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EXPLAINING INTERNATIONAL INVESTMENT PATTERNS: A NEURAL NETWORK APPROACH

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Abstract. This paper aims to explain foreign portfolio investment impact on the dynamics of regional (Central and East Europe) capitalization structure in terms of sectorial investment distribution. Complexity of the problem domain has predetermined the use of interdisciplinary research framework. The ultimate result of this data analysis is a universally applicable model aimed at the nontraditional estimation of sectorial indices weights according to the relative capitalization of the economic sectors. The novelty of the proposed model lays in the application of neural network methods, which were thoroughly designed for the sectorial indices' weights estimation. There is no experiment in the field which would focus on such an experimental setting. The overall NN research framework has developed into the software capable considerably to automate the whole research process. The results of the new approach decidedly outperformed the multivariate linear regression forecasting performance. We argue that the proposed NN approach will extend the assessment and forecasting power of the nonlinearities present in a nowadays volatile investment environment.

Keywords: neural networks, foreign portfolio investment, nonlinear estimates.

1. Indroduction

This research is a response to increasing demand from the investment community for nonlinear means of analyses of national vs. global investment patterns. This paper aims to investigate investment inflows to the Central and East Europe (CEE) region [13]. Since the late 1990s, a fundamental shift has occurred in the pattern of private sector financial flows to developing countries. Debt flows have fallen sharply, while equity flows – mainly in the form of foreign direct investment – have remained comparatively robust [10].

In recent years, Multilateral Investment Agreement (MIA) directly influences dynamics of national capitalization structure. MIA proposed by the EC in the WTO aims at eliminating all flexibility which a country may have at present to permit foreign investment and allocate foreign investments to priority sectors. The implementation of the obligations of governments is sought to be ensured by locating the MIA in the WTO, so that for any perceived infringement, actions can be taken against exports of the country. Some industrialized countries are pressing for a multilateral discipline.

These and many other economic policy matters constitute nowadays investment actualities. Meanwhile, our primary concern here is not about investment policies, but rather about narrow technical (application) aspects of sectorial investment analyses. Many researches are concerned about the appropriateness of traditional research approaches and methodologies in the today's complex environment [7, 11, 12]. This paper also provides insights and an overview for employment of the neural networks (NN) approach (error backpropagation multilayer perceptron method – MLP), which helps to shed new light on the heterogeneous nature of investment dynamics. In the research, the author proposes interdisciplinary approach, which embraces finance theory, econometric and artificial intelligence (AI) methods. The focus of this paper is on evaluating how AI and NN in particular may be employed for the investigation of nonstationary and complex investment market behavior. It considerably eases investigation of the otherwise too complex reality.

The remainder of the paper is organized as follows: Section 2 briefly discusses the scope of the problem domain and methodical issues from the application of the sectorial indices formation technique, Section 3 focuses on evaluating how AI and neural networks in particular might be employed for the investigation of nonstationary and complex investment market behaviour, Section 4 describes the original technology developed for SI weights estimation using NN methods and Section 5 finally concludes.

2. Model and Methodology

This section (i) estimates the scope of the problem domain and suggests some nontraditional approaches to deal with contemporary complexities in the stock exchange (SE) markets, (ii) discusses methodic issues and statistical results from the application of the sectorial indices formation technique.

2.1. The Scope of the Research

Recent decade has witnessed the explosion of global financial crises and growing volatility [2, 3, 7]. Traditional investment approaches do not meet new challenges as well as before. The focus of this study is on evaluating how investment decision makers might advance their performance by the employment of some of the AI methods (our concern is primary focused on the use of neural networks).

Nonlinear dynamic methods became popular in the financial investment market analyses after such well-known researchers like E. Peters, D. Chorafas, M. Mendelsohn, B.M. Friedman, B. Mandelbrot (see for references in [3, 14]) etc. had made profound contributions in the field. New methods were found useful only after modern information technologies and artificial intelligence systems (AIS) were capable of modeling nonlinear dynamics in real time.

AIS made an extraordinarily huge influence on the techniques of complex data analyses, interpretation, and solution space generation. We could refer herein to the research on AIS made by worldwide known scholars like R. Trippi, K. Lee, S. Deboeck, K. White, D. Hsieh, J.A. Scheinkman, B. LeBaron etc (see for reference in [4]). Artificial neural networks, chaos theory, fractal theory, fuzzy logic, and genetic algorithms are well suited for the modeling of nonlinear dynamics and are capable of overtaking other techniques in short term forecasting, trend prognosis, recognition of structural shifts, nonlinear correlations, and chaotic behavior. AIS are capable of coping with the modern financial market problems, which are more likely to resemble adaptive, chaotic and evolutionary rather than static or equilibrium nature. Given the present number of complexity, the best choice is to take the advantage of the interdisciplinary approach, embracing finance theory, econometric and artificial intelligence methods [15]. It considerably eases the investigation of the otherwise quite complex model, see Figure 1.

Following three main research steps were formulated:

1. Search for the best representatives of global market SE sectorial indices (SI).
2. Search for the Central and East Europe (CEE) stock exchange (SE) sectorial indices.
3. Employment of NN methods for discovery of capitalization dynamics of sectorial indices.

