of Direction and Modified Direction

	Kajiji-4	SPSS	StatSoft
Min Direction	ALL (0.988)	Dedicated Short Bias (0.440367)	Managed Funds (0.522936)
Max Direction	ALL (0.988)	Global Macro (0.678899)	Convertible Arbitrage (0.853211)
Min Modified Direction	ALL (1.000000)	Managed Funds (-0.013723)	Fixed Income Arbitrage (0.041528)
Max Modified Direction	ALL (1.000000)	Distressed (0.525463)	Convertible Arbitrage (0.586124)

Computed values in parentheses

Table 11. Rankings of the SPSS Direction / Modified Direction

	Direction	Modified Direction	Rank Direction	Rank Modified Direction
Global Macro	0.678899	0.449631	1	3
Convertible Arbitrage	0.669725	0.308014	2	6
Fixed Income Arbitrage	0.651376	0.486157	3	2
Risk Arbitrage	0.605505	0.273533	4	10
E.D. Multi-Strategy	0.596330	0.364352	5	4
Equity Market Neutral	0.577982	0.327091	6	7
Dis-tressed	0.568807	0.525463	7	1
Event Driven	0.559633	0.291165	8	9
Managed Funds	0.541284	-0.013723	9	13
Long / Short	0.522936	0.311213	10	8
Emerging Markets	0.513761	0.210284	11	11
CSFB/T Hedge Fund	0.504587	0.342460	12	5
Dedicated Short Bias	0.440367	0.152098	13	12

Table 12. Rankings of the StatSoft Direction / Modified Direction

	Direction	Modified Direction	Rank Direction	Rank Modified Direction
Convertible Arbitrage	0.85321	0.58612	1	1
Equity Market Neutral	0.75229	0.05556	2	12
Event Driven	0.74312	0.52108	3	3
Risk Arbitrage	0.72477	0.28904	4	7
Fixed Income Arbitrage	0.68807	0.04153	5	13
Distressed	0.64220	0.47917	6	4
Emerging Markets	0.64220	0.52163	7	2
CSFB/T Hedge Fund	0.63303	0.19008	8	10
Dedicated Short Bias	0.60551	0.32448	9	6
E.D. Multi-Strategy	0.60551	0.23148	10	9
Global Macro	0.59633	0.06593	11	11
Long / Short	0.55963	0.41419	12	5
Managed Funds	0.52294	0.24208	13	8

5.6 Directional Profit Efficiency

The TDDP measure is a correction weight that is designed to compensate for incorrect directional forecasts by overall magnitude of the movement. The weight is applied to future forecasts generated by the forecasting model. The smaller the weight, the more accurate the training phase of the model. By definition, large weights are indicative of a missed direction, an incorrect magnitude adjustment, or some combination of the two. Table 13 presents the TDDP measures for the three RBF ANN under study here.

The TDDP also provides a new layer of support for the efficiency of the Kajiji-4 algorithm. In profit induced scenarios where it is important to predict the correct turning point of a time series as well as the magnitude by which the time series is expected to move, the Kajiji-4 algorithm requires the least weighted adjustment. An improvement ratio is presented in the last two columns of table 13. This is simply the TDDP of the selected method divided by the TDDP produced by solution of the Kajiji-4 method. Of the seven funds that exhibited asymmetrical return distributions, only one (Emerging Markets) had an improvement ratio over 60. This observation confirms that the while the Kajiji-4 method is more efficient when predicting returns associated with asymmetrical and leptokurtic distributions, the gains are not as great when the distributions exhibit fat-tails and skewness.

