Institut für Höhere Studien (IHS), Wien
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Abstract

In most of the empirical research on capital markets, stock market indexes are used as proxies for the aggregate market development. In previous work we found that a particular market segment might be less efficient than the whole market and hence easier to forecast. In this paper we extend the focus of this investigation by taking a comprehensive look at the Vienna Stock Exchange. We use feedforward networks and linear models to forecast the all share index WBI as well as various subindexes covering the highly liquid, semi-liquid, and initial public offering (IPO) market segment. In order to shed some light on network construction principles, we compare different models as selected by hold-out crossvalidation (HCV), Akaike's information criterion (AIC), and Schwartz' information criterion (SIC). The forecasts are subsequently evaluated on the basis of hypothetical trading in the out-of-sample period.

Zusammenfassung

In der empirischen Kapitalmarktforschung werden Aktienindizes oft als Maß für die aggregierte Marktentwicklung herangezogen. Frühere Arbeiten ergaben, daß spezifische Marktsegmente nicht so effizient wie der Gesamtmarkt und daher leichter zu prognostizieren sind. Hier wenden wir diesen Ansatz auf Wiener Aktienkursdaten an. Wir verwenden lineare und feedforward Netzwerke Modelle, um den Gesamtmarktindex WBI sowie verschiedene Subindizes für das hochliquide, semi-liquide und Erstemissionsmarktsegment zu prognostizieren. Um die Transparenz bei der Architekturselektion für neuronale Netzwerke zu erhöhen, vergleichen wir Modelle auf der Basis von Hold-out Kreuzvalidierung (HCV), Akaike Informationskriterium (AIC) und Schwartz Informationskriterium (SIC). Die Güte der Prognosen wird anhand einer Tradingsimulation für die out-of-sample Periode bestimmt.

Keywords
Neural network architecture selection, information criteria, stock market indexes, trading strategy

JEL-Classifications
C45, C52, C53, C43

Remark

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1 Introduction

Profit-seeking institutions and individuals find it increasingly interesting to explore investment opportunities off-side mainstream attention. In response to the ensuing demand for instruments that document the performance of particular markets and market segments, chiefly financial intermediaries have introduced specific indexes to meet their own and their customers' information needs. In compensation for its industry in index creation, the index industry now witnesses a boom in the development of financial indicators. To illustrate, a diversity of new benchmarks such as emerging market indexes, small cap indexes, and warrant indexes supplements the analyst's toolbox.

However, despite the intensive activity in the financial sector to create and implement a multitude of new instruments, the scholarly domain has largely stood aloof so far. While dramatic events on emerging capital markets have had an impact on the frequency of occasional country studies, investigations concerning specific market segments remained an exceptional undertaking.

In the present paper we conjecture that the exposition of a market segment to analysts' coverage is negatively correlated with the probability to detect profitable trading strategies. If so, it may be rewarding to develop indicators that focus on largely neglected market segments. Specifically, we consider a set of interrelated subindexes that document the performance of various segments of the Austrian stock market.

We color – at least partially – the black box that neural networks often represent by empirically comparing three criteria commonly applied to the determination of an optimal neural network architecture with respect to its out-of-sample performance. Recently Swanson and White (1995) argued that "the in-sample SIC does not appear to be a reliable guide to out-of-sample performance, so it fails to offer a convenient shortcut to true out-of-sample performance measures for selecting models and for configuring nonlinear ANN models." We will provide a thorough comparison between hold-out crossvalidation, Akaike's information criterion, and the Schwartz information criterion which is also known as the Bayesian information criterion. By combining this undertaking with stock market index forecasting, we can simulate trading and calculate hypothetical trading profits. Thus, we arrive at a well defined loss function on which the assessment of the different estimates for prediction risk can be based.

In section 2 we provide a brief overview of the development of feedforward neural networks, and section 3 discusses the concept of prediction risk. Section 4 presents the data as well as the index sampling and construction principles, and section 5 discusses the empirical results on the basis of which we conclude in section 6.

2 Artificial Neural Networks

In the recent literature a class of flexible nonlinear functions called artificial neural networks (ANNs) has been proposed. White (1988) uses them to test the efficient market hypothesis, Swanson and White (1995) investigate whether the forward interest rate contains information on the spot rate, Natter, Haefke, Soni and Otruba (1994) forecast GNP, and Hutchinson, Lo and Poggio (1994) apply a special class of neural networks to option pricing. All this work is based on McCulloch and Pitts (1943) who constructed models to mimic brain functionality. Widrow and Hoff (1960) called the neurons that McCulloch and Pitts used, adaptive linear elements (ADALINEs) and described the output of one such ADALINE as:

$$f(\tilde{x}_t, \alpha) = G(\tilde{x}_t' \alpha), \tag{1}$$

with $\tilde{x}_t$ being an input vector x_t augmented by a constant and α a set of weights. We see that for $G(u) = u$ we arrive at the simple linear model which is a standard paradigm in economic and econometric modelling. Kuan and White (1994) point out that for $G(u) = \frac{1}{1+\exp^{-u}}$, we arrive at the binary logit model, and for $G(u)$ being any normal cumulative distribution function, we obtain a binary probit. Hence even at the outset of neural network modelling, standard econometric models could easily be included as special cases. Later Werbos (1974) and Rumelhart, Hinton and Williams (1986) combined such neurons into one function and called them multilayer perceptron. This function can be represented as:

$$f(\tilde{x}_t, \beta, \gamma) = F\left(\sum_{q=1}^{Q} G(\tilde{x}_t' \gamma_q) \beta_q\right), \tag{2}$$

$\beta = (\beta_1, \beta_2, \ldots, \beta_q)'$, $\gamma = (\gamma_1', \ldots, \gamma_q')'$. Lee, White and Granger (1993) adopted this approach to conduct tests for neglected nonlinearity. In a first step they estimate a linear regression. Subsequently Q is set to 1, thus introducing an additional regressor for the residuals of the linear model. This is represented by

$$f(\tilde{x}_t, \theta) = \tilde{x}_t{}' \alpha + \sum_{q=1}^{Q} G(\tilde{x}_t' \gamma_q) \beta_q \tag{3}$$

with $\theta = (\alpha', \beta', \gamma')'$, $\beta = (\beta_1, \beta_2, \ldots, \beta_q)'$, and $\gamma = (\gamma_1', \ldots, \gamma_q')'$. Under the null $\beta_q^\star = 0$ the test will have power whenever $\sum_{q=1}^{Q} G(\tilde{x}_t{}' \gamma_q) \beta_q$ is capable of extracting structure from the residuals $(y_t - \tilde{x}_t{}' \alpha)$. Q represents the number of hidden units where each unit represents an additional regressor.