The focus of the first step is on evaluation and selection of the global SE sectorial indices. This task deals with the examination of various possible indices, which can represent investment climate for the economic sectors in the global scale, see Figure 2. We need such data in order to compare it vs. Eastern Europe investment dynamics.

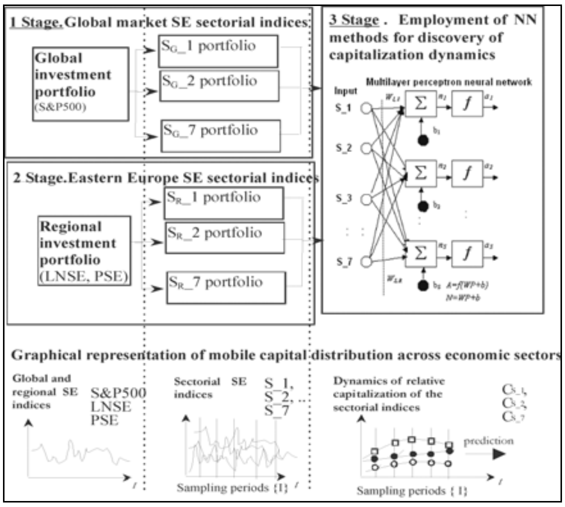


Figure 1. NN based general research scheme for the investigation of SE sectorial indices dynamics

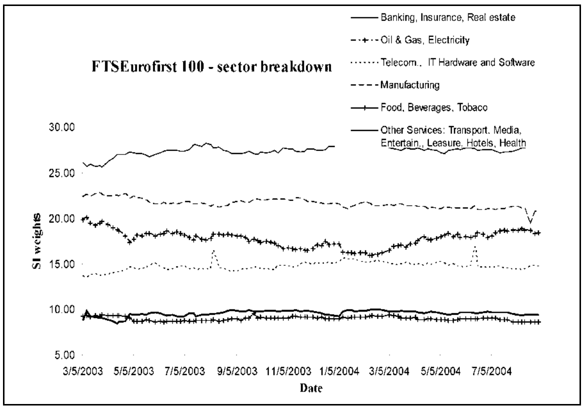


Figure 2. European sectors' weights according to the FTSEurofirst 100 – sector breakdown (including UK market) [5]

The index series is capitalization-weighted and adjusted for free float to ensure that the index reflects the actual stock available for trading [5, 6]. FTSEurofirst Indices include Europe's largest and most liquid equities. This wider inclusion means that FTSEurofirst Indices allow investors to track broad-based benchmarks more accurately. Because the FTSEurofirst Index Series comprises more constituent equities, it offers portfolio investors better coverage than any existing Eurozone and pan-European indices. This is the main reason why it was chosen for the sectorial breakdown.

The focus on the second step (see Figure 1) rests on the search of SI (sectorial indices), which can represent the Eastern Europe major economic sectors [10, 13]. The focus of the third step is based upon neural network methods for discovery of the SE capitalization dynamics having in mind the data non-linearity and nonstationary assumption. Both factors implied the use of non-traditional approach as it was examined by the number of successful previous research [9, 10, 12, 14].

2.2. Methods Used for Sectoral Indices Evaluation

At the preparation stage of the current research, the main task was to form indices of economic sectors using the same calculation methodology. These indices express the ratio of the total stock capitalization at a certain moment to the base capitalization, i.e. total stock capitalization at the index inception. Share issues with larger capitalization have greater weighting in the index and thus have a greater influence on the changes in the index.

As the base of the sector classification NACE (" (Statistical classification of economic activities in the Europe Union) classification standard was chosen. Only ordinary shares are eligible for inclusion into the index base, neither preference shares, nor holding companies' stocks or subscription rights are allowed into the index. Different issues made by the same company are included into the index as separate stocks. Due to changes in share list, the composition of shares, being grouped according to the sector, could be changed any time, and every such change caused the recalculation of index adjustment factor.

The capitalization-weighted equity indices are calculated according to the following formula:

$$IND_t^{Sector\ S1} = 1000 * K_t * M_t \ / \ M_o \ , \qquad (1)$$

where M_o – base capitalization of the issues on the index base (at the index inception); M_t – total capitalization of the issues included in the index base at time t; K_t – adjustment factor, which insures index continuity after any adjustments are made to the index composition. $K_t = K_t\ (A_1, A_2, A_3)$ -the adjustment factor K_t is being recalculated, if one or more of the following cases, requiring adjustment due to non-market changes (A_1, A_2, A_3), appear: A_1 – the size of the share issue included into the index base increases or decreases (issue split, assimilation of issues); A_2 – par value of shares changes; A_3 – issues in the index base are changed following the decision of the NSEL Management Board (upon removal/admission of shares from/to the SE lists of securities).

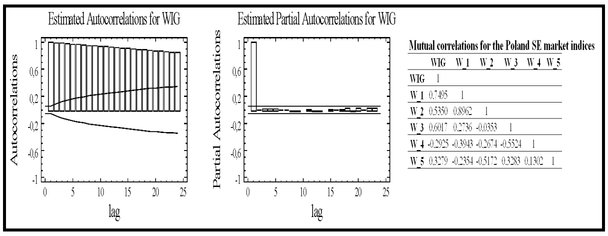
The K_t is recalculated according to the following formula

$$K_t = \frac{IND(before\_index\_factors\_composition\_change)_t}{IND(after\_index\_factors\_composition\_change)_t} \cdot K_{t-1} \qquad (2)$$

Recalculating of the adjustment coefficient ensures the consistency in index calculation and allows avoiding non-market caused index value leaps.

