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COMPARISON OF STOCK SELECTION METHODS: AN EMPIRICAL RESEARCH ON THE BORSA ISTANBUL

Ali Sezin Ozdemir♣
Faculty of Management, Institute of Social Sciences, Istanbul Technical University, Turkey

Kaya Tokmakcioglu
Faculty of Management, Department of Management Engineering, Istanbul Technical University, Turkey

ABSTRACT

This paper compares the performances of stock selection methods developed by artificial neural network (ANN), second order stochastic dominance (SSD), and Markowitz portfolio optimization by generating annual portfolios whose stocks are selected from several types of indexes traded in the Borsa Istanbul. Daily returns in SSD and Markowitz, and annual ratios in ANN models, are taken as inputs, with the following annual returns as outputs. By the perspective of stock selection literature, this study carries unique value for including comparisons of these methods with the purpose of generating portfolios with higher returns. Thus, two questions emerge: "Are these methods able to overcome losses during financial crises and bear or bull periods, and can they provide positive alpha?" Results indicate that average returns of portfolios generated by ANN are relatively higher than SSD and Markowitz, but all three models provide positive alpha over indexes. However, none of the models could overcome negative returns during economic crises.

Keywords: Stock selection, portfolio diversification, Borsa Istanbul, artificial neural network, second order stochastic dominance.

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1. INTRODUCTION

Portfolio selection or optimization—from Markowitz's (1952) mean-variance model to hybrid models such as the one implemented by Chen et al. (2020) — is one of the most fundamental affairs of modern investment theory. Technical and fundamental analysis clinging to strategic trading rules can be used for the selection process (Ince, 2014). Since generated portfolios based on stocks selected from different types of indexes or derivative instruments co-moved with the market may cause negative returns during bear periods, investment firms improve certain types of models to avoid negative effects of bear periods (Tas et al., 2016). Secondly, the instinct of investors stems from achieving greater returns than established indexes or fixed assets having stable, risk-free profits (van der Hart et al., 2005; Lee et al., 2009). The performance of a portfolio yielding more returns than indexes is called a positive alpha performance by portfolio managers (Cuthbertson &

♣ Corresponding author: Institute of Social Sciences, Istanbul Technical University, Ayazaga Campus, 34469, Istanbul, Turkey. Email: ozdemirali12@itu.edu.tr

Nitzche, 2013). Moreover, low interest rates in the market encourages investors to research stock market opportunities to seek higher returns (Chang & Lee, 2017).

Methods for a stock selection to generate a successful portfolio vary from type to type, such as predicting future stock prices by studying their past patterns (Goumatianos et al., 2013), predicting risk by using size or book-to-price ratio as firm-specific characteristics (Lucas et al., 2002), comparing performances of previous stock selection methodologies based on liquidity, size, mean reversion, and momentum (van der Hart et al., 2003), applying learning-to-rank algorithms to understand investors' sentiment toward a group of stocks by comparing long-term and short-term performances (Song et al., 2017), using candlestick charts to predict future returns to generate a cherry-picked portfolio (Horton, 2009), using case-based reasoning (CBR) relying on fundamental and technical analyses to recognize winning stocks around earning announcements by comparing classification accuracy and Sharpe ratio (Ince, 2014), using false discovery rate (FDR) to examine the model selections to be used in stock selection (Cuthbertson & Nitzche, 2013), using abnormal news volume information and rate of analysts' attention toward targeted stocks to detect golden stocks for generating a global portfolio (Gillam et al., 2015), analyzing stock-buying or stock-selling actions of mutual fund firms (Ratanabanchuen & Saengchote, 2020), using Markov decision process on genetic algorithms to define trading strategies (Chang & Lee, 2017), using fuzzy model based on fuzzy ranking (Tiryaki & Ahlatcioglu, 2005), using chaotic bagging indicator to select risk-averse actions to allocate stocks (Suzuki & Okhura, 2016), using consensus temporary earnings forecasts (CTEF) data (Xia et al., 2015), combining analysts' forecasts, momentum data, and fundamental ratios of firms into a model (Guerard et al., 2015), investigating large shareholders' behaviors toward listed stocks (Sun et al., 2020), and using Gordon model improved with multiple criteria decision making (MCDM) model (Lee et al., 2009). Thus, the purpose of all stock selection methods defined above—and similar methods based on statistical, linear regression, fuzzy analyses, cluster analyses, and weighted average stock selection (Yang et al., 2019), and the methods revealed in Section 2—is generating higher returns and providing positive-alpha situations at least in the portfolio management business.