Table 13. TDDP Measures with Asymmetrical Identification

	Kajiji-4	SPSS	StatSoft	SPSS/Kajiji-4	StatSoft/Kajiji-4	Asymmetrical
Convertible Arbitrage	0.0052	0.8222	0.3143	158.1	60.4	A
Equity Market Neutral	0.0001	0.2697	0.1067	2697.0	1067.0	
Event Driven	0.0718	0.8478	1.1203	11.8	15.6	A
Risk Arbitrage	0.0229	0.4540	0.4369	19.9	19.1	A
Fixed Income Arbitrage	0.0308	0.1597	0.3822	5.2	12.4	A
Distressed	0.1374	0.6223	0.8245	4.5	6.0	A
Emerging Markets	0.0114	5.3780	3.0278	471.8	265.6	A
CSFB/T Hedge Fund	0.0054	1.6879	1.0963	312.6	203.0	
Dedicated Short Bias	0.1418	7.8533	6.4969	55.4	45.8	
E.D. Multi-Strategy	0.0361	1.0244	1.1080	28.4	30.7	A
Global Macro	0.0001	1.7682	4.3435	17682.0	43425.0	
Long / Short	0.0087	3.4983	2.1328	402.1	245.1	
Managed Funds	0.0802	3.5241	3.0088	43.9	37.5	

5.7 The Informational Content of Model Residuals

In this section we first apply a PCA with Varimax rotation to the residual returns extracted from the application of equation [7] above. Specifically, we subject *E* to the PCA procedure, where $E = \{HFI - f(S_1 ... S_k)\}$. The section continues by reformulating [7] to incorporate the latent information uncovered in the first step. The results of this reformulation are designed to account for the impact of skewness in an effort to improve the forecasting properties of the method.

5.7.1 Latent Structure of Model Residuals

The results of this application are presented in table 14. As with the earlier factor analytic presentation, we replace factor loadings below the absolute value of 0.40 with a period. Additionally, only those factors with eigenvalues of 1.0 or higher are retained for display purposes. Two factors are reported in the table. Factor 2 is differentiated from factor 1 by the asymmetry characteristics of the hedge fund indices. For the skewness dimension, only the Emerging Markets index has a negative skewness above -3.0. Similarly, for the kurtosis

dimension (with the same exception for the Emerging Markets index) each index that loads on factor 2 has a kurtosis measure that exceeds 14.0. The factor analytic results provide additional support for the MSE directional analysis that produced observed differences in model efficiency based on the existence of asymmetry in the observed hedge fund returns.

Table 14. Varimax Results: After Model Residuals

Fund Name	Factor 1	Factor 2	Row %
Global Macro	0.9625	.	96.73%
Managed Funds	0.9509	.	94.38%
SFT/Tremont Hedge Fund	0.9197	.	88.71%
Distressed	0.8138	.	67.95%
Dedicated Short Bias	0.8037	.	67.97%
Equity Market Neutral	-0.7893	.	63.69%
Long/Short	-0.7252	.	53.55%
Risk Arbitrage	-0.6540	.	45.39%
Fixed Income Arbitrage	-0.5113	-0.5972	61.81%
Emerging Markets	.	0.7347	68.48%
Event Driven	.	-0.9171	93.40%
E.D. Multi-Strategy	.	0.8562	78.47%
Convertible Arbitrage	.	0.6195	38.70%
Eigenvalue	6.1157	3.0765	
Percent of Variance Explained	47.04%	70.71%	

5.7.2 Model Reformulation

We reformulate equation [7] to explicitly control for skewness in the return distributions of the hedge fund indexes. The modeling process as described in section 4 is repeated under the application of

$$HFI_m = f\left\{S_1,...,S_k, HFI^3_{m,t-1}\right\} \qquad (15)$$

where $HFI^3_{m,t-1}$ captures the prior period effect of skewness. Upon the application of the Kajiji-4 algorithm the model residuals are subjected to a PCA analysis as in section 6.1 above. The results of this application are presented in table 15.

Table 15. Varimax Results: Skewness Adjusted Residuals

Fund Name	Factor 1	Factor 2	Row %
Global Macro	0.9873	.	99.11%
Event Driven (A)	0.9860	.	99.06%
E.D. Multi-Strategy (A)	0.9837	.	98.66%
Managed Funds	0.9795	.	97.58%
Distressed (A)	0.9781	.	97.42%
SFT/Tremont Hedge Fund	0.9687	.	94.30%
Risk Arbitrage (A)	0.8202	.	69.43%
Dedicated Short Bias	0.7961	0.5280	91.26%
Equity Market Neutral	-0.7849	.	62.42%
Emerging Markets (A)	0.7670	.	61.11%
Convertible Arbitrage (A)	0.7576	0.5611	88.87%
Long/Short	-0.7114	.	50.99%
Fixed Income Arbitrage (A)	.	-0.9408	88.98%
Eigenvalue	9.3645	1.6276	
Percent of Variance Explained	72.03%	84.55%	