The graph presented in Figure 3 shows an example of the estimated autocorrelations and partial autocorrelations for WIG index (Poland SE market), where horizontal line marks the statistical significance level.

SI dynamics has been compared in a percentage growth, assuming the same base value year. Such an approach let us to compare global and regional SI dynamics. Global and European sectorial indices were formed according to FTSE Global Classification System [6]. In order to get comparable data sets, six aggregate groups of global and regional indices, including similar sectorial definitions were formed: (i) manufacturing and industries, (ii) food and light industry, (iii) energy and utilities, (iv) finance and banking, (v) transport and telecommunications, (vi) information technologies.



	WIG	W_1	W_2	W_3	W_4	W_5
WIG	1					
W_1	0,7495	1				
W_2	0,5350	0,8962	1			
W_3	0,6017	0,2736	-0,0353	1		
W_4	-0,2925	-0,3943	-0,2674	-0,5524	1	
W_5	0,3279	-0,2354	-0,5172	0,3283	0,1302	1

Figure 3. Search for the statistically significant partial autocorrelations for WIG index

Some preprocessing tasks were exhibited like assigning group period, allocating particular index values to a proper group data, transforming of the index values to percentage of base date record index value, which is the same for all indices in the group etc. Finally, each group's data content was presented as a chart, see an example shown in Figure 4 for the manufacturing and industries, food & light industry charts.

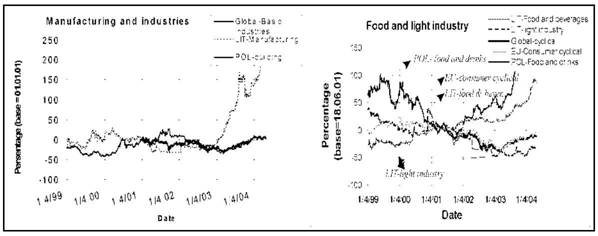


Figure 4. SI comparisons for Lithuania, Poland, EU and Global SE markets: manufacturing & industries, food & light industry

To sum up, the more thorough analyses made clear the existence of nonstationary, high variance and nonlinearities in the time series movements. The results provided an insight into the combined effect from endogenous and exogenous market factors. However, the search for the exact driving factors is beyond the research scope. Therefore, we are not going any deeper into the statistical modeling of the CEE investment market behavior. Instead of a standard statistical approach, we assume the need for nonlinear dynamics analyses, which are further explored using NN methods.

3. Employment of the Neural Networks

The focus of this section is on evaluating how NN have been employed for the investigation of nonstationary and complex investment market behavior. In addition, the author argues into the unique software (using Matlab platform) designed specifically for automation of NN optimization technique.

3.1. Premises for MLP Designing

Neural network (NN) methods should satisfy a number of compulsory conditions: a) well approximate and predict nonlinearities, which are very common in SE movements, b) be very sensitive to unique and seldom occurring events, c) have integrated complex technical and fundamental means of analyses.

Review of related literature suggests [4, 8, 9] that error backpropagation (learning feedforward) neural network method fits the investigation conditions mentioned above and is well related to the input data properties described in the sections above.This method is mostly known and popular among financial analysts in the field [9]. Therefore, it was chosen for the research purposes.

Backpropagation method refers to input data p (p_1 ... p_k) weights (W – vector of input weights on the neuron's junctions), summation (n function) and transformation (a function) in a single net element – the so called artificial neuron [8, 9]. Parallel neurons' structures with couple layers are capable of approximating any function with a limited number of breaks.

We have used batch NN training: weights matrix was updated each time when all input data were presented to the net. All input data were normalized. Effective neural net construction required employment of various optimisation techniques like: 1) search for effective NN learning algorithms, 2) search for an optimal number of iterations, 3) search for an optimal data form factor, 4) search for the best fitting of NN configuration, 5) search for recurrence etc.

The following basic learning algorithms were investigated: a) gradient descent, b) batch gradient descent with momentum, c) variable learning rate, d) conjugate gradient and e) the fastest known Levenberg-Marquet (quasi-Newton method). The mean square error MSE, the R^2-determination coefficient and learning duration were chosen as the main criteria for the mutual comparison of NN learning algorithms.

The overall NN research framework is depicted in Figure 5. It emphasizes some important research stages like input data selection and prewhitening, the search for the best NN method and neural net optimization.

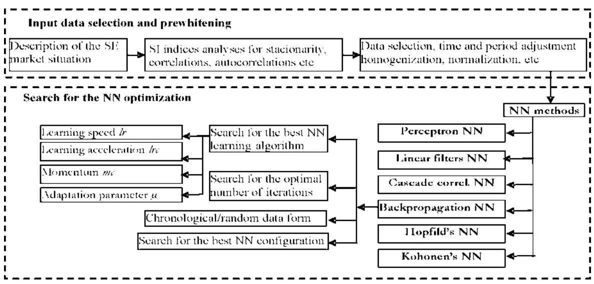


Figure 5. The overall NN research framework: search for the best NN configuration

Usually, the data for NN learning are presented in a random order: in such a case, NN could perform approximation better than many trends are present in SE index movements [14]. If just several basic trends persist, then a common practice is to present data to NN in a chronological order (the current case), because then NN learns trends within its learning stage.