In this paper we use the same functional form as specified in equation 3 with a transfer function $G(u) = \frac{2}{1+\exp^{-u}} - 1$, mapping u into the $]-1;+1[$ interval. Estimation of the parameters is performed using the Polak Ribière Conjugated Gradient algorithm. As this is a local optimization method, every set of parameters θ is estimated five times, and the parameters of the run with the minimal in-sample cost-function are chosen. The next section discusses how to obtain non-arbitrary criteria for the determination of the hidden units.

3 Prediction Risk

Hornik, Stinchcombe and White (1989, 1990) showed, amongst others, that feedforward neural networks can approximate any Borel-measurable function arbitrarily well provided that the number of Q is sufficiently large. Therefore numerous early applications in the field of finance and economics are far off from being parsimoniously constructed. The number of elements in the parameter vector θ for a model is:[1] $W = Q(\Xi + 2) + 1$ where Ξ is the number of columns in the set of regressors $\tilde{x}$. The multiplicative relationship between Ξ and Q lets the number of weights shoot into dimensions beyond those econometricians are used to deal with when designing their models. A regression with just three explaining variables, one independent variable, and a Q of 3 results in 16 parameters as opposed to just 3 with OLS.

In financial applications that involve forecasting, the main focus of interest is not the in-sample performance of any forecasting model but rather how well the model deals with previously unseen data. We denote this *prediction risk* with R which can either be determined through one of the various kinds of crossvalidation and bootstrapping or through criteria that are based on the in-sample error of the respective model. If we take into account that the estimation of a moderately sized feedforward neural network can take a quarter of an hour or more, criteria based on in-sample information lure like sirenes in a model builder's quest for the right neural net architecture. The appeal of such criteria is that they represent the tradeoff between good fit and parsimony, and they do so in various ways and with different emphasis.

3.1 Hold-out Crossvalidation

Hold-out crossvalidation (HCV) constitutes a very simple method of estimating R. For the computation of the prediction risk estimate a set of observations is set aside that is neither used for estimating the parameters nor for the final out-of-sample evaluation. Amari, Murata, Müller, Finke and Yang (1995) suggest to take a fraction $\left(1 - \frac{\sqrt{2W-1}-1}{2(W-1)}\right)$ of total observations for this set, which in this paper amounts to 65 observations. However, sometimes it might be very unfavourable to have to exclude even one single observation from training, and then in-sample estimates for prediction risk have to be used. Based on simulation and theoretical analyses, Amari et al. (1995) recommend this approach whenever the number of observations, n, is less than $30W$.

[1] Henceforth we will call the parameters "weights" or "connections", and W the total number of weights.

3.2 Akaike's Information Criterion

The Information Criterion A (AIC) as it was called by Akaike (1974) is computed as

$$AIC\,(W) = n \log MSE + 2W \tag{4}$$

for a Gaussian process. It represents an explicit formulation of the principle of parsimony where the first term penalizes a bad forecast quality while the second term unfavourably increases with the number of parameters. The AIC was derived as an approximately unbiased estimate for the Kullback-Leibler Information Criterion which measures the minimum possible distance between the model and the true distribution. However, asymptotically the AIC selects too large models even for AR processes, and hence the search for more appropriate criteria continues.

3.3 Schwartz Information Criterion

Sawa (1978) and Schwartz (1978) suggested a criterion which is now called Schwartz information criterion (SIC). SIC puts more emphasis on the parsimony of the models than the AIC. The AIC assumes for a given class of nested alternative models that for each model the estimate of the variance is nearly true in the sense that the difference to the true variance tends to zero as n tends to infinity. Unlike the AIC, the SIC for each model is evaluated assuming that the most complex model within the class would be nearly true but the others not necessarily so. Taking this difference in the underlying assumptions into account, Sawa (1978) arrives at the SIC

$$SIC\,(W) = n \log MSE + W \log n \tag{5}$$

which can also be derived from a Bayesian framework. Rissanen (1987) introduced another criterion that can be used with nonlinear and ARCH models but which again leads to the same criterion as in equation 5.

4 Data

In the context of stock market index construction, the selection of the index stocks and the determination of the index formula are two aspects which refer to conceptually distinct issues. We start with considering the latter subject, and subsequently we will also comment on the former.

The choice of the specific index formula is a sensitive issue. Haefke and Helmenstein (1996) find that due to different index formulae, two indexes which draw upon an *identical* sample of historical stock market data may not be cointegrated, that is there may not exist a long-run equilibrium relationship between the two. The results of econometric analyses may therefore crucially depend on the particular index formulae chosen. In order to prevent a systematic deviation of the indexes from each other, all indexes discussed in this study obey three identical construction principles. First, the decision-making process on the index formulae requires considerations regarding the selection of appropriate weighting schemes. If a weighted index is preferred, a decision about the kind of weigths has to be taken. Frequently used indexes are either price-weighted, capitalization-weighted, or turnover-weighted. The indexes employed in this paper consistently use the market capitalization of the index stocks as weights. Second, all indexes correspond to a capitalization-weighted price index. Third, a stock market index should not be influenced by stock price changes which are solely due to technical measures, for example the addition (deletion) of a stock to (from) the index sample or rights issues. In order to compensate for the impact of such measures on the index, all indexes are adjusted using identical procedures.

The choice of these specific index construction principles, however, does not imply that the determination of the sample of index stocks needs to follow the criterion of market capitalization as well. On the contrary, for the composition of the sample of index stocks a large set of selection criteria is at hand, such as a certain minimum market capitalization and/or turnover in either absolute or relative terms or the membership in a particular market segment (Helmenstein and Haefke, 1995). It is the distinctive property of the indexes presented subsequently that the respective index samples are constituted according to index-specific selection criteria. While the Austrian Traded Index (ATX) and the Semi-Liquid Market Index ($SEMIX$) employ the market capitalization and the turnover of stocks, respectively, to determine the upper and lower limits for inclusion, the Initial Public Offerings IndeX ($IPOX$) draws upon the criterion of membership in the market segment of initial public offerings. Recall, however, that all three indexes follow common index construction principles and differ only with respect to the sample of index stocks chosen.

