FORECASTING CHANGE and DIRECTION OF CHANGE IN ISE SECTOR INDICES: AN APPLICATION OF ARTIFICIAL NEURAL NETWORKS

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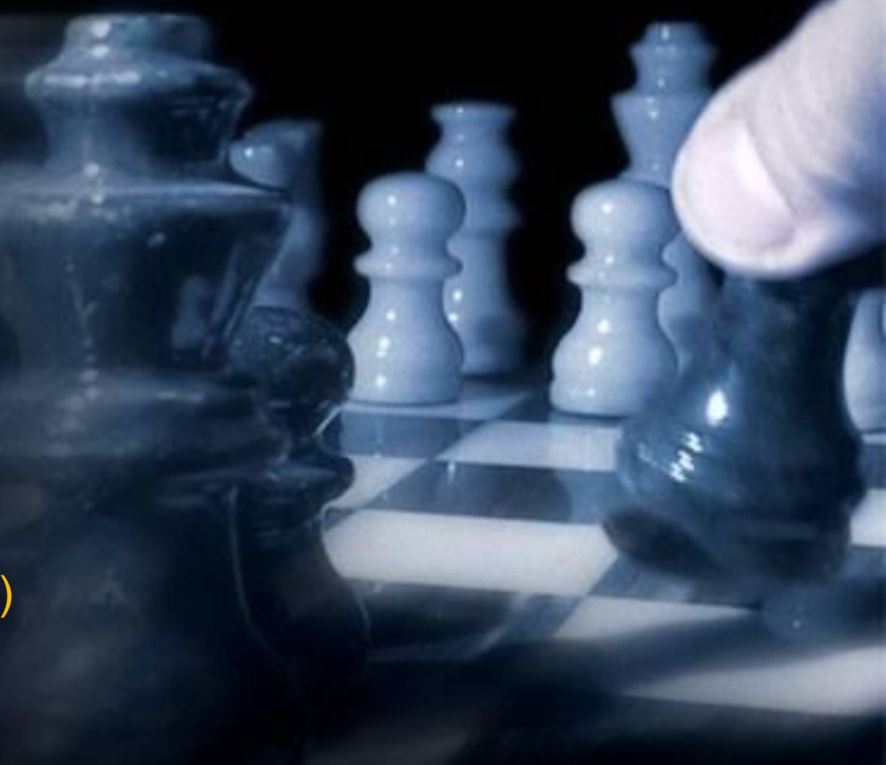

3 rd International Conference on
Business, Management and Economics (ICBME'07)
13-17 June 2007, İzmir, TURKEY

AGENDA

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- *Aim*
- *Scope*
- *The Model*
- *Data*
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- *Conclusion*

Motivation

- Effects of economic variables on stock prices and stock indices have been subject of interest for many years.
- There are a number of studies proves that economic variables have, to some extent, effects on stock prices. These effects are analyzed through using a number of methods and models.
- There are a number of studies focused on different aspects of Istanbul Stock Exchange (ISE) and stocks traded in it.
- Uniqueness of this study is that it employs ANN models with a large number of variables to forecast direction of change in sector indices.
- Forecasting the direction of change in stocks and stock indices is especially important for institutional investors who make speculation and get their profit from minor movements in prices.

Aim

- Main objective of this paper is to evaluate whether composite index and sector indices of Istanbul Stock Exchange (ISE) could be forecast using publicly available economic time series data by employing Artificial Neural Network (ANN) models.

- Another objective is to search for suitability of ANN models as an investment decision support tool .

Scope

- Publicly available economic variables are used to forecast the direction and magnitude of change in ISE sector indices.

- Economic variables are selected to reflect a well-known fact that not only domestic macroeconomic variables have an effect on indices but also depending on the level of globalization in financial markets some variables belong to other countries have an effect.

- Since macroeconomic variables are available monthly or for longer time horizons, it is adopted to use monthly data for all variables.

Organisation

- This paper is organized as follows:
  - **In the first part**, ANN's were introduced and discussed in detail. To do so, a brief history, nature and mathematics of ANN's, ANN structures, ANN operational framework, training and memory in ANN's, building steps of an ANNs were discussed.
  - **In the second part**, a comprehensive literature review on the application of ANN's in stock market analysis was provided.
  - **In the third part**, data, models and time series used were introduced.
  - **Fourth part** is about the methodology of the study about the forecasting and evaluating direction of change in sector indices.
  - **In the fifth part**, empirical results were discussed in detail. At the end, a general overview and summary of the results presented.