Moreover, this study of Turkey's stock market (Borsa Istanbul) was inspired by the major and crucial incidents between 1999 and 2018. In 1999, a destructive earthquake devastated Marmara region, the main industrial zone of Turkey, causing huge budget deficits on housing, trade, and substructure. In the following year, Turkey made a stand-by agreement with IMF covering a 3-year period. The name of this program was "Curbing Inflation Rate," and it included structural adjustments and rigid policies on foreign currency. Although the program provided amelioration of short-term capital inflow, decrease of the inflation rate was not on the expected level. Secondly, foreign deficit increased due to increase of importation. Such incidents increased liquidity demands of banks, whose assets were mainly treasury bonds. This liquidity crunch caused an increase of interest rates from 35% to 183% within the last quarter of 2000. On 19th February, 2001, the so-called Black Wednesday, political tension escalated between the government and the presidency of Turkey regarding the economic situation, and stocks in Borsa Istanbul (BIST, former Istanbul Stock Exchange) decreased around 18% on average. In the following days, fixed exchange rate regime was left out, and floating rate regime commenced with the value of Turkish Lira decreasing 40% (Bagci, 2014). In 2002, a center-right party took the government after election, and it caused an increase on BIST's various indexes within the last quarter of the year. Between 2002 and 2008, Turkish economy became stabilized due to structural ameliorations on treasury disciplines. In 2008, the global mortgage crisis emerged and caused around 50% decrease in the BIST market within one year. In 2010, Turkey's first constitutional referendum was executed, and it caused a 25% decrease of the market within the following year. In 2013, the "Gezi Protests" led by opposition groups spread to cities across Turkey. These protests caused another 13% decrease of the market in the last two quarters of 2013. In 2016, a coup was attempted by opposite groups, and it caused more than 15% decrease in the market stocks. In the following year, the second Turkish constitutional referendum was executed, resulting in the approval of a presidential system and the removal of the parliamentary system. When the presidency election took place with new governmental system in 2018, it caused a 22% decrease on BIST-100 index with a decrease in the value of TL. All these incidents, which negatively impacted the stock market, proved important in the stock selection process. Turkey's stock market is a good model for other markets in tough circumstances, where investors or pension fund managers must structure portfolios with a positive-alpha performance at least.

The core purpose of this paper is to compare the performances of three stock selection methods in both the 2001 economic crisis—and the other historical incidents in Turkey mentioned above—and the 2008 global mortgage crisis, and the broad money supply periods which followed on its heels. The secondary purpose of this paper is to investigate the ability of these three methods in overcoming negative return situations and in providing positive-alpha performances even in crises. Thirdly, the performances of these three methods have not been compared in the literature yet. Fourthly, this paper compares the performances of both technical and fundamental analysis. Hence, the findings of this paper may have a leading role for investors, and portfolio and fund managers, to structure their portfolios in line with unexpected financial, political, or economic crises in the future.

The rest of this article is structured as follows: Section 2 contains literature review of the stock selection methods of ANN and SSD, and discusses related studies; Section 3 describes theories behind ANN, SSD, and the Markowitz portfolio optimization; Section 4 describes the data set and the empirical methodology; Section 5 presents the observed results of the models applied, and Section 6 concludes the study.

2. LITERATURE REVIEW

2.1. Literature Review of Stock Selection Method with ANN

Quah and Srinivasan (1999) published a study on selecting stock portfolios that beat market return in Singapore Stock Market with back propagation algorithm on ANN, using 7 financial ratios, i.e., historical P/E ratio, prospective P/E ratio, cash-flow yield as yield factor, market capitalization as liquidity factor, earnings per share uncertainty as risk factor, return on equity as growth factor, and momentum factor, as inputs of ANN and returns of each individual stock over market as output. Their study asks whether a portfolio formed by selecting stocks with the ANN method could beat market returns. The design of this study follows the Moving Window Stock Selection System, which is also used in our study as the training strategy of ANN model defined in Section 4. In conclusion, portfolios generated by selecting top 25 stocks outperform portfolios of other stocks, so this model has the ability to select stocks that generate excess returns over market.

