THE IMPACT OF FINANCIAL CRISIS ON THE PREDICTABILITY OF THE STOCK MARKETS OF PIGS COUNTRIES – COMPARATIVE STUDY OF PREDICTION ACCURACY OF TECHNICAL ANALYSIS AND NEURAL NETWORKS

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Abstract: To a degree the financial crisis influenced all European countries but the most affected are the PIGS (Portugal, Ireland, Greece and Spain). We investigated the effect of the financial crisis on the prediction accuracy of artificial neural networks on the Portuguese, Irish, Athens and Madrid Stock Exchange. We applied three-layered feed-forward neural networks with backpropagation algorithm to forecast the next day prices and we compared the paper returns achieved before and after the recent financial crisis. This method failed in forecasting the direction of the next day price movement but performed well in absolute price changes. However, it achieved better results than the strategy based on technical analysis in the period before the crisis. On the other hand, technical analysis performed better during the crisis.

Key words: Stock return, Prediction, Feed-Forward Neural Network, Technical Analysis, Financial Crisis

JEL Classification: G15, G17

Introduction

Lane and Milesi-Ferretti 0 probed possible differences across European economies in their vulnerability to shift in global imbalances. There is a bi-modal distribution of account balances within the European economy. While one group runs sizeable surpluses, Portugal, Ireland, Greece, Spain and Central and Eastern European countries have deficits of a magnitude similar to the US deficit. The correction of global imbalances involves an increase in global interest rates with a positive impact on the financial terms of trade of countries with a positive net debt and position and a corresponding negative impact on countries with a negative net debt position. This analysis was confirmed in the recent financial crisis where Portugal, Ireland, Greece, and Spain (hereinafter PIGS) became the most affected European countries. According to the study executed by Rose and Spiegel 0, there is little evidence that the intensity of the crisis across countries can be easily modelled using quantitative techniques. Hence we tried to undertake research focused primarily on the prediction of stock price indexes using artificial neural networks.

The prediction of complex stock market data requires nonlinear techniques 0. Artificial neural networks (ANNs) are a significant tool for solving classification and prediction problems and therefore attract a great attention from the field of financial markets. ANNs mimic the human brain in two aspects: information is collected in ANNs during learning and connections between neurons (synaptic weights) are used to store knowledge. ANNs are able to supplement or substitute statistical estimations and techniques of Moving Averages 0 used in technical analysis.

Halbert White 0 was the first to apply ANNs to the prediction of stock prices in 1988. He employed the feed-forward network to analyze the daily stock returns of IBM. He did not find any predictive rules but his research pointed out the prediction potential of ANNs on stock markets. Recently there is an abundance of studies attempting to forecast the price levels of international stock market indices 0000. Researchers suggest utilizing ANNs for a trading strategy to encourage higher returns than alternative strategies 00. Our goal was to set up an ANN model with a good prediction performance in price changes to create a profitable trading strategy on analyzed markets.

Aim and methodology

The objective of our research was to build a prediction system with a capability to forecast closing prices of Portugal PSI General Price Index, Ireland SE Overall Price

Index, ATHEX Composite Price Index, and Madrid SE General Price Index. As an alternative strategy for paper return comparison a trading strategy based on technical analysis was built.

Analysis of price indexes

The descriptive statistic for daily returns of price indexes (Fig. 1) shows differences in logarithmic return during the analysed periods. The variance in returns is higher during the crisis for each index, which confirms the higher volatility on stock markets during unstable phases of economic cycles. The analysed returns have negative relative skewness which implies frequent small gains and few extreme losses except Portugal PSI General and Madrid SE General during the crisis period. The excess kurtosis is leptokurtic for each of analysed stock return although for the period during the crisis the frequency of extremely large deviations from mean is higher than a normal distribution. The lowest kurtosis during the crisis in comparison to period before the crisis is observable only in returns of ATHEX Composite Price Index.