ANN Model

In this study, to forecast ISE indices we employ Multilayer Perceptrons (MLPs) which are layered feed-forward networks typically trained with static back-propagation.

Let L be number of layer (L-1 hidden layer), $z^0 \in R^{r_0}$ is input vector and $\phi(z^0) = z^L \in R^{r_L}$ output vector. A recursive input-output relation in this network could be expressed as:

$$y^j = w^j z^{j-1} + v^j$$

$$z^j = \hat{\sigma}_j(y^j) = \left[\sigma_j(y_1^j), \sigma_j(y_2^j), \dots, \sigma_j(y_{r_j}^j)\right]'$$

In equation (1), weights are $w = \{w^j, u^j\}$ where $w^j \in R^{r_j x r_{j-1}}$ and , bias is $u^j \in R^{r_j}$ and $j = 1,2, \dots, L$ dimensions of y^j and is shown by z^j . In equation (2), r_j scalar activation functions $\sigma_j(.)$ in hidden layers are $\sigma_j(.)$ sigmoid functions and activation functions

in output layer are linear functions such as $\sigma_j(.) = (.)$

Data-1

- **1st Step**: we collected data for 10 sector indices for the period of May 1991-December 2003. A list of sector indices are provided in the Table below. Sector indices are indices defined by the data provider Data Stream.

ISE Sector Indices	
ISE-COMPOSITE	ISECOMP
1-DS-RESOURCES	ISEDS1
2-DS BASIC INDUSTRIES	ISEDS2
3-DS GENERAL INDUSTRIALS	ISEDS3
4-DS CYCLICAL CONSUMPTION GOODS	ISEDS4
5-DS NON CYCLICAL CONSUMPTION GOODS	ISEDS5
6-DS CYCLICAL SERVICES	ISEDS6
7-DS NON CYCLICAL SERVICES	ISEDS7
8-DS UTILITIES	ISEDS8
9-DS INFORMATION TECHNOLOGY	ISEDS9
10-DS FINANCIALS	ISEDS10

Data-2

- **Second step:** we determined the economic variables to be used as independent or explanatory variables in the analysis
- In the selection of economic variables, we adopted following criteria.
  - **First criteria** in selecting economic variables was about the consistently publicly availability of data. We chose data publicized and available in public in a consistent basis.
  - **Second criteria** was about the timely availability of data.
  - **Third criteria** was about the rationalization of data with economic theory and there should be rational good reasons to believe that it had an effect on stock market.

Data-3

- We selected 22 economic variables, from the economic theory which are effective on stock prices.

Domestic Macroeconomic Input Variables		International Macroeconomic Input Variables		Leading World Stock Market Indices	
Leading Economic Indicators	TRLEAD	US Industrial Production Index 2002=100	USIND-PRO	SP500 Comp. Index	SP500
Producer Price Index	TRPPI	US Capacity Utilization: Total index	USCAP-UTIL	FTSE Comp. Index	FTSE
3 months bank deposit rates	BDR	US Producer Price Index 1982=100	USPPI	DAX Comp. Index	DAX
Total exports	EXP	Euro 12 Producer Price Index, 2000 = 100	EUPPI	Nikkei225 Index	NKK
Total imports	IMP	JP yen; Libor interbank 3 months deposit rate	YDR	HSE Comp. Index	HSE
Reel effective exchange rate	REIR	US 3-month Libor interbank deposit rate	UDR		
TR Capacity Utilization	TRCAP-UTIL	Euro area 10 year gov.bond yield	EUGBY		
		US 10 year gov.bond yield	USGBY		
		Japan 10 year gov.bond yield	JPGBY		
		W.Texas Intrm.Crude Oil	OIL		

Data-4

- Domestic economic time series data were taken from
  - TCMB-EVDS system
  - DPT
  - TUİK
- International economic times series data were collected from
  - REUTERS,
  - Federal Reserve Systems-FRED,
  - European Central Bank-ECB,
  - Economagic.