4.1 The ATX

The leading international stock market indexes currently in use are based on a small sample of stocks which generally represents a considerable fraction of total stock market capitalization and/or turnover. A typical representative of these aggregate measures is the ATX which represents the blue chip market segment of the Vienna Stock Exchange. The ATX comprises about 50 % of total market capitalization. At present the index sample consists of 18 consecutively traded stocks. The ATX started with a base value of 1,000.00 on January 1^{st}, 1991. Since the ATX is calculated real-time, a new index value is available after every single trading operation. For the purpose of this study we have opted for using ATX closing values.[2]

[2] The index formula is provided in the IPOX section.

4.2 The SEMIX

We now turn to the concept of a Semi Liquid Market Index ($SEMIX$). Other indexes such as small cap and mid cap indexes, which focus on a market segment similar to the one represented by the $SEMIX$, use a certain market capitalization as upper limit and a certain minimum turnover as lower limit for a stock to qualify for inclusion in the index. In contrast to this approach, we prefer to use the same criterion for both the upper and the lower bounds. By reducing the number of variables relevant for qualification, our approach facilitates the interpretation of changes in the index sample.

It is a well-known observation that the turnover on relatively small stock markets is usually strongly skewed towards a few high turnover stocks. The upper limit for the $SEMIX$ was therefore fixed to the *average* turnover registered during a period of three months prior to the quarterly revision of the index sample. With 20 % of this value the lower limit is still sufficiently restrictive to ensure (almost) daily trading of the index stocks. The index is calculated using mid-day price settlement data.[2]

4.3 The IPOX

The $IPOX$ covers all IPOs in the official market segment of the Vienna Stock Exchange. Newly issued stock of companies whose stock other than the new category has been listed earlier is also included in the sample of index stocks. IPOs in the regulated and in the unregulated market segments are, by contrast, excluded from consideration. In order to prevent the short run underpricing phenomenon from distorting the aftermarket performance analysis, each IPO enters the $IPOX$ with the first price in public trading and *not* with the offering price. The ATX, $IPOX$, and $SEMIX$ are computed according to

$$ATX_t = ATX_{t-1}\left[\frac{\sum_{k=1}^{K} P_{k,t}Q_{k,t-1}}{\sum_{k=1}^{K} P_{k,t-1}Q_{k,t-1}}\right], \tag{6}$$

$$IPOX_t = IPOX_{t-1}\left[\frac{\sum_{i=1}^{I} P_{i,t}Q_{i,t-1}}{\sum_{i=1}^{I} P_{i,t-1}Q_{i,t-1}}\right], \tag{7}$$

$$SEMIX_t = SEMIX_{t-1}\left[\frac{\sum_{j=1}^{J} P_{j,t}Q_{j,t-1}}{\sum_{j=1}^{J} P_{j,t-1}Q_{j,t-1}}\right], \tag{8}$$

with $IPOX_t$ ($SEMIX_t$, ATX_t) as the $IPOX$ ($SEMIX$, ATX) value at time t, $P_{i,t}$ ($P_{j,t}$, $P_{k,t}$) the price of share i (j, k) at time t, $Q_{i,t-1}$, ($Q_{j,t-1}$ $Q_{k,t-1}$) the number of shares of stock i (j,k) issued at time $t-1$, and I (J, K) the number of stocks in the $IPOX$ ($SEMIX$, ATX).

The projections of expected future profits by the issuing company are a distinctive feature of IPOs. As the underwriting bank(s) can, beside others, be held liable for wrong or misleading statements, the prospectus contains more comprehensive and reliable information than any other information source available to the outside investor. Considering the additional information as being a typical attribute of a stock to be defined as an IPO, we have reason to expect that this status will vanish at the end of the forecasting horizon which is 18 months on average. For this reason one and a half years after the first listing on the stock exchange a stock does no longer qualify as an IPO and is thus withdrawn from the index. The legal framework affects the time trend properties of the $IPOX$ returns[3] in terms of lower volatility relative to the stock market average since the discounted value of future profits is less uncertain (Table 1).

Table 1: Descriptive statistics of the index returns

	ΔATX	$\Delta IPOX$	$\Delta SEMIX$	ΔWBI
Sample mean	0.00103	0.00063	0.00042	0.00074
Standard deviation s	0.00998	0.00753	0.00581	0.00695
Standard error of sample mean $\frac{s}{\sqrt{n}}$	0.00051	0.00038	0.00029	0.00035
# of observations n	390	390	390	390

For the purpose of comparison we conduct the same analysis for the Vienna Stock Exchange Share Index (WBI). The WBI differs from the indexes introduced before in terms of both the index construction principle and the criteria for the selection of the index stocks. In contrast to the other indexes, the WBI is a capitalization-weighted price index of type Paasche. The index sample does not refer to a specific market segment but comprises all domestic shares listed in the official market segment. The index was scaled to a base value of 100.00 on December 30^{th}, 1967.

The data is of length 663, starts on December 1^{st}, 1993, and ends on August 31^{st}, 1995. For estimating the parameters of our models we draw upon the first 390 to 395 observations, depending on the number of lags used for estimation. 63 observations are set aside for hold-out crossvalidation, and the remaining 200 observations are used to calculate the out-of-sample error measures and the out-of-sample trading profits.

5 Results and Out-of-Sample Error Measures

The selected error measures are chosen in such a way that they focus on different dimensions of goodness of fit. Mathews and Diamantopoulos (1994) analyse the most widely used error measures and identify four factors that together provide

[3] Returns are defined as log changes.

a more comprehensive assessment of a forecast than any of them on its own. The first and most important factor in their analysis is a ratio-type accuracy measure such as the adjusted mean absolute percentage error, $AMAPE$. The second factor can be described by volume-based accuracy measures, such as mean absolute error, MAE, and mean squared error, MSE. Factor three as measured by the mean error, ME, accounts for the bias in a forecast, whereas factor four, R^2, constitutes a measure of fit. Hence the information it provides can be interpreted as a pattern-matching indicator rather than a pure distance metric.