3.2. Premises for MLP Optimization

Let us assume that the financial problem domain $\Omega(\Omega^{in};\ \Omega^{put})$ is characterized by 1) sub domain Ω^{in}, which consists of the set of input data space vectors $\{I^i_n\}$ (where n denotes the input space dimensionality and $i=[1,..\ k]$ indicates the input data vector); 2) sub domain Ω^{put}, which consists of the set of output data space vectors $\{O^i_m\}$ with appropriate output dimensionality m. NN is used for mapping given input space onto the desirable output space (NN decisions). Our goal further consists in investigating the mapping function Φ

$$\Phi(\{I^i_n\}) \rightarrow \{O^i_m\}. \tag{3}$$

Multilayer perceptron (MLP) network serves as an universal approximator, which learns how to relate the set of the input space vectors $\{I^i_n\}$ to the set of output (solutions) space vectors $\{O^i_m\}$. Not to forget, we have chosen MLP because it is widely used in the finance sector. Transformation function Φ is then characterized by the MLP structural parameters like weights' matrix W, biases B, number of neurons N, topology structure T, learning parameters L

$$\Phi = \Phi(W, B, N, T, L). \tag{4}$$

This is supervised learning. MLP gains experience by learning how to relate the input space vectors $\{I^i_n\}$ to the known output vectors $\{O^i_m\}$. Now we parameterize Eq. (3)

$$\Phi_{W, B, N, T, L}(\{I^i_n\}) \rightarrow \{O^i_m\}. \tag{5}$$

For the effective implementation of MLP networks, we had to investigate the major NN structural parameters like W, B, N, T and L in the decompositional manner, see Figure 6.

The investigation results are worth of it, because NN optimization software, developed consequently (executable code generated on Matlab platform), reduces substantial part of the technical work. After all, the result is an autonomous intelligence capable not only to recognize the movements in SE markets, but also to make forecasting decisions, justify them and improve the performance from the acquired experience.

NN performance extremely depends on the NN configuration: the number of layers, connections topology and neuron numbers in the layers [4]. Research results revealed: 1) if the net has too few neurons or connections, then bad approximation results occur, 2) if the net has too many neurons or connections, then bad prediction occurs. Besides, the net performance strongly depends on the number of variables and interdependencies between the variables and the data amount [1].

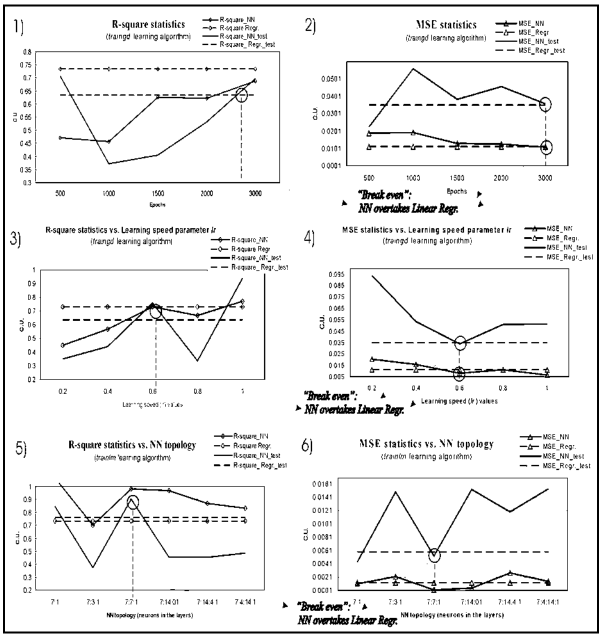


Figure 6. Search for the optimal NN configuration using MSE and R-square criteria: (1) and (2) for optimal epochs number (for avoiding the overtraining); (3) and (4) for optimal learning speed; (5) and (6) for fitting in NN topology structure

Best fit of NN performance to the given input data were obtained for the Levenberg-Marquet (quasi-Newton) learning algorithm, NN topology 7:7:1, number of epochs (iterations) 10, learning rate *lr* = 0.4, learning momentum *mc* = 0.35. The learning data set (for the LNSE market data) consisted of 1600 and the testing data set consisted of 126 input vectors.

Notwithstanding the appealing power of NN methods, we have also applied multivariate linear regression method (MLR). It gives to us the estimation of the comparative validity of the NN method. The MLR method returns the least squares fit of y on X by solving the linear model $y = X * \beta + \varepsilon$, were $\varepsilon - (0, \sigma^2 I)$, y is an n-by-1 vector of observations, X is an n-by-p matrix of regressors, β is a p-by-1 vector of parameters, ε is an n-by-1 vector of random disturbances, see Table 1.

Table 1. MLR method: vector of parameters and 95% confidence interval for the learning and testing data

MLR (learning data)			MLR (testing data)		
β-regr. param.	95% confid. int. for β		β-regr. param.	95% confide. int. for β	
-0.0445	-0.0667	-0.0223	0.1445	0.1228	0.1663
-0.0994	-0.1354	-0.0633	0.0208	0.0136	0.0280
0.1552	0.1336	0.1767	0.1191	0.0983	0.1400
0.3684	0.3462	0.3905	0.2236	0.2140	0.2331
0.2029	0.1859	0.2198	0.3759	0.3632	0.3886
0.66	0.6044	0.7155	0.1819	0.1589	0.2050
0.0682	0.0488	0.0876	0.0339	0.0163	0.0516
-0.0527	-0.0615	-0.0439	-0.0623	-0.0654	-0.0591

The final comparison of MLP and MLR methods is presented in Table 2. The NN optimization technique has made MLP method in a comparative advantage against the MLR, as we can see it from the data.