Methodology-1

- **Preliminary Data Analysis**
- **Network Models**
  - Multilayer Perceptron Neural Network Models
- **Network Building**
  - With adopting genetic algorithms (GA), a number of layers and perceptron in each layer were tested.
  - Results compared and models provided the least error were selected.
  - Each model had 4 hidden layers and 60 PE's in each hidden layer.
- **Network Training**
  - supervised learning strategy was adapted.
  - QuickBackpropagation learning rule was employed
  - High number (5.000 epoch) of simulation chosen
- **Estimation (Training) & Forecast Period**
  - Models are estimated & trained for the period of May 1991-December 2002
  - Out-of-sample forecast performances were tested for the 12 monthly period of January 2003-December 2003.
- **Performance Assessment**
  - Forecast success/failures analyzed.
  - Passive vs active investment results analyzed

Methodology-2

- Three separate approaches were adopted:
- **First approach**:
  - Each sector index was separately modeled with lagged data (12 months) on each of the 22 economic variables.
  - In each model, 13 input variables (current and 12 lagged values of each variable) were used.
  - Objective of adapting this approach was to evaluate the effect of each economic variable on stock indices individually.
  - In total, 22 x 11 = 232 separate ANN models were built & trained
  - Each of 232 models were tested for out of sample forecast performance for consecutive 12 months.

Methodology-3

- **Second approach:**
  - 22 macroeconomic variables were grouped as domestic macroeconomic, international macroeconomic and world stock markets.
  - Objective of adapting this approach was to evaluate the effect of each group of variables on stock indices in isolation.
  - As inputs, 22 variables with 12 lagged values were used.
  - In total, 3 x 11 = 33 separate ANN models were estimated and tested for out of sample forecast performance.
  - Each of 33 models were tested for out of sample forecast performance for consecutive 12 months

Methodology-4

- **<u>Third approach:</u>**
  - All economic variables were used in the same model simultaneously.
  - <u>Objective</u> was through using the biggest model, to forecast and test out of sample forecast performance of ANNs on the basis of each sector.
  - In total, 11x1 models were estimated and tested for out of sample forecast performance.
  - As inputs, 22 variables with 12 lagged values are used.
  - Each of 11 models were tested for out of sample forecast performance for consecutive 12 months

Methodology-4

- In total
  - We built (232 + 33 + 11) 276 separate ANN models
  - We made (232x12) + (33x12) + (11x12)= 3312 point forecast.

Literature

- A comprehensive literature review on the application of ANNs in stock market analysis was provided.

Empirical Findings
Forecast Performance

- For the first approach:
  - Individual economic variables generally had higher success rates in forecasting negative changes than positive changes in indices.
  - Average success rate was 50%.
  - DAX model had the highest success rate: %71 pos, %41 neg., in aggregate 58%.
- For the second approach:
  - All 3 group of models were more successful in forecasting positive changes than negative changes. Success rates ranges from 27% to 100%.
  - For positive changes the most successful model was the INTMACRECON model with 88% success rate, TRALL and WRLDSTKMRK followed with %72 and %61.
  - For negative changes the most successful model was theWRLDSTKMRK model with 45% success rate. TRALL and INTMACRECON followed with %35 and %29.3.
  - In aggregate INTMACRECON had highest success rate (62%), TRALL (55%) and WRLDSTKMRK (54%) followed it.

Empirical Findings

Forecast Performance

- For the third approach
  - The most comprehensive model with 343 input variables
  - It was more successful in forecasting positive changes than negative changes.
  - Aggregate success rate was 52%, poorer than more parsimonious models.

Empirical Findings

Forecast Performance

	Model:	TRLEAD		
	Actual	Forecast		
	Jan-03	Jan-03	BothPos	BothNeg
ISEDS1	9,0657%	-0,2669%	0	0
ISEDS2	11,9882%	5,3808%	1	0
ISEDS3	4,6060%	6,8099%	1	0
ISEDS4	6,0928%	-7,0943%	0	0
ISEDS5	3,5811%	5,0768%	1	0
ISEDS6	5,4650%	3,6457%	1	0
ISEDS7	14,7186%	-4,2464%	0	0
ISEDS8	5,2977%	1,8535%	1	0
ISEDS9	6,5536%	-7,1510%	0	0
ISEDS10	6,5622%	-10,4579%	0	0
ISECOMP	-10,7917%	-0,5762%	0	1
p	10	SUM	5	1
n	1	%Correct	50%	100%
	Total %	Correct	55%	