In addition to the error measures suggested by Mathews and Diamantopoulos we also compute Theil's measure of inequality (Theil, 1966) and a confusion matrix. Furthermore we conduct hypothetical trading, thereby obtaining a well defined loss function for the comparison of our models. In detail the error measures are:

- **Adjusted mean absolute percentage error**

$$AMAPE = \frac{1}{M} \sum_{m=1}^{M} \left| \frac{y_m - \hat{y}_m}{y_m + \hat{y}_m} \right|; \tag{9}$$

- **Mean absolute error**

$$MAE = \frac{1}{M} \sum_{m=1}^{M} \left| y_m - \hat{y}_m \right|; \tag{10}$$

- **Mean error**

$$ME = \frac{1}{M} \sum_{m=1}^{M} y_m - \hat{y}_m; \tag{11}$$

- **Coefficient of determination**

$$R^2 = 1 - \frac{\sum_{m=1}^{M} (y_m - \hat{y}_m)^2}{\sum_{m=1}^{M} (y_m - \bar{y})^2}; \tag{12}$$

- **Normalized mean squared error**

$$NMSE = \frac{\sum_{m=1}^{M} (y_m - \hat{y}_m)^2}{\sum_{m=1}^{M} (y_m - \bar{y})^2} \tag{13}$$

  $NMSE$ was used by Weigend and Gershenfeld (1994) to evaluate entries into the Santa Fe Time Series Competition and normalizes the MSE by dividing it through the variance of the respective series;

- **Theil's coefficient of inequality**

$$Theil = \frac{\sum_t (y_t - \hat{y}_t)^2}{\sum_t (y_t - y_{t-1})^2} \tag{14}$$

  This measure constitutes a simple sanity check of our forecasts against a no-change forecast which performs better for $Theil > 1$;

- **Confusion matrix**
  The up and down signals of the forecasts are used to compute a confusion matrix. We find the number of correct classifications in the main diagonal and the errors off the diagonal. The columns contain the actual ups and downs, while the rows contain the forecasts. As Swanson and White (1995) note, this is simply a $2x2$ contingency table, and the hypothesis that a given model is of no value in forecasting the sign of the price movement can be expressed as the hypothesis of independence between the actual and predicted directions. A binomial test is performed to check if the confusion rate – this is the sum of the off diagonal elements over the total number of elements – differs significantly from 50 %;

- **Trading scheme**
  We apply a very simple and conservative trading scheme with transaction costs. We start out on the first day of the evaluation period. If the forecast for the following day indicates a rise in prices and we do not yet hold the index portfolio, we buy. If we already hold, we do not buy again. In the case of falling prices we sell if we hold but never go short. Returns are annualized and compared to a Buy and Hold strategy. Transaction costs are assumed to be 1% of each transaction which is the amount usually faced by private investors at the Vienna Stock Exchange.

For each series we compute all error measures for the forecasting models from 1 to 5 lags with 1 to 3 hidden units. Generally we find only little predictability when we consider the Theil measure or any other of the statistical error measures. With just one lag as input the net tends to forecast a constant rather than a volatile price series. For all indexes except the WBI, however, this constant provides higher returns than the other – linear as well as nonlinear – forecasts. The best WBI forecast draws upon two lags with $Q = 1$ where the cumulated loss is significantly lower than with any other configuration. The negative returns, which are by far better than the buy-and-hold trading strategy, though, are to some extent due to the relatively high transaction costs. If we had incorporated the transaction costs into the buy/sell decision, even positive returns would have been possible.

The comparison of the estimates for the prediction risk reveals that both HCV and AIC constantly opt for overly large models. The SIC, by contrast, selects the return-best model in the case of the $IPOX$, an unduly large model in the case of the $SEMIX$, and too small models in the case of both the ATX and the WBI. A correlation analysis of cumulated returns (table 2) and values of the SIC indicates a negative relationship between the two variables while the AIC unexpectedly exhibits a positive correlation. For HCV we obtain ambiguous results.

Table 2: Correlation between information criteria and trading returns

Information Criteria	ATX	IPOX	SEMIX	WBI
HCV	0.136	-0.329	-0.754**	-0.406
(F-value)	(0.338)	(2.182)	(23.663)	(3.550)
AIC	0.411	0.297	0.813**	0.778**
(F-value)	(3.667)	(1.745)	(35.166)	(27.629)
SIC	-0.593**	-0.442*	-0.467*	-0.327
(F-value)	(9.752)	(4.372)	(5.016)	(2.162)

Critical value for 20 d.f., 95%: F=4.3513;
critical value for 20 d.f., 99%: F=8.0960.

6 Conclusion

The object of this paper is twofold. First, we investigated the predictability of Viennese submarket indexes and concluded that such a predictability exists for the univariate case. Further improvements of the forecasts may be accomplished in a multivariate setting by exploiting relationships that are likely to exist between the indexes.

Second, the suitability of two different information criteria as computational shortcut towards neural net architecture selection was compared to hold-out crossvalidation. Whereas HCV and AIC selected models that were larger than the one yielding the highest profit, SIC once found the profit maximizing model but generally favoured undersized models.

The latter results are in line with previous findings. It remains to be investigated how SIC compares to criteria tailor-made for neural networks, such as Generalized Prediction Error (GPE) or the Network Information Criterion (NIC), and for datasets with higher degrees of nonlinearity. These projects will be left for future work.

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References

Akaike, H., "A New Look at Statistical Model Identification," *IEEE Transactions on Automated Circuits*, 1974, *19*, 716–723.

Amari, S., N. Murata, K.R. Müller, M. Finke, and H. Yang, "Asymptotic Statistical Theory of Overtraining and Cross-Validation," Technical Report METR95-06, Department of Mathematical Engineering and Information. Physics University of Tokyo, Hongo 7-3-1, Bonkyo-ku, Tokyo 113 August 1995.

Haefke, C. and C. Helmenstein, "Predicting Stock Market Averages to Enhance Profitable Trading Strategies," in A.N. Refenes, ed., *Neural Networks in the Capital Markets 1995*, London: World Scientific Publishers, 1996. Forthcoming.

Helmenstein, C. and C. Haefke, "A Comparative Analysis of Stock Market Indexes," 1995. mimeo, Institute for Advanced Studies: Vienna.

Hornik, K., M. Stinchcombe, and H. White, "Multi-Layer Feedforward Networks Are Universal Approximators," *Neural Networks*, 1989, *2*, 359–366.

