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Neural network forecasting in prediction Sharpe ratio: Evidence from EU debt market

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ABSTRACT

This study analyzes a neural networks model that forecast Sharpe ratio. The developed neural networks model is successful to predict the position of the investor who will be rewarded with extra risk premium on debt securities for the same level of portfolio risk or a greater risk premium than proportionate growth risk. The main purpose of the study is to predict highest Sharpe ratio in the future. Study grouped the data on yields of debt instruments in periods before, during and after world crisis. Results shows that neural networks is successful in forecasting nonlinear time lag series with accuracy of 82% on test cases for the prediction of Sharpe-ratio dynamics in future and investor's portfolio position.

1. Introduction

For the last 30 years, many authors used neural network model in portfolio optimizations and forecast financial performance [1–10] with projection method [11–13]. In the early 2000s, computer methods of the portfolio selection problem developed heuristic methods that use evolutionary algorithms, tabu search and simulated annealing [14–18]. A growing interest of researches to use neural network in finances and economics is in their characteristic to imitate flexible nonlinear modeling relationship capabilities, from one side, [19], and its commercial applications due to the high stakes and the kinds of attractive benefits that it has to offer, from other side [20].

According to Han [21], artificial neural network models are popular because of capabilities to approximate lot of type non-linear function to a high degree of accuracy. Neural network model or artificial neural network use historical and present data to predict future trends. Ko and Lin [22] constructed neural network model which forecast financial distress.

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Their model uses evolutionary algorithm to extract different financial ratios and integrates more evaluation function modules to achieve a better forecasting. According to Ko and Lin [19], this methodology helps improving final forecasting accuracy. A similar model, which forecast is based on different financial ratios is developed previously by Eakins and Stansell [23]. This neural network model forecast variables after determination intrinsic value of assets which enter the property portfolio. The obtained results showed that such ratios provide useful information that permits the selection of portfolio with superior investment returns than DJIA and S&P500. In other words, previous researches are based on fundamental analysis. In research of Fernández and Gómez [18], experimental results shown that Hopfield neural network model gave the highest quality results in forecasting the general mean–variance portfolio selection. Liu et al. [24] tested one-layer recurrent neural network model with a simple structure for solving constrained pseudoconvex optimization of dynamic portfolio. They used Lyapunov method and differential inclusion theory to show that simulation results on numerical examples are given to illustrate the effectiveness and performance of the proposed neural network. According to their results, neural network model is useful for dynamic portfolio optimization. In research of Obeidat et al. [9], neural network prediction was based on Long Short-Term Memory approach (LSTM). This model estimates the expected return, volatility, and correlation for the selected assets (stocks in their case). The biggest advantage of this neo-network model is in model assisting in automating portfolio management, which actually improves risk-adjusted returns.

Portfolio optimization models refer to the optimal distribution of financial instruments in the portfolio, which will achieve high expected returns by spreading the risk of possible loss due to low expected performance. One of the most significant models of portfolio optimization is created by Markowitz [25,26]. In his mean–variance model with efficient diversification of a large number of instruments it is possible to minimize the portfolio's risk at a desired portfolio return, or, in the dual problem, maximizes the portfolio's return at a given risk. According to Markowitz, investor preferences were defined through the variance of the aggregate portfolio return. Markowitz inspired many authors to research this area and to continue to develop models of the portfolio's expected return given by the linear combination of the participations of instruments (stocks) in the portfolio and its expected returns (the mean returns) [27]. After Markowitz other authors also gave the central place to standard deviation as an appropriate risk measurement [28–31], as also one of the most famous risk-return model — capital asset pricing model [32]. However, the application of these models has shown that the variance (or standard deviation) of the returns an inappropriate measure of stocks' (instrument's) risk [27,33–35].

The most of studies are related to the stock market (especially for prediction with artificial neural network models). Also, not too much papers deal with the optimization of the portfolio only with assets with fixed income and even more are rare those with the use of smart technology in portfolio forecasting. Fong and Wu [36] analyzed sovereign bond returns using technical trading rules, in both, developed and emerging markets. They forecast returns on 48 sovereign bond markets based on a strategy of 27,000 technical trading rules. In addition to moving averages and other tools of technical analysis, the authors used a machine learning algorithm to determine the best trading rule strategy. In the studies that deal with optimization of portfolio, which consists of assets with fixed income, methodologies refer to immunization of such portfolio. In here, we can single out the studies of Cheng [37], Roll [38], Yawitz and Marshall [39], Kaufman [40], Fabozzi [41] and Korn and Koziol [42]. In the paper of Korn and Koziol [42], term structure models for $\mu - \delta$ optimization are used for the portfolio fixed income assets optimization. The same authors constructed portfolio of German government bond and use parameter estimation for this portfolio performance prediction. The contribution of work is more in the theoretical than in the practical area. In an effort to overcome certain limitations of term structure models, especially because of: only (a) theoretical contribution (and less practical), (b) simplicity of models and (c) problems of different national bond markets applications; we will use new model and forecasting abased on learning machines. Specifically, we will use Artificial Neural Networks (ANN) to predict future performances of our model.