Table 2. Comparison of performance of multilayer perceptron NN (MLP) vs. multivariate linear regression (MLR) for learning and testing data sets

	Learning set		Testing set	
	MLP	MLR	MLP	MLR
R-square	0.9822	0.9452	0.8797	0.8434
MSE	1.82E-04	0.0013	0.0053	0.0059

Note: estimations are done for the LNSE market data.

The results from this study demonstrate the fact that after the relevant NN optimization techniques have been employed, the researcher is armed with the more powerful analysis tool, which gives him comparative advantage over the traditional linear tools. For the effective implementation of the MLP method, we made a software solution, which finds the best MLP configuration automatically.

4. Analysis of SI dynamics using NN approach

This section describes the original technology developed for SI weights estimation using NN MLP method. Here also some results of SI weights dynamics based on LNSE market investigation are submitted.

4.1. Premises for SI weights estimation

To begin with, we have to distinguish the differentces than we are talking about weights. First, what do we mean by capitalization-weighted price indices? These indices express the ratio of the total stock capitalization at a certain moment to the base capitalization, i.e. total stock capitalization at the index inception. Share issues with larger capitalization have greater weighting in the index and thus have a greater influence on the changes in the index.

These indices reflect no changes in the securities turnover, nor they allow for any adjustments related to dividend distributions, but take into account the number of shares issued, i.e., every issue included into the index base is allocated a certain weight, which is proportional to its market capitalization (capitalization = shares in the issue multiplied by the market price of the mentioned shares), see Eq. 1 and 2.

Shares were grouped into sectors, according to capitalization-weighted price and economic activity of the company. Therefore, indices for economic sectors (SI) are capitalization-weighted with their weights in the particular SE market. In other words, these are share driven weights. This is so according to a common practice in investment markets [5, 6, 14].

Let us go one-step further apart from the share driven weights. Our experiments, discussed in this paper, focus on testing the other kind of weightings, which are driven by the main index dynamics. In fact, the simplest linear approach to this idea is multidimensional linear regression method (MLR), which returns the least squares fit of the main index (e. g. LITIN-G) on sectorial indices (e.g. S_1, S_2…S_7) by solving the linear model. In this model, each SI has its own weight by which it influences dynamics of the main market index. It gives us the understanding of the market constituencies (in sectorial terms) leading to the main index dynamics.

Meanwhile, our task is not only the use of NN in SE indices analyses and prognoses, but also search for the parameters, which can estimate nonlinear weights of the market constituencies (SI) leading to the observed main index dynamics (for the current research LNSE market data were used). Technically, the task is not a trivial one, because of the complicated NN structure itself. We have to explore the mapping function Φ (see Eq. 3, 4 and 5) in more detail.

In our point of view, main parameters of NN such as NN weights might be interpreted in a special way giving nonlinear estimations for the alternative assessment of SI weights. Notice, we should not be confused by terms "NN weights" and "SI weights", because these are different entities. The former describes NN input and layer weight matrices, while the latter describes the weights associated with the SE market constituencies (SI) leading to the observed main index dynamics. In the linear case (see discussion above), both weights are superposed (MLR coefficients might be interpreted as SI weights for each sector), but in the nonlinear model this is not so any more. Therefore, we will treat differently both terms further in the text.

4.2. Empirical validation

Based on the SI calculation methods established in Section 2, for the first time in LNSE market history the major sectorial indices for Lithuania SE market were generated, see LITIN-G index values and seven data sequences for Lithuanian sectorial indices in Figure 7.

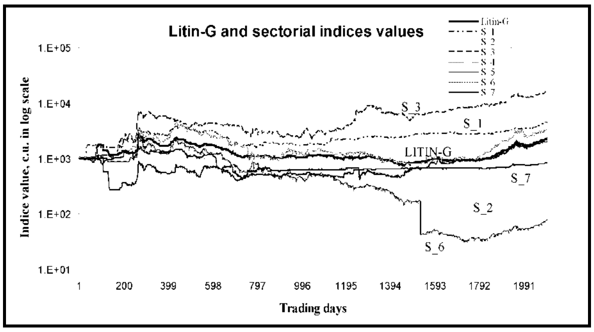


Figure 7. LNSE market: major index (LITIN-G) and seven sectorial indices (S_1, S_2,...S_7) in the logarithmic scale, period 1996 Jan - 2004 Apr.

According to the above discussion and previous experimentation results, five different cases for SI nonlinear weights' estimation were found and distinguished (LNSE case, see Figure 7):

1. Weights analysis for the "standard" NN (standard in our case means 7:7:1 configuration of the optimized NN, see previous section).
2. Exploring input weights matrix for the MLR like MLP configuration (NN topology 1:7:1) or "perceptron" case.
3. Simulation of a standard NN while making zeros nondiagonal elements of the input weight matrix (or "zeros in nondiagonal elements" case).
4. Simulation of a standard NN input weights matrix performance with zero input weights from all inputs, except from the one at a time (or "nonzero from one input" case).
5. Formation of a special kind of the standard NN with nine layers, but having 7:7:1 topology. We have titled it "natural", because it gives straightforward estimation of SI weights (see description below).