____ , ____ , and ____ , "Universal Approximation of an Unknown Mapping and Its Derivatives," *Neural Networks*, 1990, *3*, 551–560.

Hutchinson, J., A. Lo, and T. Poggio, "A Nonparametric Approach to Pricing and Hedging Derivative Securities via Learning Networks," *Journal of Finance*, 1994, *49*, 851–889.

Kuan, C.M. and H. White, "Artificial Neural Networks: An Econometric Perspective," *Econometric Reviews*, 1994, *13*, 1–91.

Lee, T., H. White, and C.W.J. Granger, "Testing for Neglected Nonlinearity in Time Series Models: A Comparison of Neural Network Methods and Alternative Tests," *Journal of Econometrics*, 1993, *56*, 269–290.

Mathews, B.P. and A. Diamantopoulos, "Towards a Taxonomy of Forecast Error Measures," *Journal of Forecasting*, 1994, *13*, 409–416.

McCulloch, W.S. and W. Pitts, "A Logical Calculus of the Ideas Immanent in Nervous Activity," *Bulletin of Mathematical Biophysics*, 1943, *5*, 115–133.

Natter, M., C. Haefke, T. Soni, and H. Otruba, "Macroeconomic Forecasting Using Neural Networks," in Y. Abu-Mostafa, ed., *Neural Networks in the Capital Markets 1994*, 1994.

Rissanen, J., "Stochastic Complexity and the MDL Principle," *Econometric Reviews*, 1987, *6*, 85–102.

Rumelhart, D.E., G.E. Hinton, and R.J. Williams, *Learning Internal Representations by Error Propagation*, Vol. 1, Cambridge, MA: MIT Press, 1986.

Sawa, T., "Information Criteria for Discriminating Among Alternative Regression Models," *Econometrica*, 1978, *46*, 1273–1291.

Schwartz, G., "Estimating the Dimension of a Model," *Annals of Statistics*, 1978, *6*, 461–464.

Swanson, N. and H. White, "A Model Selection Approach to Assessing the Information in the Term Structure Using Linear Models and Artificial Neural Network Models," *Journal of Business and Economic Statistics*, 1995, *13*, 265–275.

Theil, H., *Applied Economic Forecasting*, Amsterdam: North Holland Publishing Company, 1966.

Werbos, P., "Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences." PhD dissertation, Harvard University, Department of Applied Mathematics, 1974.

White, H., "Economic Prediction Using Neural Networks: The Case of IBM Daily Stock Returns," in "Proceedings of the Second Annual IEEE Conference in Neural Networks," New York: IEEE Press, 1988, pp. 451–458.

Widrow, B. and M.E. Hoff, "Adaptive Switching Circuits," *Institute of Radio Engineers WESCON Convention Record*, 1960, *4*, 96–104.

Table 3: Statistical error measures for the ΔATX

Lags	Q	NMSE	Theil	AMAPE	MAE	ME	R^2	Confusion Matrix	t-value
1	0	0.986	0.990	2.828	0.005	-0.001	0.014	$\begin{bmatrix} 63 & 65 \\ 30 & 42 \end{bmatrix}$	0.708
1	1	2.133	2.143	4.137	0.008	-0.007	-1.133	$\begin{bmatrix} 93 & 107 \\ 0 & 0 \end{bmatrix}$	-0.992
1	2	8.912	8.953	1.451	0.019	-0.019	-7.912	$\begin{bmatrix} 93 & 107 \\ 0 & 0 \end{bmatrix}$	-0.992
1	3	64.722	65.018	1.037	0.053	-0.053	-63.722	$\begin{bmatrix} 93 & 107 \\ 0 & 0 \end{bmatrix}$	-0.992
2	0	0.995	0.999	2.573	0.005	-0.001	0.005	$\begin{bmatrix} 64 & 66 \\ 29 & 41 \end{bmatrix}$	0.708
2	1	0.998	1.002	3.981	0.005	-0.001	0.002	$\begin{bmatrix} 62 & 63 \\ 31 & 44 \end{bmatrix}$	0.850
2	2	1.020	1.025	2.032	0.005	-0.001	-0.020	$\begin{bmatrix} 56 & 56 \\ 37 & 51 \end{bmatrix}$	0.992
2	3	1.124	1.129	2.637	0.006	-0.001	-0.124	$\begin{bmatrix} 53 & 54 \\ 40 & 53 \end{bmatrix}$	0.850
3	0	1.001	1.005	3.169	0.005	-0.001	-0.001	$\begin{bmatrix} 69 & 66 \\ 24 & 41 \end{bmatrix}$	1.421
3	1	6.491	6.521	4.249	0.014	-0.006	-5.491	$\begin{bmatrix} 59 & 63 \\ 34 & 44 \end{bmatrix}$	0.424
3	2	21.325	21.423	2.222	0.026	-0.014	-20.325	$\begin{bmatrix} 71 & 80 \\ 22 & 27 \end{bmatrix}$	-0.283
3	3	153.818	154.522	1.294	0.070	-0.004	-152.818	$\begin{bmatrix} 58 & 66 \\ 35 & 41 \end{bmatrix}$	-0.141
4	0	1.016	1.021	3.324	0.005	-0.001	-0.016	$\begin{bmatrix} 68 & 67 \\ 25 & 40 \end{bmatrix}$	1.135
4	1	2.780	2.793	6.090	0.009	0	-1.780	$\begin{bmatrix} 46 & 45 \\ 47 & 62 \end{bmatrix}$	1.135
4	2	118.047	118.587	1.007	0.070	-0.010	-117.047	$\begin{bmatrix} 52 & 59 \\ 41 & 48 \end{bmatrix}$	0
4	3	858.868	862.797	1.247	0.160	-0.148	-857.868	$\begin{bmatrix} 70 & 74 \\ 23 & 33 \end{bmatrix}$	0.424
5	0	1.012	1.017	5.380	0.005	-0.001	-0.012	$\begin{bmatrix} 67 & 69 \\ 26 & 38 \end{bmatrix}$	0.708
5	1	1.323	1.329	3.742	0.006	0	-0.323	$\begin{bmatrix} 43 & 41 \\ 50 & 66 \end{bmatrix}$	1.278
5	2	15.922	15.995	1.660	0.023	0.002	-14.922	$\begin{bmatrix} 39 & 52 \\ 54 & 55 \end{bmatrix}$	-0.850
5	3	42.110	42.302	1.169	0.038	0.007	-41.110	$\begin{bmatrix} 41 & 47 \\ 52 & 60 \end{bmatrix}$	0.141