In this paper, we will show that neural networks can be used as a great prediction technique of portfolio performance, consisting only of fixed income assets. Furthermore, this will overcome limitation of term structure models of mostly theoretical contribution. ANN models are excellent for practical application. Our theoretical contribution lies in the construction of the modified capital allocation line model and investor's portfolio position model, whose performance we can forecast by neural network technique. In this way we will support further scientific discussion on fixed income assets portfolio performance (as theoretical contribution) and also practical implications on financial markets. Furthermore, financial market is essentially dynamic, non-linear, complicated, nonparametric and chaotic in nature [43]. For effective using of neural network for the financial market data analysis the tremendous noise and complex dimensionality should be decreased. From the theoretical side, Hicks [44] and Pratt [45] claims that the mean-standard deviations approach are inadequate and objective for using von Neumann–Morgenstern utility function with the quadratic form $U(x) \equiv ax + bx^2$ for $b \leftarrow 0$ (on which the most of the previous researches were based). Other authors, like Samuelson [46], Borch [47] proved with stronger facts that von Neumann–Morgenstern utility function does not explain adequately the preferences in the mathematical model of mean-standard deviation approach, which influenced to appear several models with the mean absolute deviation, the interquartile range and the classical statistical measures of entropy.

In recent years, Bodie et al. [48] claim that variance is the appropriate measure of risk for a portfolio of assets with normally distributed returns. Furthermore, returns on stocks and bonds (especially government and central banks bonds) can often move in different directions, especially in the conditions of the crisis, which was shown by numerous empirical researches from Bodie et al. [48,49,50]. Having this in mind, we will retain the standard deviation as appropriate measures of risk of portfolio with different maturity bonds of European Central Bank. Secondly, with including mid-term and long-term ECB bonds, we will overcome the problem of short time horizons for experiments. In short time horizons,

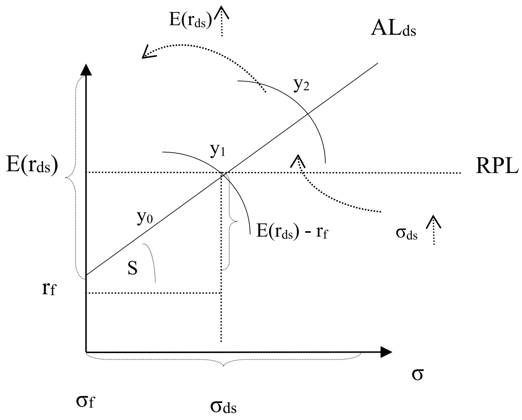

Fig. 1. ALds Capital allocation line model.

experimental results may be tampered by situational effect and economic fluctuations [51]. Finally, such portfolio can be of relevance to low risk hedge funds, low or medium risk mutual funds, pension funds, insurance companies, commercial banks and other financial institutions.

The aim of this paper is to: 1st create a model of allocation of debt securities assets and Sharpe ratio for different debt instruments issued by the Central Bank of the European Union; 2nd on the basis of the obtained data and previously discussed literature, we will create a neural network model that will foresee future Sharpe ratio. Our goal is to demonstrate the potential of such an approach in our empirical study. We especially believe that this situation can be achieved in the period of the crisis or in period close after crisis. Data on yields of debt instruments are grouped in periods: before crisis (2004–2007), crisis (2008–2011), early post-crisis period (2012–2014) and post-crisis period (2015–2017). As a practical implication, according to the research results, investors can use the tested model in creating their portfolios. The novelty of research is in the new theoretical model which shows investor positions predicted by ANN networks.

2. Methodology

2.1. The model

In our research we use the modified portfolio model — Capital allocation line (see more Bodie et al. [49] and also Vukovic and Prosin [52]). Basically, this model shows the relationship between risk-free and risky assets for a given level of standard deviation, as a measure of risk. As risk-free assets we determined low volatile assets which indicate money market instruments (r_f). All the money market instruments are virtually immune to interest rate risk (unexpected fluctuations in the price of a bond due to changes in market interest rates) because of their short maturities and all are fairly safe in terms of default or credit risk [48].

As risky assets, we analyze medium-term and long-term debt securities issued in the EMU zone. The risk of these bonds is reflected only in changes in future interest rates, they default risk free. This is a modification compared to the original model of portfolio allocation of assets (we have excluded risky assets that do not belong to the debt market). Our line of allocation is AL_{ds} — debt securities allocation line which shows risk-return combinations available by varying debt securities allocation, choosing different values of y (see Fig. 1). The difference between risk-free and risky assets is expected risk premium on debt securities ($E(r_{ds})$). We can say that the expected risk premium is potential reward or expected yield for the risk taken above risk-free rate. Standard deviation for the risk premium asset is denoted as (σ_{ds}). Standard deviation is a measure of volatility of instruments from the mean. It is the appropriate measure of risk for a portfolio of assets with normally distributed returns. In this case, no other statistic can improve the risk assessment conveyed by the standard deviation of a portfolio.