Fig. 1 The descriptive statistic of logarithmic returns on price indexes of PIGS countries before and during the financial crisis

	PORTUGAL PSI GENERAL		IRELAND SE OVERALL		ATHEX COMPOSITE		MADRID SE GENERAL	
Mean	1E-05	(8E-05)	2E-04	(-4E-05)	-5E-04	(7E-05)	-9E-05	(10E-05)
Mean Error	2E-04	(8E-05)	3E-04	(1E-04)	4E-04	(1E-04)	3E-04	(1E-04)
Median	2E-04	(2E-04)	0.000	(9E-05)	0.000	(3E-05)	1E-04	(2E-04)
St. Dev.	0.007	(0.004)	0.009	(0.005)	0.010	(0.005)	0.009	(0.005)
Variance	4E-05	(1E-05)	8E-05	(3E-05)	9E-05	(2E-05)	7E-05	(2E-05)
Kurtosis	10.458	(5.641)	5.601	(4.626)	1.792	(3.367)	6.657	(3.703)
Skewness	0.155	(-0.866)	-0.646	(-0.224)	-0.121	(-0.124)	0.420	(-0.170)
Minimum	-0.046	(-0.026)	-0.061	(-0.029)	-0.044	(-0.028)	-0.042	(-0.032)
Maximum	0.044	(0.015)	0.042	(0.033)	0.040	(0.033)	0.060	(0.027)

Note: Entries in brackets correspond to the values before the crisis.

Source: Authors

We tested the null hypothesis of equal mean returns within two periods (before and during the crisis) to test the weak form efficiency on selected markets (Fig. 2). The rejection of null hypothesis indicated a specific observable pattern in the Greece stock market returns and a possibility to build a profitable trading strategy.

Fig. 2 T-statistic for distribution comparison of logarithmic returns on price indexes of PIGS countries before and during the financial crisis

	Logarithmic returns before crisis → Logarithmic returns during crisis	
	p-value	t-statistic
PORTUGAL PSI GENERAL	0.554	0.592
IRELAND SE OVERALL	0.134	1.498
ATHEX COMPOSITE	0.018	**2.364***
MADRID SE GENERAL	0.326	0.983

* rejection at significance level α = 0.05

Note: The table represents t-statistic for differences in forecasting errors measured as absolute differences between the real and the forecasted values. Only ANNs with the best prediction accuracy for each price index and different groups of inputs were used for final comparison.

Source: Authors

Artificial Neural Network for stock market forecasting

Artificial neural networks are composed of simple elements operating in parallel. Like in a biological nervous system, the function of ANNs is determined mostly by the connections between elements. With the explicit knowledge about target values the network is able to “learn” by adjusting the values between connections (weights between elements).

The feed-forward neural network (FFNN) is one of the most applied ANNs for one-step ahead stock return forecasting. The topology of FFNN is designed as a network with one input layer, one or more hidden layers and one output layer (a three-layered network). Each neuron from the input layer is connected with each neuron in the hidden layers and each neuron from hidden layers is linked with each neuron in the output layer.

FFNN is used to process information from one layer to the next by an activation function. The *j*th node in the hidden layer is defined as

$$g_j = f_j\left(\alpha_{0j} + \textstyle\sum_{i\to j} w_{ij} x_i\right), \tag{1}$$

where x_i is the value of the *i*th input node, $f_j(.)$ is a logistic activation function

$$f_j(z) = \frac{ex\,p(z)}{1+ex\,p(z)}, \tag{2}$$

α_{0j} is called the bias, the summation $i \to j$ means summing over all input nodes feeding to j, and w_{ij} are the weights.

For the output layer the node is defined as

$$o = f_o\left(\alpha_{0o} + \sum_{j \to o} w_{jo} g_j\right), \tag{3}$$

where the activation function f_o is linear.

$$o = \alpha_{0o} + \sum_{j=1}^{k} w_{jo} g_j, \tag{4}$$

where k is the number of nodes in the hidden layer. Combining the layers in one also allows for a direct connection from the input layer to the output layer, the output of FFNN can be written as

$$o = f_o + \left[\alpha_{0o} \sum_{j \to 1} w_{jo} g_j \left(\alpha_{0j} + \sum_{i \to j} w_{ij}\, x_i\right)\right], \tag{5}$$

where the first summation is summing over the input nodes 0. There is no transformation in the output units (f_0 is an identity function).