Model:	TRLEAD		
Actual	Forecast		
Jul-03	Jul-03	BothPos	BothNeg
-3,3233%	-0,2669%	0	1
-2,0706%	5,3808%	0	0
-2,8018%	6,8099%	0	0
-4,6176%	-7,0943%	0	1
5,2404%	5,0768%	1	0
3,5649%	3,6457%	1	0
-1,3449%	-4,2464%	0	1
-14,5021%	1,8535%	0	0
-1,2353%	-7,1510%	0	1
-3,6102%	-10,4579%	0	1
-3,0019%	-0,5762%	0	1
2	SUM	2	6
9	%Correct	100%	67%
Total %	Correct	73%	

Empirical Findings

Forecast Performance

TRALL	BOTHPOS	% CORRECT	BOTHNEG	%CORRECT	AGGREGATE SUCCESS RATES	
TOTAL CORRECT	53	71,62%	20	34,48%	SUCCESS	55,30%
TOTAL INCORRECT	21	28,38%	38	65,52%	FAILURE	44,70%
NUMBER of FORECAST	74	100,00%	58	100,00%	AGGREGATE	100,00%
INTMACROECON						
TOTAL CORRECT	65	87,84%	17	29,31%	SUCCESS	62,12%
TOTAL INCORRECT	9	12,16%	41	70,69%	FAILURE	37,88%
NUMBER of FORECAST	74	100,00%	58	100,00%	AGGREGATE	100,00%
WRLDSTCKMRKTS						
TOTAL CORRECT	45	60,81%	26	44,83%	SUCCESS	53,79%
TOTAL INCORRECT	29	39,19%	32	55,17%	FAILURE	46,21%
NUMBER of FORECAST	74	100,00%	58	100,00%	AGGREGATE	100,00%
ALLVARIABLES						
TOTAL CORRECT	46	62,16%	23	39,66%	SUCCESS	52,27%
TOTAL INCORRECT	28	37,84%	35	60,34%	FAILURE	47,73%
NUMBER of FORECAST	74	100,00%	58	100,00%	AGGREGATE	100,00%

Empirical Findings

Investing with Models

- We searched for suitability of ANN models as an investment decision support tool.
- We analysed if investor used the model results in his/her investment decision. For this purpose, we utilised an investment matrix:

Actual Change	Forecast Change	Action taken	Result
Positive	Positive	Invest	Gain
Positive	Negative	Not invest	Gain foregone
Negative	Positive	Invest	Loss
Negative	Negative	Not invest	Loss avoided

Empirical Findings

Investing with Models

- Comparison of model results yielded that INTMACROECON models outperformed other models in terms of highest gains achieved, least gains avoided and net gain to forecasts.
- In terms of least loss beared and loss avoided WORLDSTCK models outperformed other models.
- As a conclusion, model results indicated that although some models outperformed others in some areas, all models had capability to be used in forecasting ISE indices.

Empirical Findings

Investing with Models

- TRALL: Gains and losses from forecasts vs. passive strategy

	% Change in sector indices		Investment Strategy				Passive Strategy	
Sector Indices	**Actual**	**Forecast**	**Investment Decision**		**Gain/Loss from Investment**	**Sector Points from Forecast**	**Position**	**Sector Points from Passive Strategy**
ISECOMP						**0,432**		**0,432**
Jan.2003	-10,79%	5,00%	INVEST	LOSS	-10,79%		-10,79%	
Febr.2003	7,36%	5,03%	INVEST	GAIN	7,36%		7,36%	
Marc.2003	-10,65%	4,70%	INVEST	LOSS	-10,65%		-10,65%	
Apr.2003	8,11%	4,89%	INVEST	GAIN	8,11%		8,11%	
May.2003	-0,39%	4,74%	INVEST	LOSS	-0,39%		-0,39%	
June.2003	0,48%	5,02%	INVEST	GAIN	0,48%		0,48%	
July.2003	-3,00%	4,91%	INVEST	LOSS	-3,00%		-3,00%	
Aug.2003	9,60%	4,99%	INVEST	GAIN	9,60%		9,60%	
Sept.2003	9,86%	4,73%	INVEST	GAIN	9,86%		9,86%	
Oct.2003	17,92%	4,82%	INVEST	GAIN	17,92%		17,92%	
Nov.2003	4,82%	5,03%	INVEST	GAIN	4,82%		4,82%	
Dec.2003	9,88%	4,42%	INVEST	GAIN	9,88%		9,88%	