Investment budget is denoted as (y) and it is decomposed into the following (Fig. 1):

(a) y_0 — equally consists of risk-free and risky assets of debt securities. In such situation $y_0 = 0.5$ (50% of both kind of assets).
(b) y_1 — consists of only risky assets of debt securities. In such situation $y_1 = 1$. Risk-free assets are remaining proportion $(1 - y)$.
(c) y_2 — consists of risky assets and borrowed funds for investment. For example, value above 1 means a short position in the risk-free asset, or a borrowing position. If $y_2 = 2$, it means that portfolio consists risky assets $y_1 = 1$ plus the same amount of borrowed funds (or a short position) + 1. Such portfolios are the most risky, but they also offer the biggest the expected risk premiums.

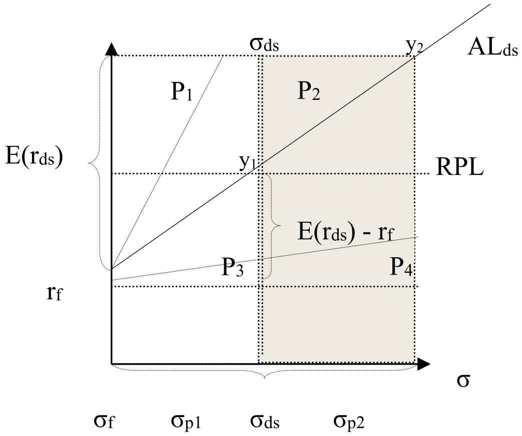

Fig. 2. Investor's portfolio position.

Both the risk premium and the standard deviation of the complete portfolio increase in proportion to the investment in the risky portfolio. *Sharpe ratio* is denoted as (S). This proportion shows the increase in expected return that an investor can obtain per unit of additional standard deviation or extra return per extra risk [53], or:

$$S = \frac{E(r_{ds}) - r_f}{\sigma_{ds}} \tag{1}$$

Bearing in mind positive correlation between risk and returns (growth of risk affects the increase of return) we indicate different situations in relationship which influence on portfolio position:

Position P_1 is in square $(E(r_{ds}) - y_1 - \sigma_{ds})$ and shows a situation in where AL_{ds} moves to the left (Fig. 2). This means that expected returns grow faster than risk. The standard deviation in this scenario is less or equal than standard deviation for the risk premium asset: $\sigma_f \leq \sigma_{p1} \leq \sigma_{ds}$, for $\sigma_f > 0$. This position offers investors the largest expected risk premium on debt securities with minimum risk. However, such a situation is only theoretically possible or it can exist in a very short period of time. Standard deviation for the risk-free assets is bigger than zero ($\sigma_f > 0$). This situation is paradoxical in the money market, which is characterized by risk-free assets and requires more precise explanation. If the standard deviation is greater than zero, it means that assets are risky in some way. Moreover, some experiences have shown that the standard deviation increases during the period. That is exactly what happened with sovereign debt crisis. Bodie et al. [48] argued that in the period of Euro crisis and also US downgrade in their credit rating in 2011, sovereign debt has been treated as risk-free. According to the same authors (2013), governments that issue debt securities (debt is denominated in their domestic currency) can repay this debt by printing more money in the same currency. Such situation will lead to runaway inflation and the real return on the debt securities actually will not be risk-free.

Position P_2 (Fig. 2) is in square $(y_1 - \text{RPL} - y_2 - \sigma_{ds})$ and shows a situation in where AL_{ds} passes through the investor's portfolio position. Left from AL_{ds} expected returns grows faster than risk and right from AL_{ds} expected returns grows slower than risk. The standard deviation in this scenario is equal or bigger than standard deviation for the risk premium asset. Relation is the following: $\sigma_{ds} \leq \sigma_{p2.}$ The worst position for the investor is in the fields P_3 and P_4. The situation when expected returns decline with the standard deviation less or equal than standard deviation for the risk premium asset is shown in the field P_3. The investor's position is even worse in the field P_4 where expected returns decline with the standard deviation bigger than standard deviation for the risk premium asset.

It is notable that the amplitude of the Sharpe-ratio dynamics is not time dependent. Therefore additive model should be used. This model is the following:

$$Y_t = T_t + S_t + \varepsilon_t, \tag{2}$$

where Y_t - time series, T_t - trend component, S_t - seasonal component, ε_t - "white" noise (occasional component) [54]. We used the method of seasonality indices for seasonal components filter. Firstly, time series smoothing using the moving average was calculated. It gives opportunity to filter out small fluctuations and to identify the basic trend of time series. It is numerically equal to the arithmetic mean value of time series for several periods. Generally, the simple moving average for point t is defined as follows:

$$SMA_t = \frac{1}{n}\sum_{i=0}^{n-1} y_{t-i} \tag{3}$$

where n - the number of values of time series, y_{t-i} - value of time series in point $(t-i)$. Since the obtained values for the moving average are shifted relatively to the real values of time series, they must be averaged once more with the