The application of ANN involves two steps. The first step is to train the network (in-sample analysis) and the second step is to execute the forecasting (out-of-sample analysis). The available data for network training is defined as

$$\{r_t . x_t | t = 1. \dots T\}, \tag{6}$$

$$r_t = ln \frac{P_t}{P_{t+1}}, \tag{7}$$

where x_t denotes the vector of inputs, r_t is the logarithmic stock return in a given period, P_t is a stock price in time t, and o_t is the output of the network.

Fitting criterion of the least squares can be used during the network training. To ensure the smoothness of the fitted function the Levenberg-Marquardt back propagation learning algorithm can be applied

$$S^2 = \sum_{t=1}^{T} (r_t - o_t)^2. \tag{8}$$

The data used for the analysis employing ANNs were 5,901 daily closing prices for the period of 9/30/1988 to 5/13/2011. Daily normalized closing prices were used as inputs into ANNs. Normalization was used to reduce the range of the dataset to values appropriate for inputs (the range between 0 and 1) defined as

$$x = \frac{y - min}{max - min}, \tag{9}$$

where *x* is the normalized variable, *y* is the variable before normalization *min* is the minimum value and *max* is the maximum value of variable during the reference period.

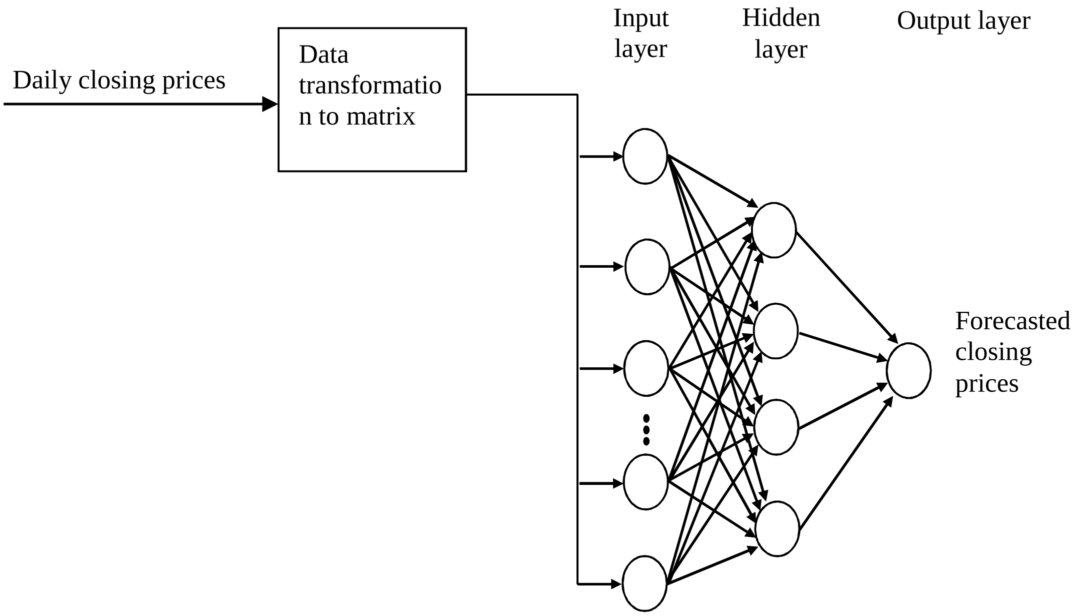
The 90% of the entire dataset was used to train the network (in-sample analysis). The rest of the data were used in the second step to execute the forecast (out-of-sample analysis) and to calculate the profitability of the strategy. The data were divided into two non-overlapping subsamples in the training stage. The first 90% subsample of the training dataset was used to estimate the parameters of a given FFNN. To prevent overtraining the remaining 10% of the training subsample was used as a validation set. These data were used to test the generalisation ability of the network.

FFNN has been used with a different number of neurons in the hidden layers. The number of neurons in the input layer which corresponded with the length of the input vector was stable. A 5-day delay of each input variable was used to set up the input matrix. The number of neurons in the hidden layers varied from 1 to 7. The aim of the testing was to predict one variable (next day closing price); therefore, the number of neurons in the output layer was set to 1. ANNs with different topologies were created and ANN of every topology was trained. The criterion of stopping training was set to 99% prediction accuracy and 250 cycles if no progress was attained. After attaining this goal, the training was stopped. The investigated set up is depicted in Fig. 3. The forecast accuracy of networks with the best performance for each index were analyzed before[3] the financial crisis (03/22/2002 – 09/12/2008) and during[4] the crisis (09/15/2008 – 05/13/2011). This required dividing the testing (out-of-sample) data into two samples. The paper returns achieved with the trading strategy based on the forecast of the *ANN* for both periods were compared to the profitability of the strategy based on technical analysis.