Table 4: Statistical error measures for the $\Delta IPOX$

Lags	Q	NMSE	Theil	AMAPE	MAE	ME	R^2	Confusion Matrix	t-value
1	0	0.961	0.965	3.006	0.004	-0	0.039	$\begin{bmatrix} 81 & 62 \\ 22 & 35 \end{bmatrix}$	2.292
1	1	6.927	6.953	1.486	0.017	0.016	-5.927	$\begin{bmatrix} 0 & 0 \\ 103 & 97 \end{bmatrix}$	-0.424
1	2	4.168	4.184	3.317	0.012	-0	-3.168	$\begin{bmatrix} 64 & 46 \\ 39 & 51 \end{bmatrix}$	2.146
1	3	57.854	58.072	1.112	0.051	-0.051	-56.854	$\begin{bmatrix} 103 & 97 \\ 0 & 0 \end{bmatrix}$	0.424
2	0	0.961	0.965	6.072	0.004	-0	0.039	$\begin{bmatrix} 82 & 62 \\ 21 & 35 \end{bmatrix}$	2.440
2	1	0.941	0.945	2.059	0.004	-0	0.059	$\begin{bmatrix} 75 & 54 \\ 28 & 43 \end{bmatrix}$	2.588
2	2	0.976	0.980	3.340	0.004	-0	0.024	$\begin{bmatrix} 54 & 36 \\ 49 & 61 \end{bmatrix}$	2.146
2	3	1.023	1.027	5.449	0.005	-0	-0.023	$\begin{bmatrix} 53 & 40 \\ 50 & 57 \end{bmatrix}$	1.421
3	0	0.957	0.961	2.958	0.004	-0	0.043	$\begin{bmatrix} 81 & 60 \\ 22 & 37 \end{bmatrix}$	2.588
3	1	16.914	16.978	1.532	0.024	-0.002	-15.914	$\begin{bmatrix} 55 & 45 \\ 48 & 52 \end{bmatrix}$	0.992
3	2	1.797	1.804	3.954	0.007	-0.002	-0.797	$\begin{bmatrix} 58 & 48 \\ 45 & 49 \end{bmatrix}$	0.992
3	3	30.200	30.314	1.223	0.033	0	-29.200	$\begin{bmatrix} 56 & 42 \\ 47 & 55 \end{bmatrix}$	1.565
4	0	0.969	0.973	2.439	0.004	-0	0.031	$\begin{bmatrix} 82 & 59 \\ 21 & 38 \end{bmatrix}$	2.887
4	1	5.400	5.420	7.856	0.013	-0.003	-4.400	$\begin{bmatrix} 59 & 60 \\ 44 & 37 \end{bmatrix}$	-0.566
4	2	1.051	1.055	2.298	0.005	-0	-0.051	$\begin{bmatrix} 71 & 49 \\ 32 & 48 \end{bmatrix}$	2.737
4	3	79.294	79.593	1.026	0.052	0.023	-78.294	$\begin{bmatrix} 49 & 40 \\ 54 & 57 \end{bmatrix}$	0.850
5	0	0.962	0.966	2.668	0.004	-0	0.038	$\begin{bmatrix} 82 & 56 \\ 21 & 41 \end{bmatrix}$	3.342
5	1	4.149	4.165	2.304	0.011	-0	-3.149	$\begin{bmatrix} 58 & 38 \\ 45 & 59 \end{bmatrix}$	2.440
5	2	50.911	51.103	1.458	0.043	-0.003	-49.911	$\begin{bmatrix} 54 & 53 \\ 49 & 44 \end{bmatrix}$	-0.283
5	3	50.214	50.403	1.815	0.041	-0.003	-49.214	$\begin{bmatrix} 46 & 57 \\ 57 & 40 \end{bmatrix}$	-2

Table 5: Statistical error measures for the $\Delta SEMIX$

Lags	Q	NMSE	Theil	AMAPE	MAE	ME	R^2	Confusion Matrix	t-value
1	0	0.980	0.984	1.480	0.006	-0.001	0.020	$\begin{bmatrix} 82 & 84 \\ 14 & 20 \end{bmatrix}$	0.283
1	1	1.353	1.357	5.430	0.008	-0.005	-0.353	$\begin{bmatrix} 96 & 104 \\ 0 & 0 \end{bmatrix}$	-0.566
1	2	1.623	1.628	2.666	0.009	0.007	-0.623	$\begin{bmatrix} 0 & 0 \\ 96 & 104 \end{bmatrix}$	0.566
1	3	4.244	4.258	3.717	0.015	0.005	-3.244	$\begin{bmatrix} 43 & 30 \\ 53 & 74 \end{bmatrix}$	2.440
2	0	1.008	1.011	2.211	0.006	-0.001	-0.008	$\begin{bmatrix} 75 & 82 \\ 21 & 22 \end{bmatrix}$	-0.424
2	1	1.014	1.017	2.058	0.006	-0.001	-0.014	$\begin{bmatrix} 72 & 78 \\ 24 & 26 \end{bmatrix}$	-0.283
2	2	1.004	1.007	2.153	0.006	-0.001	-0.004	$\begin{bmatrix} 66 & 77 \\ 30 & 27 \end{bmatrix}$	-0.992
2	3	1.056	1.060	1.794	0.006	-0.001	-0.056	$\begin{bmatrix} 72 & 70 \\ 24 & 34 \end{bmatrix}$	0.850
3	0	1.011	1.014	1.857	0.006	-0.001	-0.011	$\begin{bmatrix} 79 & 81 \\ 17 & 23 \end{bmatrix}$	0.283
3	1	3.449	3.460	3.285	0.015	0	-2.449	$\begin{bmatrix} 45 & 42 \\ 51 & 62 \end{bmatrix}$	0.992
3	2	2.863	2.873	4.347	0.013	0.001	-1.863	$\begin{bmatrix} 44 & 42 \\ 52 & 62 \end{bmatrix}$	0.850
3	3	1.706	1.712	3.214	0.009	0.001	-0.706	$\begin{bmatrix} 45 & 44 \\ 51 & 60 \end{bmatrix}$	0.708
4	0	1.009	1.013	1.990	0.006	-0.001	-0.009	$\begin{bmatrix} 75 & 79 \\ 21 & 25 \end{bmatrix}$	0
4	1	1.916	1.923	3.133	0.010	-0.001	-0.916	$\begin{bmatrix} 45 & 59 \\ 51 & 45 \end{bmatrix}$	-1.421
4	2	4.172	4.185	6.314	0.016	0.002	-3.172	$\begin{bmatrix} 32 & 54 \\ 64 & 50 \end{bmatrix}$	-2.588
4	3	104.032	104.373	1.141	0.085	-0.024	-103.032	$\begin{bmatrix} 56 & 72 \\ 40 & 32 \end{bmatrix}$	-1.709
5	0	1.011	1.015	2.255	0.006	-0.001	-0.011	$\begin{bmatrix} 74 & 77 \\ 22 & 27 \end{bmatrix}$	0.141
5	1	15.989	16.041	3.004	0.033	0.001	-14.989	$\begin{bmatrix} 48 & 52 \\ 48 & 52 \end{bmatrix}$	0
5	2	249.799	250.617	1.384	0.118	-0.016	-248.799	$\begin{bmatrix} 50 & 56 \\ 46 & 48 \end{bmatrix}$	-0.283
5	3	13.367	13.410	1.323	0.029	-0.004	-12.367	$\begin{bmatrix} 57 & 57 \\ 39 & 47 \end{bmatrix}$	0.566