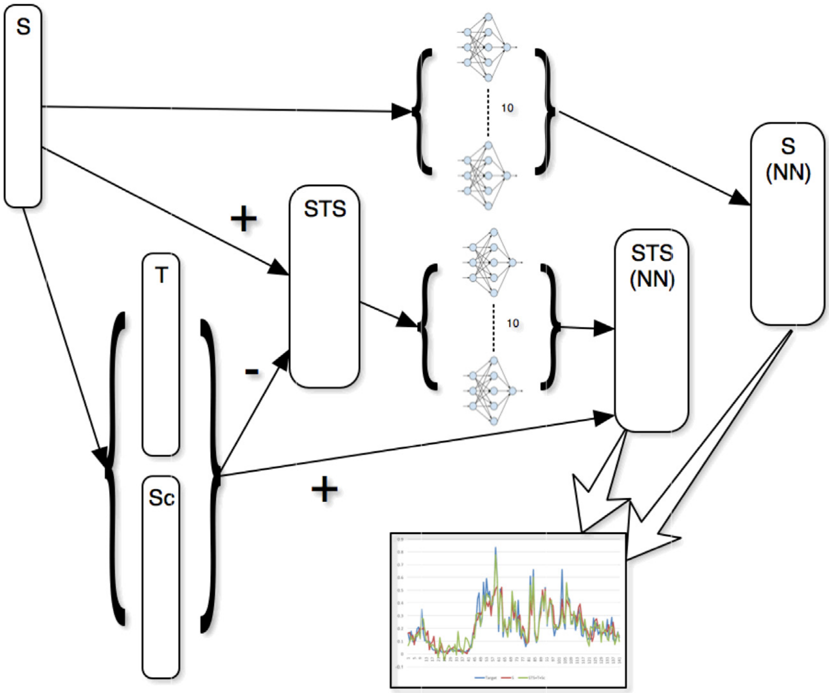

Fig. 3. Schema of learning and forecasting under Delphi method for S and STS.

averaging period equal to 2, which means to calculate the center moving average. Subtracting time series, formed from centered moving averages, which is a general trend of time series, from the original time series, seasonal component evaluation was obtained. In its turn, these evaluations were also averaged for the appropriate days of all the considering years. In the additive model seasonal effects in the period must be similar. Thus the adjustment factor was found for it and the value of seasonal component was corrected according to it.

2.2. Artificial neural network forecasting

As shown in [55], large databases [56,57] should use multilayer neural networks of back propagation to pay attention to the nonlinear relationships. The empirical correlation was used to determine the structure NN [58]:

$$\frac{mN}{1+\log_2 N} \le L_w \le m\left(\frac{N}{m}+1\right)(n+m+1)+m; \tag{4}$$

where n - the dimension of the input signal, m - dimension of the output signal, N - power of the training set, L_w - the number of synaptic connections of the neuron network.

Defining the scopes of synaptic weights changes enables us to determine the number of neurons in a two-layer neural network:

$$L = \frac{L_w}{n+m}. \tag{5}$$

To make forecasting was used 2 timeseries: S − time series of AL_{ds} and STS = S−T−Sc − time series of AL_{ds} without trend (T) and seasonal component (Sc). S and STS time series are the complex nonlinear indicator of complex socio-economic system. We used the ensemble of ANN models to solve the problem of forecasting stability. As preliminary analysis shown, these time series did not contain missing data and abnormal values. That is why we use them directly for forecasting.

That is why in the calculations for forecasting of each indicator every 10 neural networks were constructed and trained. The resulting ensemble value was determined by the Delphi method (Fig. 3). According to formulas (4) and (5) in the one hidden layer neural network with sigmoid activation function were used. The numbers of neurons for hidden layers of neural networks were selected randomly between 10 and 20 neurons (Figs. 3 and 4).

Training, testing and validation sets

As noted above, the method of back-propagation errors was selected as a teaching method. Since it is necessary to calculate the forecast values of output factors in the work, the data for the last known period was selected as the test set.