[3] We considered the bankruptcy of the investment bank Lehman Brothers as the critical point for distinguishing between the periods. The period before crisis excluded the time period used for in-sample analysis of Neural Network during training.

[4] We assumed that the slump still remains in the analyzed countries.

Fig. 3 Scheme of the prediction system using feed-forward neural networks with stock prices and indicators of technical analysis used as inputs into network



Source: Authors

Only ANNs with the best prediction accuracy for each stock and input groups were used for the final performance comparison. The prediction accuracy of FFNN models was compared using Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(v_t - p_t)^2}, \tag{10}$$

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{v_t - p_t}{v_t}\right|, \tag{11}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|v_t - p_t|, \tag{12}$$

where n is number of forecasting period, v_t is actual time series value at time t and p_t is the predicted value of time series.

Technical Analysis in stock market forecasting

The technical analysis is an approach of financial market prediction based on an analysis of historical prices to predict their probable future values. Technical analysis uses two elementary tools – the analysis of charts (trend lines) and the analyses based on technical indicators 0. An indicator is a mathematical calculation that can be applied to a security price and/or volume fields. The result is a value that is used to anticipate future changes in prices.

The Moving Average Convergence Divergence (MACD) used in our analysis is a trend following momentum indicator. The MACD shows the relationship between two moving averages of prices (26-day and 12-day exponential moving averages). As the “signal” line to show buy/sell opportunities a 9-day exponential moving average line was utilised. The signals for long positions were generated when MACD line crossed above the signal line (9-day EMA of MACD) and sell crossover occurred when MACD crossed down the signal line. We applied a hold strategy in the situation when no signal was created.

Trading strategies

To compare the profitability of trading strategies based on MACD and neural network the paper return was considered. The initial amount of money for trading was set to 10,000 EUR for both trading strategies and for both reference periods, before and during the crisis. The transaction costs were excluded from the calculations and during the observed periods, the maximum available amount of money was invested all the time (depending on the price of shares). All generated buy/sell/hold signals were considered (in case of neural networks the repeating buy or sell signals were considered as a hold signal). When NN forecasts gave a signal for selling at the beginning of the period, the allowed shortage amount was set to 10.000 EUR and was covered by the next buy signal.

The trading strategy based on neural network forecast followed rules:

$$p_{t+1} > v_t \rightarrow \text{buy} \tag{13}$$

$$p_{t+1} < v_t \rightarrow \text{sell} \tag{14}$$

If the forecasted value for the following day was higher than the actual closing price, we bought the stocks. Reversely, if the forecasted value for the following day was lower than the actual closing price, we sold the amount of stock which was available according to our disposable amount of money remaining from the previous trade. If the buy/sell signal continued, we kept the hold position.

Results

Only the topologies of networks with the best performance for each stock were used for final comparison. The performance of ANNs with the best prediction accuracy for each stock achieved in the two analysed periods is depicted in Fig. 4. Entries in brackets represent the forecasting error for the period before the crisis. Apart from ATHEX Composite Price Index, the forecasting error according to all error measures was lower in period during the crisis. This result suggests that the strategy based on neural network forecast should be more profitable in the period during the crisis at least for Portugal, Ireland, and Madrid Price Index.

Fig. 4 Performance comparison of feed-forward artificial network on price indexes of PIGS countries

	MAE	RMSE	MAPE
PORTUGAL PSI GENERAL	0.067 (0.249)	0.087 (0.437)	1.820 (4.664)
IRELAND SE OVERALL	0.107 (0.492)	0.119 (0.786)	6.961 (8.028)
ATHEX COMPOSITE	0.209 (0.206)	0.268 (0.245)	2.006 (3.617)
MADRID SE GENERAL	0.143 (0.778)	0.188 (1.019)	2.804 (10.508)

Notes: This table reports results from variance decomposition for the frontier emerging markets and the developed markets in the period before and during the crisis. Entries in brackets correspond to the values before the crisis period.