"Natural" NN topology case results for the LNSE market are presented in Figure 8.

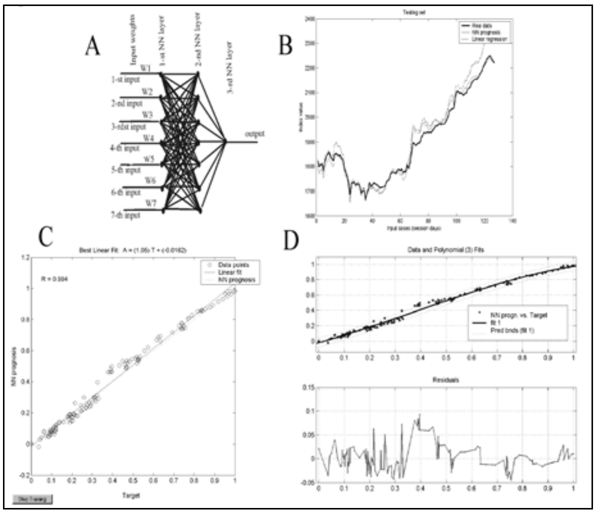


Figure 8. Research results for the "Natural"case (LNSE data): A- NN topology, B- graph for NN vs. MLR prognosis results, C- best linear regression fit (targets vs. NN prognosis) gives slope of 1.05 and interception of -0.0162, D- best polynomial cubic fit and distribution of residuals

First of all, we have three NN weight matrices a_{mxn} (input weights matrix for the first layer), b_{kxn} (2-nd layer weights matrix) and c_n (3-rd layer vector of weights), see Eq. 6

$$T\left\{\Gamma\left\{\Theta\left\{\begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} * [I_n] + B_{1-st\_layer}\right\} * \begin{pmatrix} b_{11} & \cdots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{k1} & \cdots & b_{kn} \end{pmatrix} + B_{2-nd\_layer}\right\} * [c_n] + B_{3-rd\_layer}\right\}_i = out \quad (6)$$

where $B_{1,2,3}$ - stand for biases; $[I_n]$ – input vector I; T, Γ and Θ – are transformation functions for each NN layer. One distinctive characteristic of such a setting is the complexity of weights, which like nonlinear parameters hide the relationship between the input (each input represents different SI data) and output spaces.

The NN "natural" model (network has nine layers with sustained 7:7:1 topology) is capable to reflect the issue in the most natural way. In this case, the first seven layers have one neuron and one input connection each (every junction connects to the corresponding SI input), the eighth layer has seven neurons with 7x7 layer weights matrix and the ninth layer has 7x1layer weights matrix, see Figure 8.

After all, our task is to measure factors, which might describe each input's (sectorial index) relative weight in the dynamics of the whole market index movements. We have chosen a group of meaningful factors described in Eq. 7

$$W_{SI} \Rightarrow \{[W_{1-st\_layer}], R^2_{NN}, MSE_{NN}, m_{LR}, b_{LR}, R_{LR}, P\}_{SI}\,, \quad (7)$$

$[W_{1\text{-}st\ layer}]$ – NN input weight matrix, where each input (SI) has been weighted during the NN training. Every input weight reflects the relative measure by which it influences total SE market variance. A number of empirical tests have suggested that this is highly volatile and hardly predictable measure: NN might find best solution using different weight matrices. Additionally, we had to employ some other measures, described below.

R^2_{NN} – determination coefficient. This statistic measures how successful the NN model is in explaining the variation of the whole market index data (or the amount of response variability explained by the NN model). It can take on any value less than or equal to 1, with a value closer to 1 indicating a better fit. We assume that it gives the amount of response variability explained by the given NN model and input data;

MSE_{NN} – a network performance function. It measures the network's performance according to the mean of squared errors;

m_{LR}, b_{LR}, r_{LR} – best linear fit given a linear regression between the network response and the target (m - slope of the linear regression, b - Y intercept of the linear regression). Here we can also define the correlation coefficient (r-value) between the network response and the target.

P – a set of polynomial fit parameters measured for function *Response(Target)*.

The results provide an insight into the combined effect using these factors in explaining the input's (sectorial index) relative weight in the dynamics of the whole market index movements.

In order to prove the soundness and validity of the proposed approach, we have chosen LNSE market data and brought it under smaller data sets (eight sets in total: each set consisted from 200 cases for NN learning and 100 for testing). For each set, experiments were repeated 20 times and only average values counted for NN input weights estimation, see Table 3.

As everyone can notice, nonlinear estimates for SI weights have positive and negative values also. This is due to a manner NN is learning the relationship between input and output values. This could be avoided if NN biases (biases are additional NN parameters) were used. However, we purposefully trained the NN without the biases, as they are additional parameters, which could make the input weights' analyses even harder [1].