Eakins and Stansell (2003) researched the ability of ANN for detecting stocks with higher return potential and compared these findings with the portfolios of different methods. They also highlighted the non-linear ability of the ANN method compared to regression models. However, ANN did show a possible overfitting problem and a generally higher estimation process than other models such as regression models and discriminant analysis. Nevertheless, functional form advantage of ANN is cited by Hill et al. (1994). It is revealed that ANN models have an exclusive ability for partitioning sample space and for performing in simplified, unknown, functional form when data is in noisy situation. The results of Eakin and Stansell's (2003) model are compared with the S&P 500 Index and Dow Jones Industrial Average. Fifty stocks were considered for this study in accordance with the same number of stocks used by O'Shaughnessy (1997) as an appropriate size for studying a portfolio. The 20-year average return of the portfolios selected by neural network is remarkably higher than S&P and Dow-Jones. Thus, findings indicate that ANN is a reasonable tool for identifying stocks with higher return potential.

Olson and Mossman (2003) researched an ANN model with back propagation algorithm, in which training data included a six-year period, and annual returns were forecasted the following year. Stocks were selected from the Toronto Stock Exchange located in Canada. In their research, portfolios generated through Logistic Regression (LOGIT), Ordinary Least Squares (OLS), and ANN are compared with each other. By implementing these tests, Olson & Mossman investigates whether fundamental analysis is a suitable method for high potential stocks, and whether ANN's capturing ability is higher than that of other traditional methods. The returns of portfolios generated on the ANN model is discovered to be higher than the returns of other models' portfolios.

Yildiz and Yezegel (2010) applies fundamental analysis, using NYSE, NASDAQ, and AMEX stocks with 18 financial ratios as input and the returns of the following year as output, to detect abnormal returns of the ANN model with Jacob's Enhanced Backpropagation learning algorithm. After training model, validated stocks are divided into groups of ten, with 10 (the most favorable) to 1 (the least favorable). As a result, the return of the most favorable portfolio do not show an excessive advantage over expected returns; however, the hedging strategy of holding in a long position the most favorable portfolio and in short position the least favorable portfolio is considered successful with 22% abnormal annual return.

2.2. Literature Review of Stock Selection Method with Second Order Stochastic Dominance Method

Ogryczak and Ruszczynski (2002) employed distribution-based SSD test and found a harmonic relationship with certain models using quantiles and tail characteristics of the distribution.

Kopa and Chovanec (2008) discovered a dominating portfolio based on efficiency of SSD test by utilizing the relationship between CVaR and SSD. Berleant et al. (2008) researched portfolio management under epistemic uncertainty by using SSD and information-gap theory, and their findings showed that dominant stocks have better returns over less-dominant stocks and that SSD approach in portfolio management gets the attention of risk-averse investors.

Tas et al. (2015) conducted empirical research on optimizing portfolios with the SSD method by comparing BIST and NYSE stock performances with mean-variance optimization model. Findings showed that dominant portfolios identified by the SSD test have better return performance than those identified by mean-variance methods, and portfolios including NYSE market stocks presented better performance than portfolios generated from BIST stocks. For this study, Tas et al. (2015) applied distribution-based SSD, as proposed by Ogryczak and Ruszczynski (2002).

Guran and Tas (2015) and Tas et al. (2016) reached the same conclusion that portfolios generated by SSD tests have better return performances than the BIST-100 index and the market. Moreover, Tas et al. (2016) showed that portfolios generated by dominant stocks presented positive returns, whereas the BIST-100 index gave a negative return during the tested period. Our study also uses the SSD test approach as implemented in Guran and Tas (2015), Tas et al. (2015), and Tas et al. (2016).

Liesiö et al. (2020) improved upon the existing SSD approach by adding industrial diversification to outperform the market portfolio. Industrial diversification has been found to help improve the performance of SSD-based portfolio optimization. Moreover, Post et al. (2018) improved upon the portfolio optimization method by using SSD and Empirical Likelihood (EL) estimation method.

Since there is no study comparing ANN and SSD performances in the current literature, this empirical research carries a unique value by providing said comparison.

3. THEORETICAL STRUCTURES OF METHODS

In this section, the theoretical structures of the ANN, stochastic dominance, and Markowitz optimization methods are described in that order.

3.1. Artificial Neural Network

With regard to flow order, there are three types of layer in the neural structure, i.e., the input layer, the hidden layer, and the output layer. Between the input layer and the hidden layer, there are weight functions which are optimized by certain algorithms such as backpropagation based on a gradient descent method improved by loss function, and this activity symbolizes the basis of learning principles such as in artificial neural network. In hidden nodes, activation functions such as tanh, sigmoid, ReLU, or leaky ReLU processes data from input side to output side in an arranged way with regard to their own learning capability, as defined by Mitchell (1990).