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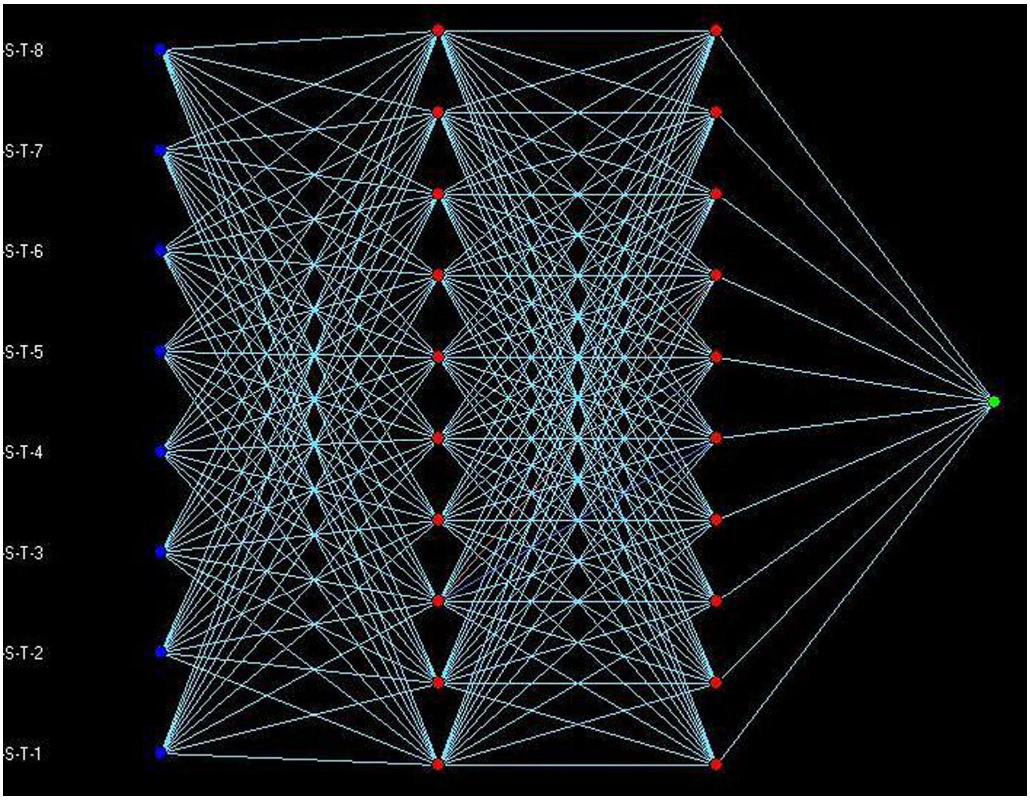

Fig. 4. The structure of the neural network [8 × 10 × 10 × 1].
Source: Authors.

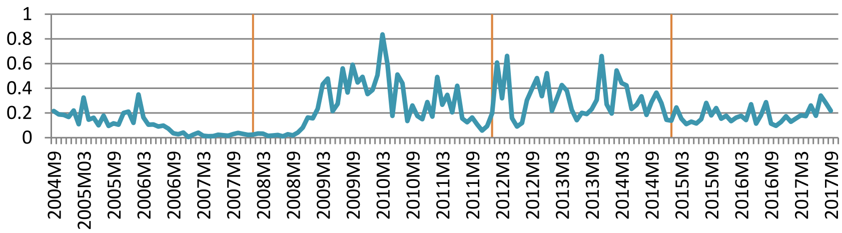

Fig. 5. Dynamics of the Sharpe-ratio.

The Initial set was divided into training and test sets in the ratio (90%/10%). The size of training set consisted 134 rows, test set — 15. The maximum allowable relative error for the test set was considered 5%. Maximum of training lasted for 10 000 epochs. To avoid overfitting, the fitting was stopped when the improvement of the loss function for the test data set was stopped during 10 epochs of fitting. As a result of studies 20 Neural Networks on training sets were recognized 82% of test samples. The python 3.5 with TensorFlow framework was used to realize this calculation.

3. Results and discussion

To determine the investor's portfolio position it is necessary to understand the tendency of ALds's moving. To find the direction of ALds's changing we need to compare Sharpe-ratio at the beginning and at the end of the period. As soon as we have a large amount of data for fairy long period including crisis it is seems appropriate to divide whole period into several sub periods: before crisis (2004–2007), crisis (2008–2011), early post-crisis period (2012–2014), post-crisis period (2015–2017).

Each of them characterized by different amplitude of risk-free and risky assets' yield changing, and therefore different behavior of the Sharpe-ratio.

To build the capital allocation daily yields of money market instruments were used as risk-free assets and medium-term (5 years) and long-term (10 years) debt securities as risky assets (influenced by interest rate risk). Monthly yields