As in table 14, two significant factors are located. However, the latent dimensions for this solution differ in their economic content. Factor 2 is no longer defined by the impact of skewness on the hedge fund index returns. Instead, factor 2 is represented by two hedge funds that actively follow short-position investing. By way of example, Convertible Arbitrage funds attempt to generate steady profits from fixed income securities as well as the short sale of stock. The dedicated short bias strategy is to maintain net short as opposed to pure short exposure in both equities and derivatives. Interestingly, extracted with an opposite sign is the Fixed Income Arbitrage hedge fund. This index includes funds that actively follow a swap-based investment strategy that targets low volatility with steady returns. Skewness is no longer the dominant latent definition of this dimension. One key question remains: Does the modeling results reported above result in an improved one-period ahead forecast?

6. Forecast of Hedge Fund Index Returns

The forecasting system presented below is formulated by embedding a delay between the observed time series (hedge fund return) and the model that is capable of generating it. Section 5 established the modeling properties from the application of the Kajiji-4 RBF to the observed variable given a reduced form vector of predictor variables to explain it. For the one-period ahead forecast, we draw upon the results of the PCA framework by choosing the variable with the highest factor loading to represent the unique dimension. Thus, the eight factor predictor variables were replaced in equation 7 with the following eight variables, respectively: MLHBF, 3TBYld, MSCIlagCC, WTXOIL, MLHBFCC, 1D20TB, 1DCPI, and 1DIP The one-period ahead results are presented in table 16. Network training is done on a one step-ahead basis. The observed values for the hedge fund index returns a time *t* are predicted by the network from the values at previous times *t-1, …, t-k* where *k* is the number of delays (*k* = 1 in this experiment).

Table 16. One-Period Ahead Forecast of Hedge Fund Returns

Name of Fund	Actual Value	Predicted Value
CSFB/T Hedge Fund Index	1.28	0.994
Convertible Arbitrage	3.02	1.311
Dedicated Short Bias	-2.73	2.438
Emerging Markets	-0.45	-0.188
Equity Market Neutral	0.31	0.848
Event Driven	2.27	0.864
Distressed	3.12	0.987
E.D. Multi Strategy	1.98	0.835
Risk Arbitrage	-0.39	0.653
Fixed Income Arbitrage	1.26	0.632
Global Macro	2.03	0.921
Long/Short	-0.07	0.850
Managed Fund	6.07	3.486

The Kajiji-4 RBF predicted the correct direction in ten of the thirteen cases. In two of the cases where the directional forecast was incorrect, the indices in question reflect a strong commitment to a short-position investment philosophy. The methodology invoked here lends itself to a multi-step ahead training approach. For high frequency investment strategies, methods

that involve 15- to 60-minute investment horizons, a multi-step forecast would prove useful. With an investment horizon of 30 days, we focus on a one-step approach as managers have risk management methods available to them that might not be available with a high frequency investment horizon (e.g., short hedges using derivatives, etc.).

7 Summary and Conclusions

The objective of this research was two-fold. In the first part of the examination we reported the results of an experiment that compared the performance of alternative RBF frameworks to model the direction and level of hedge fund returns. In this area, we report that the Kajiji-4 RBF is the dominant ANN when compared to other well-known methods in the RBF framework. Additionally, we present evidence to support previously reported findings on modeling accuracy. But, our research findings contradict the conclusion offered by Leung that classification methods are more accurate than return-level methods when modeled by an ANN framework. For six of thirteen hedge funds managed by CSFB/Tremont we find that in addition to relative volatility (coefficient of variation) both skewness and kurtosis play a significant role in the fitness measure of performance for each of the tested RBF methods. Again, the Kajiji-4 method surfaced as the most computationally efficient when confronted with high relative volatility, skewness and peaked return distributions. When controlling for the third- and fourth-moment, the Kajiji-4 method was able to lower its modeling error. Nevertheless, the gains from the additional effort to achieve these results appear minimal in the overall scheme of forecasting one or more steps ahead.