Source: Authors

We confronted the absolute difference between the real and the forecasted values in the period before and during the crisis using T-statistic (Fig. 5). We confirmed that the difference in the prediction accuracy before and during the crisis is significant across analysed indexes. The forecasting error in the period before and during the crisis was not proved as significant only for ATHEX.

Fig. 5 T-statistic for distribution comparison of feed-forward artificial networks applied on PIGS stock markets before and during the financial crisis

	Forecasting error before crisis → Forecasting error during crisis	
	p-value	t-statistic
PORTUGAL PSI GENERAL	8.1E-39	**13.268***
IRELAND SE OVERALL	2.2E-58	**16.558***
ATHEX COMPOSITE	0.62300	0.492
MADRID SE GENERAL	1.7E-46	**14.632***

* rejection at significance level α = 0,05

Note: The table represents t-statistic for differences in forecasting errors measured as absolute differences between real and forecasted values. Only ANNs with the best prediction accuracy for each price index and different groups of inputs were used for final comparison.

Source: Authors

The profitability of trading strategies based on neural networks and technical analysis are shown in Fig. 6. Trading according to MACD indicator showed more optimistic results when predicting the price during the financial crisis. All observed stocks showed positive returns from which the Athens Stock Exchange obtained the highest percentage return of 251.01%. Portuguese Stock Exchange earned 89.36%, Irish 48.35%, and Madrid Stock Exchange 12.72%. When looking at the period before the crisis, all positions ended with losses out of which the Portuguese was the highest (-40.76%). The trading strategy based on neural networks achieved generally lower returns in comparison to the technical analysis. However ANNs performed better in the period before the crisis except the Irish Stock Market where the return was -18.24% in comparison to -4.15% achieved by MACD. The average return before the crisis gained with the neural network was 5.61% in comparison to -25.92% with the Technical analysis. The strategy based on neural networks was profitable both in the period before and during the crisis for the Portuguese and Madrid Stock Exchange. On the other hand, for the Irish and Athens Stock Exchange the returns were negative both in the period before and during the crisis. The comparable results within the analysed period were expected in ATHEX Composite Price Index because the difference between forecasting error means was not rejected.

Fig. 6 The comparison of paper returns achieved by trading strategy based on neural network and technical analysis [5] applied on PIGS stock markets

	Neural Network		MACD	
PORTUGAL PSI GENERAL	36.83	**(21.28)**	**89.36**	**(-** 40.76)
IRELAND SE OVERALL	- 31.83	**(-** 18.24)	**48.35**	**(- 4.15)**
ATHEX COMPOSITE	- 31.28	**(- 6.29)**	**251.01**	**(-** 20.30)
MADRID SE GENERAL	**87.91**	**(25.69)**	12.72	**(-** 38.45)

Note: The table represents the paper return (in %) of trading strategies with initial amount of 10,000 EUR excluding transaction costs. Entries in brackets correspond to the values before the crisis period and only neural networks with the best performance for each Price Index were considered.

Source: Authors

We can conclude that during the crisis the strategy based on MACD seems to be more appropriate while before the crisis the neural networks performed better. Better performance in the period before the crisis was anticipated according to a lower absolute error between the real and the forecasted values in comparison to the period during the crisis.

Conclusion

This article focused on the analysis of the predictability of PIGS Stock Markets before and during the financial crisis. The neural networks failed in forecasting the direction of next day price movement but performed well in absolute price changes. When comparing the profitability of the trading strategies, the strategy based on the technical analysis was more profitable during the crisis while the strategy based on *ANN* forecast performed better in the period before the crisis. Although the ANN strategy seemed to be more stable because of a lower variance in returns, the MACD strategy always achieved a positive return in the period during the crisis. ANN did not perform well in forecasting extreme changes in stock prices in the period of huge bubbles appearing in Portuguese, Irish, and Spanish stock markets.

[5] The table reports the percentage of paper returns while only the Neural Networks with the highest achieved prediction accuracy was used.