Table 3. Input weights values for "Natural" NN case using LNSE market data

SI	**NN input weights for 8 data sets**							
	0-300	**200-500**	**400-700**	**600-900**	**800-1100**	**1000-1300**	**1200-1500**	**1400-1700**
S_1	0.21	0.17	0.23	0.27	-0.96	-0.26	-0.05	-0.01
S_2	0.13	0.26	0.37	-0.52	0.15	-0.30	-0.13	-0.25
S_3	-1.02	-0.07	0.27	0.22	-0.29	0.52	0.18	0.25
S_4	1.52	0.32	0.50	0.14	-0.37	-0.53	-0.17	-0.21
S_5	-0.76	0.08	-0.70	0.00	-1.40	-0.86	0.12	-0.02
S_6	-0.77	0.00	1.09	-0.21	-0.67	0.41	0.93	0.75
S_7	0.02	-0.34	-0.32	-0.71	-0.73	-0.62	-0.17	-0.20

The next step, as one could suggest, is about comparison between NN input weights (presented in Table 3) and LNSE capitalization weighted sectorial indices (presented in Figure 9). For the comparison between both data sets, we have (i) to adjust them to the same periodicity, (ii) to look for a numerical measure, capable to evaluate comparative similarity between them.

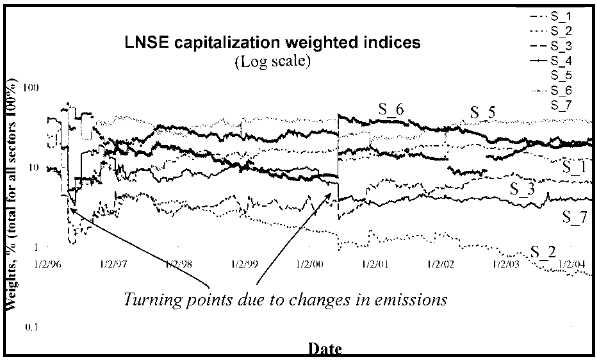


Figure 9. For the first time designed and presented dynamics of LNSE capitalization weighted indices

The first issue was resolved by averaging out LNSE capitalization weighted sectorial indices for the data sets used for NN input weights estimation (8 sets). Meanwhile, for the second issue we have chosen correlation coefficient as a normalized measure of the strength of the linear relationship between two quantities.

The fitting results have shown that the similarity effect assumption has quite a moderate effect, see Figure 10. The main reason is due to a weak share representation for each index. Let us recall that LNSE sectors were formed only on the bases of 3-7 different companies from the adequate sector, which is clearly not enough to smooth the effects of sudden increments of a particular share emission (see Figure 9). However, this is so to speak, a local problem related with this particular (LNSE) data set. Meanwhile in the case of FTSE data (see Figure 2), capitalization weighted SI indices do not have such a problem (EU wide market is large enough to smooth out all non-price market disturbances within a sector). This let us to assume that further tests on the other data sets will have much better correlations with NN SI weights estimates.

In our case (for the LNSE data), the way out from this problem is the use of sectorial indices data, see Figure 7. In fact, this data technically has been already adjusted according to various non market price disturbances like A_1, A_2 and A_3 factors, see Eq. 1 and 2. Therefore, we can expect even the better correlation effect between NN SI input weights and LNSE sectorial indices than with capitalization weighted SI. Related empirical results are depicted in Figure 10.