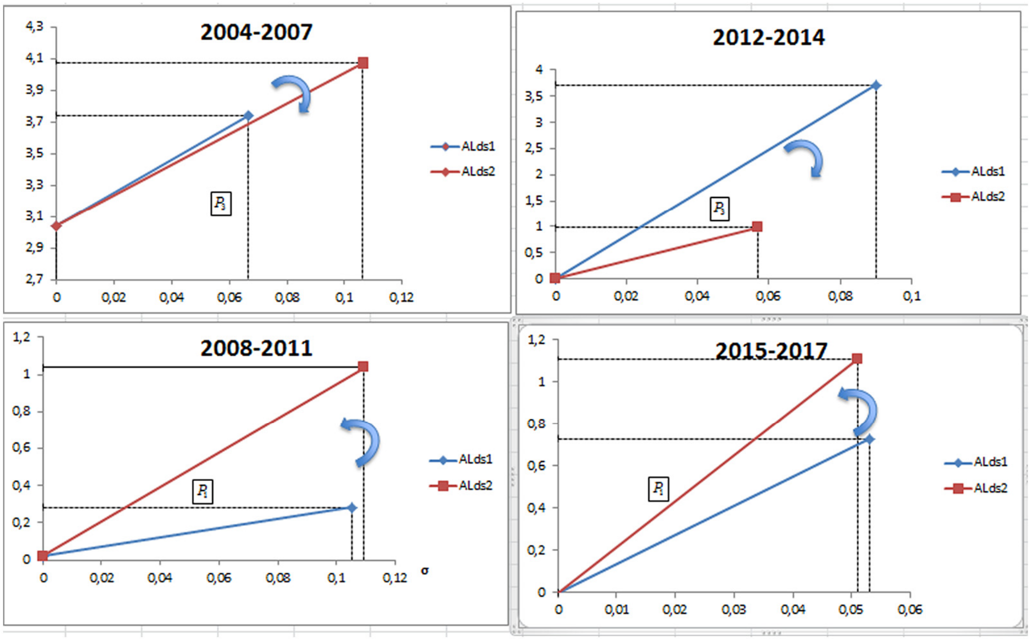

Fig. 6. Dynamics of AL_{ds} for the each sub period.

and standard deviation of all assets were estimated on the base of daily yields. The capital allocation line was constructed for the each sub period. The r_f was found as average of monthly yields of money market instruments for the each sub period. The assumption about equal part of medium-term and long-term debt securities was made. The proportion in general may differ. The measure of moving the capital allocation line may be estimated through finding the changes of the angle of the slope, which is described by Sharpe-ratio. If the Sharpe-ratio is increasing during the period of time, the capital allocation line is moving to the up and left. Otherwise, it is moving down and right. On the graph we can see the capital allocation lines for the beginning and the end of each sub period. (See Fig. 5.)

In the case that we have information about investment budget, we would have opportunity to make a conclusion about investor's portfolio position on the base of this graphs for the each sub period. As far as we have investment budget y_0, only positions *P1* and *P3* are available. As we can see from the Fig. 6 during 2004–2007 and 2012–2014 investor's portfolio position is *P1* and for the period of 2008–2011 and 2015–2017 it is P3 (according to the model in Fig. 2). Here we can notice another interesting situation. Sharpe-ratio grew tremendously during the crisis (2008–2011), with a proportional increase in risk. This situation is normal during market shocks, given that the increase in risk is accompanied by an increase in returns (yields in our case). In the period of sovereign crisis (2012–2014), there was a significant decline in both returns and risks. It is caused by previous saturation and the completion of crisis cycles. However, in the aftermath of the sovereign crisis (2015–2017), standard deviations increased slightly with very high rates of returns. This was a very attractive investment position.

On Fig. 7 we can see the cyclical nature of the Sharpe-ratio. As soon as the fluctuations are repeated during the whole period of time it seems sensible to use seasonal decomposition of time series. The methodology of it is described in detail in [54].

As Fig. 7 shows, Sharpe-ratio has no linear trend. Therefore, after identification of seasonal component with annual frequency it was tried several types of trend and chosen 5th degree polynomial trend which describes the behavior of Sharpe-ratio in the most efficient way. This equation is following:

$$y = 0.2575 - 0.0182x + 0.0005x^2 - 0.000004x^3 + 0.000000009x^4 + 0.00000000002x^5 \tag{6}$$

In our case, the non-linear trend can be considered as cyclical component. To make more conclusions we need to have more data, at least the data that include information about several crises. To make forecasting of S or STS (S without seasonality and trend) we should analyze lag dependencies of these time series. The results of such analysis are presented in Table 1.

As the table shows, in both cases time series depend strongly non-linearly on the date of the last 8 months, because of the correlation coefficients (0.6 > R > 0.2). After 8-month correlation coefficients are too small to take them into account. As can be seen from the figure, correlation coefficients for S are bigger than for STS. It is caused by removing seasonality and trend components. It confirms that STS time series consists of nonlinear accidental components. To make forecast of these nonlinear time lag series Neural Network should be used. (See Fig. 8.)

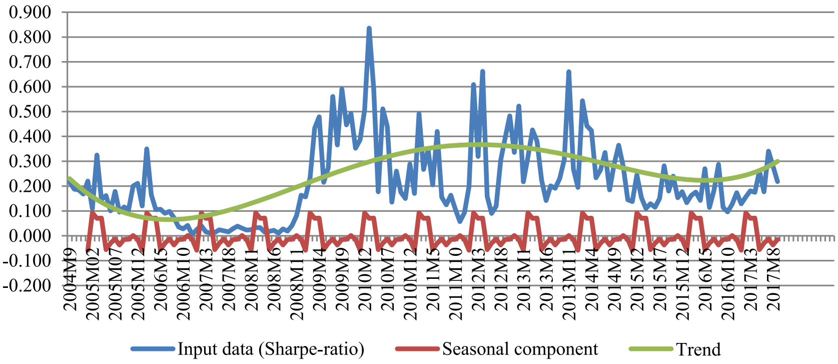

Fig. 7. Sharpe-ratio with trend and seasonal component isolation.