Hence, a different trading strategy of the neural network should be tested and more evidence is needed to prove the results achieved in this study. The proposed analysis undertaken on other European national stocks would be helpful to provide an exhaustive comparison of differences in returns before and during the crisis within Europe. Another interesting issue is also the situation in the post crisis period.

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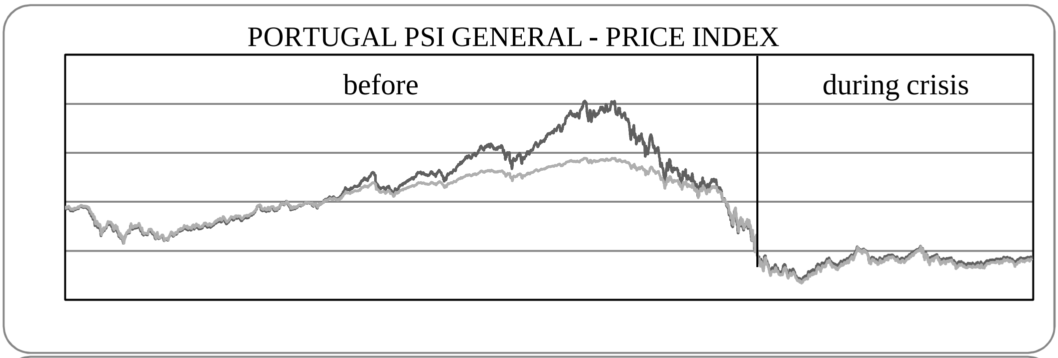
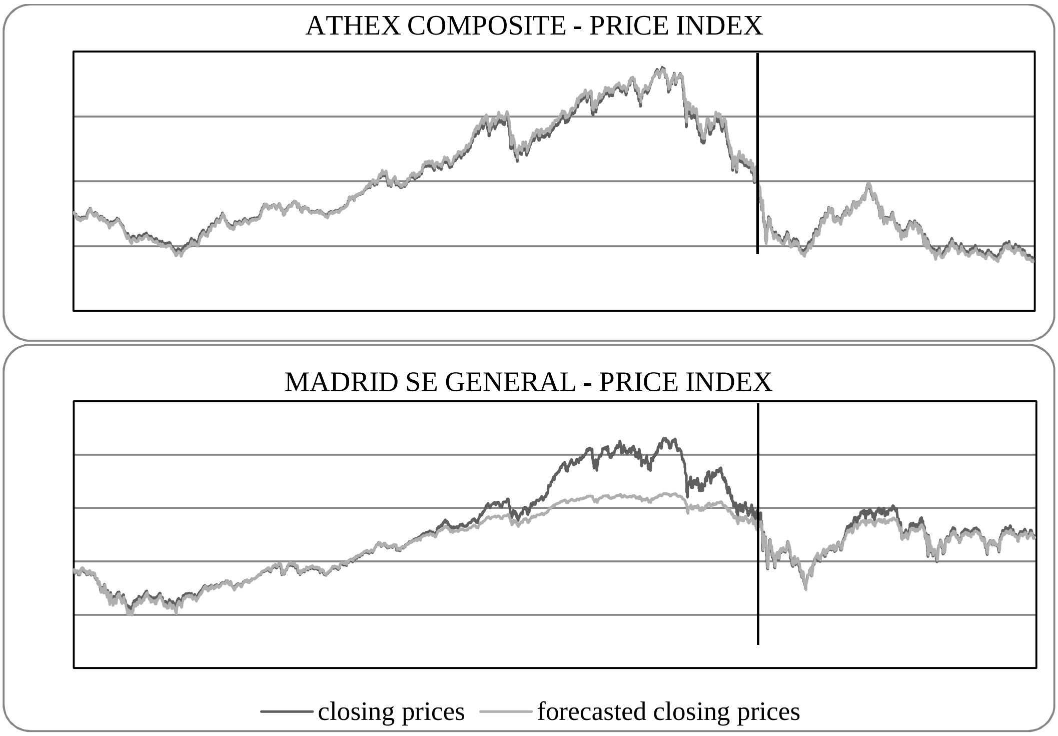
Attachment

Fig. 7 The prediction accuracy of neural network models for price indexes





Source: Authors