This paper also established the ability of the Kajiji-4 method to generate one-step ahead forecasts. For the thirteen indexes under investigation, the Kajiji-4 method predicted the correct direction of the next period return for ten of the indexes. The three incorrect forecasts were for indexes that sample investment behavior that relies upon short-investment positions. This observation leads us to conclude that in its current specification, the Kajiji-4 forecasting model is not yet capable of forecasting one-period ahead monthly returns for hedge funds that follow short-investment based philosophies. By contrast, the Kajiji-4 method appears to be a reliable method for forecasting hedge fund returns for investment philosophies that do not emphasize a short-position commitment.

REFERENCES

Amenc, N., Bied, S. E. & Martellini, L. 2002, *Evidence of Predictability in Hedge Fund Returns and Multi-Style Multi-Class Tactical Style Allocation Decisions*, Marshall School of Business, Working Paper No: 02-5.

Balci, O. 2001, 'A Methodology for Certification of Modeling and Simulation Applications', *ACM Transactions on Programming Languages and Systems,* vol. 11, no. 4, pp. 352-377.

Barberis, N. 2000, 'Investing for the Long Run when Returns are Predictable', *Journal of Finance,* vol. 55, pp. 225-264.

Bollerslev, T. 1986, 'Generalized Autoregressive Conditional Heteroskedasticity', *Journal of Econometrics,* vol. 31, pp. 307-327.

Burgess, A. N. 1995, 'Non-linear Model Identification and Statistical Significance Tests and their Application to Financial Modeling', in *Artificial Neural Networks, Inst. Electrical Engineering Conference*.

Castiglione, F. & Bernaschi, M. 2001, *Market Fluctuations: Simulation and Forecasting*, Available: [http://www.zpr.uni-koeln.de/~filippo/WEB_IAC/econophysics/econophysics.html] (Jan 31, 2003).

Chib, S., Nardari, F. & Shephard, N. 2001, *Analysis of High Dimensional Multivariate Stochastic Volatility Models*, Washington University, St. Louis, Working Paper.

Crouse, R. H., Jin, C. & Hanumara, R. C. 1995, 'Unbiased Ridge Estimation with Prior Information and Ridge Trace', *Communication in Statistics,* vol. 24, no. 9, pp. 2341-2354.

Dash, G. & Kajiji, N. 2002, 'Modeling FX Volatility: A Comparative Analysis of the RBF Neural Network Topology', in *9th International Conference on Forecasting Financial Markets*, London, England.

Dash, G. H., Hanumara, C. & Kajiji, N. 2003, 'Neural Network Architectures for Modeling FX Futures Options Volatility', in *Annual Meetings of the Northeast Decision Sciences Institute*, Providence, Rhode Island.

Debray, S., Evans, W., Muth, R. & de Sutter, B. 2000, 'Compiler Techniques for Code Compaction', *ACM Transactions on Programming Languages and Systems,* vol. 22, no. 2, pp. 378-415.

Demartines, P. & Herault, J. 1997, 'Curvilinear Component Analysis: A Self-Organizing Neural Network for Nonlinear Mapping of Data Sets', *IEEE Transactions on Neural Networks,* vol. 8, no. 1, pp. 148-154.

Dyba, T. 2000, 'An Instrument for Measuring the Key Factors of Success in Software Process Improvement', *Emiprical Software Engineering,* vol. 5, no. 4, pp. 357-390.

Fama, E. & French, K. 1989, 'Business Conditions and Expected Returns on Stocks and Bonds', *Journal of Financial Economics,* vol. 25, pp. 23-49.

Ferson, W. & Harvey, C. 1991, 'Sources of Predictability in Portfolio Returns', *Financial Analysts Journal,* vol. May / June, pp. 49-56.

Fraser, C. W. & Wendt, A. L. 1986, 'Integrating Code Generation and Optimization', *SIGPLAN Notices,* vol. 21, no. 7, pp. 242-248.

Fung, W. & Hsieh, D. 1999, 'Is Mean-Variance Analysis Applicable to Hedge Funds?' *Economic Letters,* vol. 62, pp. 53-58.

Han, Y. 2002, *The Economic Value of Volatility Modeling: Assest Allocation with a High Dimensional Dynamic Latent Factor Multivariate Stochastic Volatility Model*, Washington University, St.Louis, MO, Working Paper.