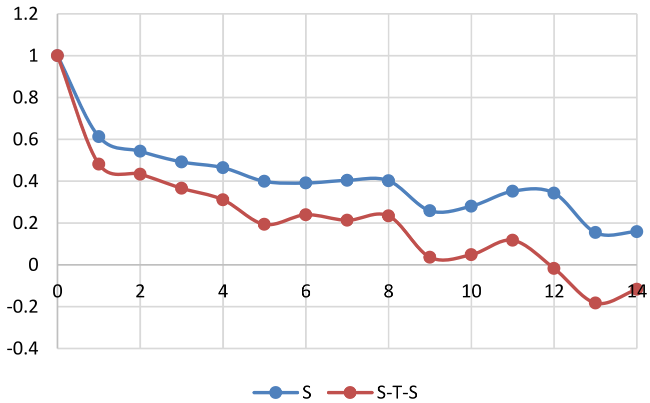

Fig. 8. Autocorrelation lag analysis for S and $S - T - S$ time series.

Table 1
The results of lag analysis.
Source: Calculations by authors.

Lag	S	STS
0	1	1
1	0,61	0,48
2	0,54	0,43
3	0,49	0,37
4	0,46	0,31
5	0,40	0,19
6	0,39	0,24
7	0,40	0,21
8	0,40	0,23
9	0,26	0,04
10	0,28	0,05
11	0,35	0,12
12	0,34	−0,02
13	0,15	−0,18
14	0,16	−0,12

So, to build a neural network the input data sample was transformed to the training set, tuples of which are as follows:

$$TS_S = \langle S_t; S_{t-1}; \ldots; S_{t-8} \rangle \quad (7)$$

$$TS_{S-T-S} = \langle STS_t; STS_{t-1}; \ldots; STS_{t-8} \rangle \quad (8)$$

According to such a transformation the power of training set comprised $card\,(TS) = 148$. The first attribute of tuples serves as the target value; the next 8 are the input parameters.

As can be seen from Fig. 9, learning for STS+T+Sc describes real data more exact. (standard error of approximation for S consist 7.6% and for STS – 6.01%). To test the accuracy of forecasting of the neural network training set was divided on 2 copies. In first copy 8 last data was excluded. After that 10 NN was learned and used for forecasting on 8 months.

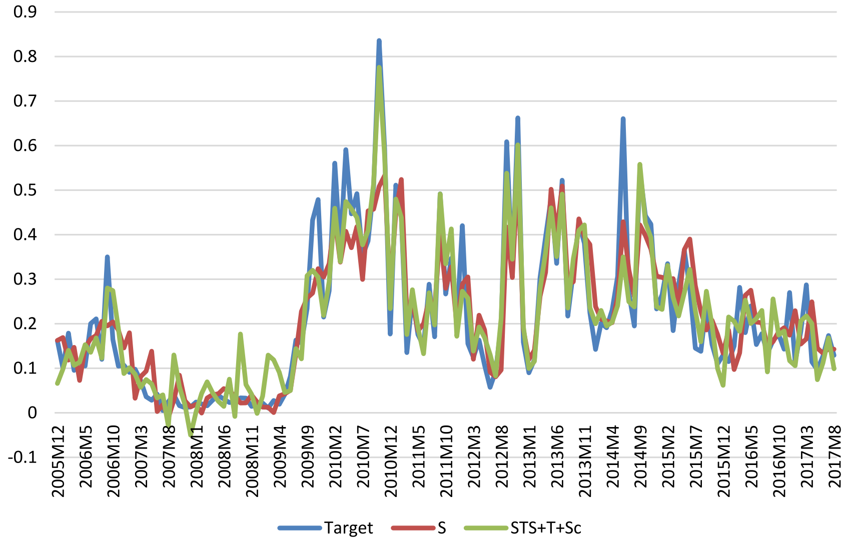

Fig. 9. Results on training of 10 Neural networks for S and STS.

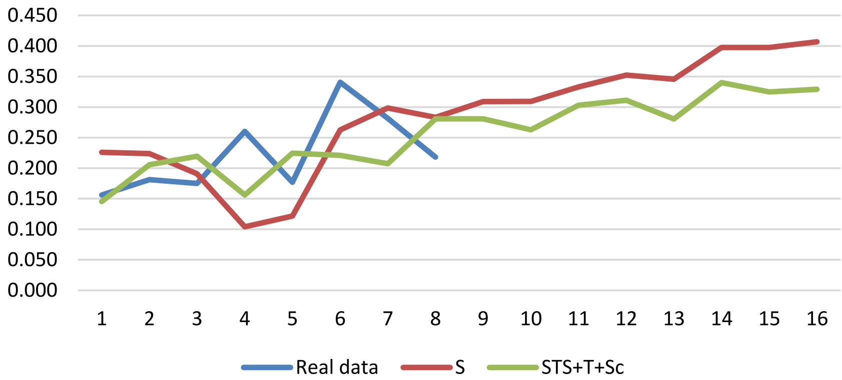

Fig. 10. Results of tests and forecasting of 10 Neural networks for S and STS.