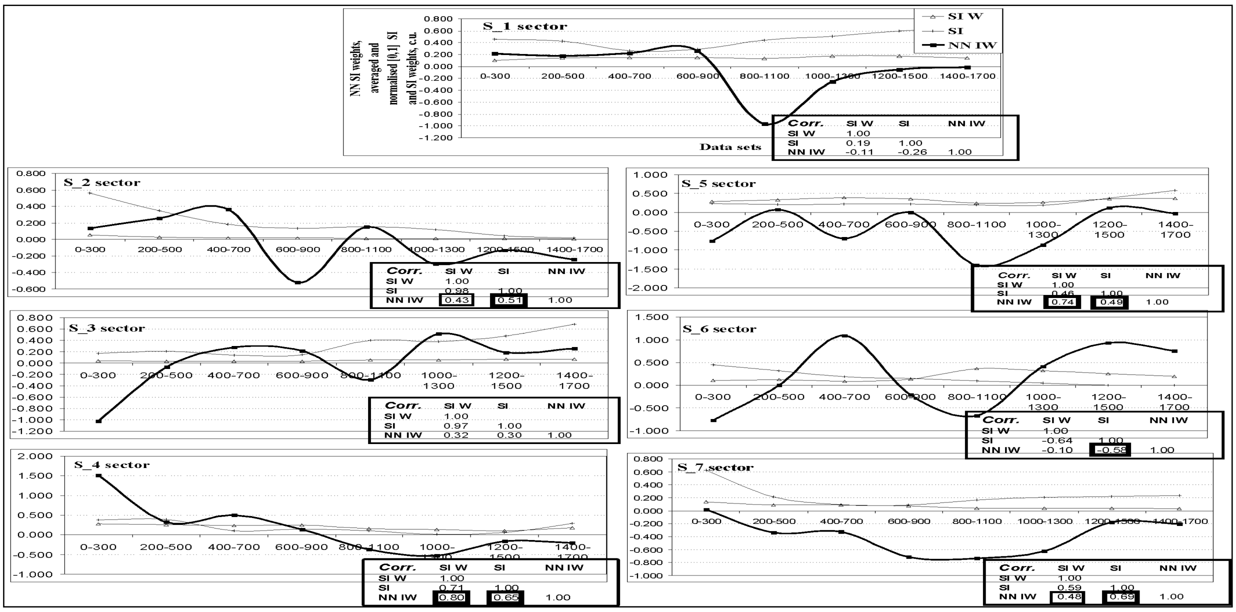


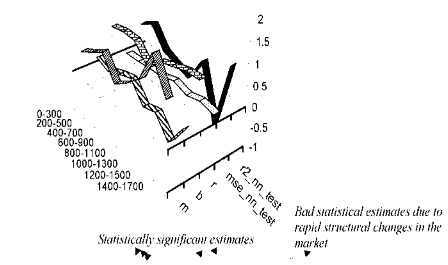
Figure 10. The averaged out fluctuations of (i) NN IW - sectorial weights generated by the NN, (ii) SI W - relative capitalization weighted sectorial indices, (iii) SI – price dependant sectorial indices. Mutual correlation tables are given under each graph. Sectorial indices values were average out for each data set

The correlation analyses between NN IW, SI W and SI (see **Figure 10**) suggested the following inferences:

1. NN weights are more volatile. They impose positive and negative values to the impact of corresponding indices to the overall market movements. This is due to NN nonlinear nature, which exhibits more sophisticated SI weights' dynamics.
2. However, correlation, as relative normalized measure, is capable to reveal linear relationship between NN IW and SI W or SI. This has been proved by the empirical data
   - the best correlations between NN IW and SI W were observed for S_2, S_4, S_5 and S_7 indices and they varied from 0.43 to 0.80.
   - the best correlations between NN IW and SI were observed for the same indices as in the SI W case and they varied from 0.51 to 0.69. However, negative correlation (-0.58) for the S_6 index, which is due to negative correlation (-0.64) between SI W and SI were observed.

In sum, the results from this study demonstrate the positive interaction effect between the traditional representations for economic sectors movements and the new ones. However, we should recall that this might not be the case at all, because NN are completely different modeling tool for this problem domain.

Let put it other way round: how could we define some other criteria for the NN IW dynamics meaningful interpretation? One possible solution is to make use of statistical estimates. We have chosen a group of such meaningful estimates described in Eq. 7. According to the expression, we have explored parameter [$W_{1\text{-}st\ layer}$], but the performance of NN is also measured by other meaningful parameters like R^2_{NN}, MSE_{NN}, m_{LR}, b_{LR}, r_{LR} and P (see Figure 11).



	0-300	200-500	400-700	600-900	800-1100	1000-1300	1200-1500	1400-1700
m	0.55826	0.7292	0.92632	0.38256	0.61172	0.92082	1.69544	0.92024
b	0,24434	0,1089	0.23986	0,33506	-0.1164	-0,02388	-0.50598	0,06634
r	0.86524	0.93516	0.89978	0.53492	0.78734	0.88128	0.97398	0.9951
mse_nn_test	0,03002	0,00848	0,0616	0,04614	0,14332	0,02318	0,1015	0,00218
r2_nn_test	0,64902	0.81518	0,3326	0,18338	0,0436	0,65758	-0.65484	0,96318

Figure 11. The main statistical estimates for the NN forecasting performance in terms of NN input weights ascribed to the corresponding LITIN-G data set, see Eq. 7

Those additional NN performance parameters showed how well combination of NN input weights represents (for each data set) the overall ITIN-G index forecasting ability. Especially of the high importance are statistical estimates R^2_{NN}, m and r, as they are clear determinants of goodness of fit for the NN model, which significantly outperformed the MLR method. The results from this study demonstrate the positive interaction effect between the NN input weights credibility and statistical validation results for each data set.

Additional research needs to be done to examine, in detail, the issues and criteria that will help firm up the new method in practice. First, there is a clear need to perform experimentations for the WSE (Poland SE) and FTSE (EU wide SE) markets using "natural" and "nonzero from one input" cases. Then follows the perfection of the Matlab software needed to automate the bulk of technical work. However, the amount of research results is definitely too big to be included in the current article. Therefore, we hope to supply the results in the next publication.

5. Conclusions

The ultimate result of data analyses is a universally applicable model aimed at the nontraditional estimation of sectorial indices weights according to the relative capitalization of the economic sectors. The novelty of the proposed model lays in the application of the neural network methods, which were thoroughly designed for the sectorial indices' weights estimation. To the author's knowledge, there is no experiment in the field focusing on the NN mechanisms of SI weights estimation in such an experimental setting.

To summarize, the proposed model estimates the NN weights dynamics and interprets them in a special way giving nonlinear estimations for the alternative assessment of SI weights. The investigation revealed five different cases for SI nonlinear weights' estimation. The empirical results provided an insight into the combined effect using additional factors in explaining the sectorial indices relative weight in the dynamics of the whole market index movements. The overall NN research framework developed into the software capable considerably to automate the whole research process. The results of the new approach decidedly outperformed the multivariate linear regression forecasting. We argue that the novel approach will extend the assessment power of the nonlinearities present in a volatile economic sectors' investment environment.

We have to admit that a very wide scope of this study cannot be fully covered in the current paper. Some other results will be submitted in the next paper due to the need for extensive empirical validation of a new approach.

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