Hanson, D. B. 1983, 'Simple Code Optimization', *Software-Practice and Experience,* vol. 13, no. 8, pp. 745-763.

Harasty, H. & Roulet, J. 2000, 'Modeling Stock Market Returns -- An Error Correction Model', *Journal of Portfolio Management,* vol. Winter, pp. 33-46.

Harvey, C. R., Travers, K. E. & Costa, M. J. 2002, 'Forecasting Emerging Market Returns Using Neural Networks', *Emerging Markets Quarterly,* vol. Summer, pp. 1-12.

Hemmerle, W. J. 1975, 'An Explicit Solution for Generalized Ridge Regression', *Technometrics,* vol. 17, no. 3, pp. 309-314.

Hoerl, A. E. & Kennard, R. W. 1970, 'Ridge Regression: Biased Estimation for Nonorthogonal Problems.' *Technometrics,* vol. 12, no. 3, pp. 55-67.

Kajiji, N. 2001, *Adaptation of Alternative Closed Form Regularization Parameters with Prior Information to the Radial Basis Function Neural Network for High Frequency Financial Time Series*, Neural Networks, statistics, and time series, University of Rhode Island.

Kat & Lu 2002, *An Excursion into the Statistical Properties of the Hedge Fund Returns*, Alternative Investment Research Center, London, UK, Working Paper.

Keim, D. & Stambaugh, R. 1986, 'Predicting Returns in the Stock and Bond Markets', *Journal of Financial Economics,* vol. 17, pp. 357-424.

Leung, M., Daouk, H. & Chen, A. 2000, 'Forecasting Stock Indices: A Comparison of Classification and Level Estimation Models', *International Journal of Forecasting,* vol. 16, pp. 173-190.

Lhabitant, F.-S. & Learned, M. July 2002, *Hedge Fund Diversification: How Much is Enough?*, FAME: International Center for Financial Asset Management and Engineering, Geneva, Switzerland, Research Paper No: 52.

Lindvall, M., Tesoriero, R. & Costa, P. 2003, 'An Empirically-Based Process for Software Architecture Evaluation', *Emiprical Software Engineering,* vol. 8, no. 1, pp. 83-108.

Lynch, A. 2000, *Portfolio Choice and Equity Characteristics: Characterizing the Hedging Demands Induced by Return Predictability*, New York University, New York, NY, Working Paper.

Mayrand, J., Patenaude, J.-F., Merlo, E., Dagenais, M. & Lague', B. 2000, 'Software Assessment Using Metrics: A Comparison Across Large C++ and Java Systems', *Annals of Software Engineering,* vol. 9, no. 1-4, pp. 117-141.

Merton, R. 1981, 'On Market Timing and Investment Performance: An Equilibrium Theory of Value for Market Forecasts', *Journal of Business,* vol. 54, no. 3, pp. 363-406.

Orr, M. J. L. 1996, *Introduction to Radial Basis Function Networks*, Center for Cognitive Science, Scotland, UK.

Orr, M. J. L. 1997, *MATLAB Routines for Subset Selection and Ridge Regression in Linear Neural Networks.*, Center for Cognitive Science, Scotland, UK.

Refenes, A.-P. N., Burgess, A. N. & Bentz, Y. 1997, 'Neural Networks in Financial Engineering: A Study in Methodology', *IEEE Transactions on Neural Networks,* vol. 8, no. 6, pp. 1222-1267.

Sheldon, F. T. & Greiner, S. 1999, 'Composing, Analyzing, and Validating Software Models to Assess the Performability of Competing Design Candidates', *Annals of Software Engineering,* vol. 8, no. 1-4, pp. 289-311.

SPSS. 2001, 'Neural Connection, Release 2.1, Build 688', SPSS, Inc., Chicago, IL.

Statsoft. 2001, 'STATISTICA', Statsoft, Inc, Tulsa, OK.

Thomson, G. H. 1951, *The Factorial Analysis of Human Ability*, University of London Press, London.

Tikhonov, A., and Arsenin, V. 1977, *Solutions of Ill-Posed Problems*, Wiley, New York.

Yao, J. & Tan, C. L. Access Year: 2003, 'A Study on Training Criteria for Financial Time Series Forecasting', J.T.Yao@massey.ac.nz, Palmerston North, New Zealand.