These data were averaged and compared with real data (Fig. 9 first 8 point). The average error for STS+T+Sc was consist 6.6% for S — 6.9%. As can be seen from the figure there are a large deviation between real and deflective values in both cases. It can be seen that in the case of NN-S, the behavior of the curve according to the criterion of coincidence of the extremum with the real data coincides in 3 cases from 6, (50% of cases). A similar situation is with the NN-STS. This is an indication that the behavior of this curve weak depends on its previous meanings.

These neural networks were used for forecasting on next 8 month. Results are shown on Fig. 10. As it can be seen, all forecasts show week growing during this period.

Accordingly to the obtained results neural networks can be successfully used for the prediction of the Sharp-ratio dynamics in the future and therefore for the finding the investor's portfolio position. The Fig. 11 shows increasing trend of Sharp-ratio for the next 8 month. We can depict such situation as dynamics of AL_{ds} on the graph.

As we can see from Fig. 11, the predictive investor's portfolio position for the next 8 months is characterized with increasing returns (from 0, 5 to 1, 5) and the same risk (0, 05 as standard deviation). This is a very good signal to invest in the bond market (to include these instruments in investor portfolio). In this case, reasons for growth of the Sharp-ratio are only changes in supply and demand on money and bonds markets. On the other hand, the situation could have been different. For example, risks are able to remain the same while reducing of returns, or even more, risks could have increased with decreasing returns. For that matter, forecasting with STS+T+Sc would suggest selling fixed income instruments.

4. Conclusion

The 2 ensembles of 10 neural networks were trained in this research. The resulting ensemble value was determined by the Delphi method. Each of the ensembles were used to predict the time series STS+T+Sc and S, respectively. Recognition

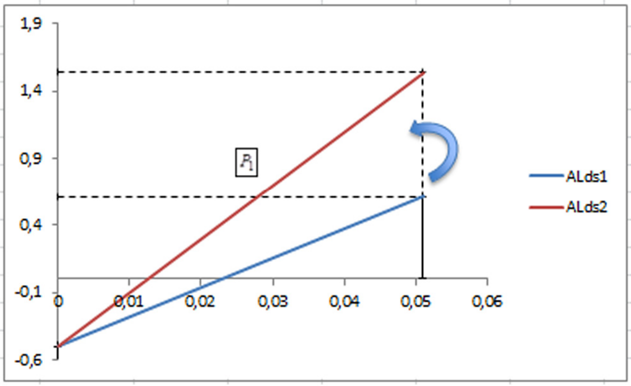

Fig. 11. Trend of Sharp-ratio.

accuracy was 82% on test cases. As was shown in the paper, forecasting for STS+T+Sc was more exact. The average error for STS+T+Sc was consist 6.6% for S −6.9%. These ensembles of neural networks were used for forecasting on next 8 month. All forecasts show week growing during this period. We can make conclusion that these dependencies are strongly nonlinear and can dependence on other factors. Sharp's ratio showed a tendency of growth in the period of the world crisis 2008–2010, in the beginning of the sovereign crisis 2011 after which decreased and continue to growth from 2015. In our case (EU debt instruments portfolio), that means that the EU sovereign crisis had the biggest impact on the fall of the Sharp ratio. However, the constructed neural networks show that in the next eight months Sharp ratio will continue to grow and that the reward for taking over the risk of investors will be higher than the percentage of increase in their standard deviation. Bearing in mind these forecasts, this methodology can be used for the process of investing in securities. There are two limitations in our study model:

1. The first one is model-specific limitation. We assumed that only interest risk exists for fixed-income assets (right-up from Y_1 in Capital allocation line model, Fig. 1) and there is no default risk. However, default risk on long term T-bonds may also exist in some countries (for example, Greece was close to bankruptcy two years ago). This situation is very rare. Next, there are also risks of borrowing (right-up from Y_2 in Capital allocation line model, Fig. 1). Such risks are related to liquidity, solvency and moreover, for changes in interest rates if the lending is in foreign currencies. The limitation does not apply only to our reduced AL_{ds} model; it is also valid for original capital allocation line model.

2. The biggest limitation of forecasting of Sharpe ratio is that can be expected on unseen data (out-of-sample). Optimized Sharpe ratio (in-sample) could overestimate predicted Sharpe ratio (out-of-sample) [59]. The reasons are: (a) in the noise fit, expected Sharpe ratio (for data out-of-sample) will be tuned according to the noise of in-sample data; (b) the estimated parameter will differ in comparing with the true parameter. This will lead to estimation error. However, such limitation is mostly common for all Sharpe ratio predictions. To understand more formal definition of noise fit and estimation error, see the error decomposition in work of Paulsen and Söhl [59]. Furthermore, we suggest for future researches to analyze more data on stronger artificial intelligence technologies, like LSTM neural networks technology (like in [9]). Such adaptive methods will allow making analysis and forecasting more accurate. This area of study needs to receive more attention and effort in the future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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