MODELS	INDICES	GAIN	GAIN FOREGONE	LOSS	LOSS AVOIDED	NET
TRALL		**716,84%**	**-218,56%**	**-242,17%**	**157,82%**	**413,93%**
	ISED1	46,90%	-19,07%	-24,78%	19,63%	22,68%
	ISED2	71,24%	-19,20%	-25,85%	0,00%	26,19%
	ISED3	95,54%	-4,61%	-23,60%	10,62%	77,96%
	ISED4	95,01%	-7,62%	-28,06%	11,42%	70,76%
	ISED5	76,56%	0,00%	-20,20%	0,00%	56,36%
	ISED6	22,64%	-70,92%	-0,17%	28,76%	-19,69%
	ISED7	52,09%	-25,39%	-22,31%	9,39%	13,78%
	ISED8	76,00%	0,00%	-34,24%	2,86%	44,62%
	ISED9	0,00%	-59,45%	0,00%	75,14%	15,69%
	ISED10	112,84%	-12,31%	-38,14%	0,00%	62,40%
	ISEDCOMP	68,01%	0,00%	-24,83%	0,00%	43,18%
INTMACROECON		**784,90%**	**-150,50%**	**-235,44%**	**164,55%**	**563,50%**
	ISED1	65,97%	0,00%	-15,63%	28,78%	79,12%
	ISED2	51,51%	-38,92%	-8,89%	16,96%	20,65%
	ISED3	100,15%	0,00%	-27,74%	6,47%	78,88%
	ISED4	95,01%	-7,62%	-39,48%	0,00%	47,92%
	ISED5	76,56%	0,00%	-20,20%	0,00%	56,36%
	ISED6	47,95%	-45,62%	-4,81%	24,12%	21,63%
	ISED7	77,48%	0,00%	-12,73%	18,96%	83,71%
	ISED8	76,00%	0,00%	-37,10%	0,00%	38,90%
	ISED9	10,70%	-48,75%	-41,27%	33,88%	-45,44%
	ISED10	125,15%	0,00%	-5,76%	32,38%	151,78%
	ISEDCOMP	58,41%	-9,60%	-21,83%	3,00%	29,99%
WORLDSTOCK		**580,18%**	**-355,22%**	**-224,85%**	**175,13%**	**175,24%**
	ISED1	62,32%	-3,65%	-0,75%	43,66%	101,57%
	ISED2	68,54%	-21,90%	-16,83%	9,02%	38,84%
	ISED3	54,82%	-45,33%	-6,47%	27,74%	30,76%
	ISED4	96,54%	-6,09%	-29,94%	9,53%	70,03%
	ISED5	35,77%	-40,79%	-8,06%	12,14%	-0,94%
	ISED6	15,22%	-78,34%	-4,99%	23,94%	-44,16%
	ISED7	75,26%	-2,23%	-7,65%	24,04%	89,42%
	ISED8	8,54%	-67,46%	-26,12%	10,98%	-74,05%
	ISED9	48,75%	-10,70%	-63,22%	11,93%	-13,24%
	ISED10	56,02%	-69,14%	-35,99%	2,15%	-46,96%
	ISEDCOMP	58,41%	-9,60%	-24,83%	0,00%	23,98%
ALLVARIABLES		**556,86%**	**-378,54%**	**-234,78%**	**165,20%**	**108,74%**
	ISED1	65,97%	0,00%	-44,41%	0,00%	21,56%
	ISED2	68,54%	-21,90%	-16,83%	9,02%	38,84%
	ISED3	100,15%	0,00%	-34,21%	0,00%	65,94%
	ISED4	102,63%	0,00%	-39,48%	0,00%	63,16%
	ISED5	36,18%	-40,37%	-12,37%	7,82%	-8,74%
	ISED6	81,58%	-11,98%	-28,93%	0,00%	40,66%
	ISED7	0,00%	-77,48%	0,00%	31,70%	-45,79%
	ISED8	41,42%	-34,58%	-30,11%	6,99%	-16,29%
	ISED9	0,00%	-59,45%	0,00%	75,14%	15,69%
	ISED10	2,25%	-122,90%	-3,61%	34,53%	-89,73%
	ISEDCOMP	58,13%	-9,88%	-24,83%	0,00%	23,42%

Conclusion

- As a general conclusion, we found that ANN models had great potential in using as a forecast tool in support of investment decisions and in determining characteristic features of stock markets and forecasting stock prices and indices.
- Their main advantage was their ability in modeling nonlinear structures and ability to work with a large number of variables without any constraint.

Thank you all…

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3 rd International Conference on
Business, Management and Economics
13-17 June 2007, İzmir, TURKEY