Table 6: Statistical error measures for the ΔWBI

Lags	Q	NMSE	Theil	AMAPE	MAE	ME	R^2	Confusion Matrix	t-value
1	0	0.930	0.933	9.452	0.004	-0.001	0.070	$\begin{bmatrix} 61 & 58 \\ 30 & 51 \end{bmatrix}$	1.709
1	1	1.513	1.517	15.062	0.005	-0.004	-0.513	$\begin{bmatrix} 91 & 108 \\ 0 & 1 \end{bmatrix}$	-1.135
1	2	18.325	18.382	1.175	0.020	-0.019	-17.325	$\begin{bmatrix} 90 & 109 \\ 1 & 0 \end{bmatrix}$	-1.421
1	3	29.935	30.029	1.083	0.027	-0.027	-28.935	$\begin{bmatrix} 91 & 109 \\ 0 & 0 \end{bmatrix}$	-1.278
2	0	0.929	0.932	3.747	0.004	-0.001	0.071	$\begin{bmatrix} 61 & 58 \\ 30 & 51 \end{bmatrix}$	1.709
2	1	0.929	0.932	1.712	0.004	-0.001	0.071	$\begin{bmatrix} 57 & 51 \\ 34 & 58 \end{bmatrix}$	2.146
2	2	0.977	0.980	3.832	0.004	-0	0.023	$\begin{bmatrix} 56 & 49 \\ 35 & 60 \end{bmatrix}$	2.292
2	3	0.981	0.984	3.034	0.004	-0	0.019	$\begin{bmatrix} 56 & 49 \\ 35 & 60 \end{bmatrix}$	2.292
3	0	0.943	0.946	4.125	0.004	-0.001	0.057	$\begin{bmatrix} 62 & 59 \\ 29 & 50 \end{bmatrix}$	1.709
3	1	29.944	30.038	1.118	0.026	0.001	-28.944	$\begin{bmatrix} 40 & 51 \\ 51 & 58 \end{bmatrix}$	-0.283
3	2	78.583	78.829	1.694	0.037	0.027	-77.583	$\begin{bmatrix} 20 & 17 \\ 71 & 92 \end{bmatrix}$	1.709
3	3	85.585	85.853	1.232	0.040	-0.002	-84.585	$\begin{bmatrix} 41 & 47 \\ 50 & 62 \end{bmatrix}$	0.424
4	0	0.962	0.965	1.682	0.004	-0.001	0.038	$\begin{bmatrix} 65 & 51 \\ 26 & 58 \end{bmatrix}$	3.342
4	1	1.333	1.337	10.495	0.005	-0.002	-0.333	$\begin{bmatrix} 83 & 106 \\ 8 & 3 \end{bmatrix}$	-2
4	2	16.364	16.415	1.704	0.018	-0.006	-15.364	$\begin{bmatrix} 50 & 71 \\ 41 & 38 \end{bmatrix}$	-1.709
4	3	583.961	585.791	0.981	0.114	0.021	-582.961	$\begin{bmatrix} 49 & 39 \\ 42 & 70 \end{bmatrix}$	2.737
5	0	0.962	0.965	1.817	0.004	-0.001	0.038	$\begin{bmatrix} 64 & 56 \\ 27 & 53 \end{bmatrix}$	2.440
5	1	4.710	4.725	3.005	0.009	0.002	-3.710	$\begin{bmatrix} 40 & 43 \\ 51 & 66 \end{bmatrix}$	0.850
5	2	100.608	100.923	2.319	0.044	0.010	-99.608	$\begin{bmatrix} 38 & 39 \\ 53 & 70 \end{bmatrix}$	1.135
5	3	730.214	732.502	1.101	0.111	-0.027	-729.214	$\begin{bmatrix} 54 & 66 \\ 37 & 43 \end{bmatrix}$	-0.424

Table 7: Information Criteria and Trading Results for the *ATX*

Lags	Q	HCV	AIC	SIC	Cumulated returns	Mean return	Std. dev. of return	Number of transactions
1	0	0.755	-18.750	-2.824	-0.656	-0.394	0.037	103
1	1	0.759	-19.782	-3.856	-0.656	-0.394	0.037	103
1	2	0.722	-20.220	7.650	-0.655	-0.404	0.037	103
1	3	0.735	-15.516	24.298	-0.491	-0.279	0.037	69
2	0	0.775	-19.192	0.703	-0.663	-0.396	0.037	105
2	1	0.779	-19.321	0.574	-0.663	-0.396	0.037	105
2	2	0.743	-19.160	16.650	-0.684	-0.410	0.037	109
2	3	0.809	-22.368	29.358	-0.667	-0.406	0.037	105
3	0	0.769	-19.977	3.881	-0.658	-0.398	0.037	103
3	1	0.766	-21.338	2.520	-0.744	-0.443	0.037	114
3	2	0.714	-25.324	18.416	-0.774	-0.453	0.037	152
3	3	0.692	-43.965	19.656	-0.757	-0.450	0.037	123
4	0	0.776	-19.443	8.374	-0.642	-0.388	0.037	99
4	1	0.765	-22.569	5.248	-0.695	-0.411	0.037	109
4	2	0.742	-25.218	26.442	-0.776	-0.460	0.037	139
4	3	0.711	-43.437	32.065	-0.770	-0.452	0.037	124
5	0	0.787	-19.013	12.757	-0.674	-0.408	0.037	101
5	1	0.786	-19.205	12.565	-0.642	-0.389	0.037	101
5	2	0.929	-38.437	21.132	-0.746	-0.434	0.037	141
5	3	1.039	-60.974	26.394	-0.693	-0.411	0.037	129

Table 8: Information Criteria and Trading Results for the *IPOX*

Lags	Q	HCV	AIC	SIC	Cumulated returns	Mean return	Std. dev. of return	Number of transactions
1	0	0.735	-17.741	-1.826	-0.576	-0.354	0.039	95
1	1	0.732	-23.322	-7.407	-0.576	-0.354	0.039	95
1	2	0.679	-33.186	-5.334	-0.660	-0.406	0.039	107
1	3	0.682	-32.547	7.242	-0.658	-0.394	0.039	109
2	0	0.734	-15.684	4.198	-0.583	-0.357	0.039	95
2	1	0.672	-27.145	-7.263	-0.583	-0.357	0.039	95
2	2	0.670	-30.608	5.179	-0.581	-0.348	0.039	97
2	3	0.737	-36.233	15.459	-0.636	-0.380	0.039	109
3	0	0.734	-13.711	10.132	-0.588	-0.361	0.039	97
3	1	0.719	-20.839	3.003	-0.794	-0.471	0.039	119
3	2	0.657	-27.344	16.368	-0.644	-0.390	0.039	117
3	3	0.749	-35.469	28.112	-0.803	-0.472	0.039	121
4	0	0.742	-13.933	13.865	-0.586	-0.358	0.039	99
4	1	0.728	-21.330	6.469	-0.764	-0.451	0.039	127
4	2	0.703	-26.829	24.797	-0.623	-0.377	0.039	101
4	3	0.684	-40.218	35.236	-0.700	-0.414	0.039	138
5	0	0.749	-12.363	19.386	-0.606	-0.373	0.039	101
5	1	0.768	-18.396	13.353	-0.775	-0.468	0.039	119
5	2	0.840	-34.095	25.436	-0.705	-0.430	0.039	139
5	3	0.799	-27.286	60.026	-0.749	-0.432	0.039	142

Table 9: Information Criteria and Trading Results for the $SEMIX$

Lags	Q	HCV	AIC	SIC	Cumulated returns	Mean return	Std. dev. of return	Number of transactions
1	0	2.786	4.105	20.020	-0.504	-0.295	0.079	83
1	1	2.791	4.084	20	-0.504	-0.295	0.079	83
1	2	2.806	9.666	37.518	-0.481	-0.283	0.079	80
1	3	2.794	0.079	39.868	-0.695	-0.438	0.079	121
2	0	2.837	4.277	24.159	-0.523	-0.329	0.079	93
2	1	2.853	4.120	24.001	-0.533	-0.332	0.079	95
2	2	2.924	11.248	47.035	-0.523	-0.329	0.079	93
2	3	3.046	-2.686	49.007	-0.564	-0.357	0.079	99
3	0	2.883	5.231	29.074	-0.526	-0.332	0.079	93
3	1	2.986	-0.310	23.533	-0.610	-0.358	0.079	92
3	2	3.118	0.350	44.062	-0.641	-0.385	0.079	108
3	3	2.974	-9.146	54.435	-0.626	-0.384	0.079	104
4	0	2.899	6.129	33.928	-0.482	-0.293	0.079	87
4	1	2.927	1.583	29.382	-0.658	-0.410	0.079	110
4	2	2.909	-3.254	48.373	-0.706	-0.436	0.079	112
4	3	2.804	-29.748	45.706	-0.794	-0.491	0.079	146
5	0	2.894	7.645	39.395	-0.485	-0.296	0.079	87
5	1	3.073	-2.522	29.228	-0.732	-0.463	0.079	106
5	2	3.105	-40.666	18.865	-0.745	-0.445	0.079	130
5	3	4.299	-18.415	68.896	-0.738	-0.451	0.079	128

Table 10: Information Criteria and Trading Results for the WBI

Lags	Q	HCV	AIC	SIC	Cumulated returns	Mean return	Std. dev. of return	Number of transactions
1	0	0.805	-30.513	-14.617	-0.616	-0.369	0.038	95
1	1	0.808	-30.595	-14.700	-0.616	-0.369	0.038	95
1	2	0.787	-32.773	-4.956	-0.636	-0.367	0.038	87
1	3	0.786	-27.040	12.698	-0.495	-0.266	0.038	61
2	0	0.800	-28.446	-8.589	-0.613	-0.366	0.038	95
2	1	0.764	-33.132	-13.276	-0.597	-0.358	0.038	91
2	2	0.806	-30.838	4.903	-0.616	-0.377	0.038	98
2	3	0.801	-23.290	28.337	-0.616	-0.377	0.038	98
3	0	0.802	-32.092	-8.279	-0.601	-0.362	0.038	93
3	1	0.778	-37.584	-13.771	-0.671	-0.394	0.038	111
3	2	0.887	-38.574	5.082	-0.717	-0.433	0.038	107
3	3	0.847	-51.373	12.127	-0.699	-0.447	0.038	107
4	0	0.832	-35.019	-7.256	-0.624	-0.363	0.038	97
4	1	0.831	-35.215	-7.452	-0.562	-0.319	0.038	84
4	2	0.849	-37.956	13.604	-0.693	-0.401	0.038	112
4	3	0.826	-40.993	34.363	-0.712	-0.427	0.038	125
5	0	0.824	-33.237	-1.528	-0.621	-0.361	0.038	97
5	1	0.818	-35.774	-4.065	-0.652	-0.379	0.038	126
5	2	0.910	-49.277	10.177	-0.721	-0.461	0.038	101
5	3	0.964	-56.870	30.328	-0.786	-0.455	0.038	123

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