A supervised neural network teaches a pattern to a network using training dataset including inputs and outputs. Furthermore, with this supervised pattern, new inputs representing test data is implemented and output results received with an expectation of low error. In this study, inputs are defined as financial ratios of firms, and outputs are defined as stock returns of the following year, and so the neural network is trained. By using this supervised pattern, the year’s financial ratios are tested to predict the following year’s stock returns.

The details of stock selection method using ANN are revealed in section 4.

Figure 1: Swallow Neural Network Example

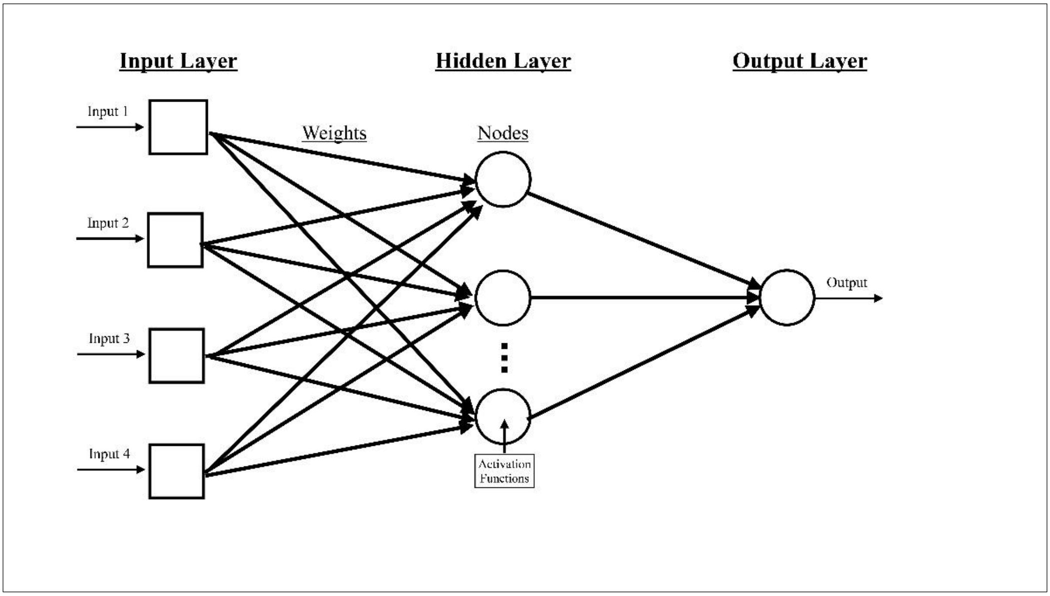


Figure 1 depicts a basic example of a neural network structure representing swallow network.

3.2. First and Second Order Stochastic Dominance

Stochastic dominance is a fundamental notion in theories of decision making in uncertain circumstances. Basing on the possibilities of stock returns, the stochastic dominance relationship of two stocks is examined. Studies based on first or second order stochastic dominance provide optimized portfolios for risk-averse investors, as asserted in Guran and Tas (2015). By first order stochastic dominance (FSD) defining an x chance variable with instinct value and f with its probability distribution, the two conditions below are thus received:

$$f(x) = P(X \leq x) \quad \forall x \in R \tag{1}$$

$$F(x) = \int_{-\infty}^{x} f(y)dy \tag{2}$$

For any two probability distribution such as *f* and g, if $g(x) \geq f(x)$ is provided for $\forall x \in R$, then we see *f* dominate g in FSD level, and it shows as:

$$f \geq_1 g \tag{3}$$

According to this definition, if *f*'s expected utility is not smaller than *g*'s expected utility, *f* dominates g in FSD level.

According to SSD, if $G(x) \geq F(x)$ is provided for $\forall x \in R$, it may be clarified as below:

$$\int_{-\infty}^{\eta} f(t)dt \leq \int_{-\infty}^{\eta} g(t)dt\,, \forall\eta \in R \tag{4}$$

If equation 4 is provided, "f dominates g in SSD level" may be stated and shown as:

$$f \geq_2 g \tag{5}$$

For a chance variable x's target η, SSD defines the threshold value as:

$$E([\eta - f]_+) \leq E([\eta - g]_+), \forall\eta \in R \tag{6}$$

In which, $[\eta - f]_+ = \max(0, \eta - f)$ (Ogryczak & Ruszczynski, 2002).

SSD is based on one-to-one comparisons of all stocks in a stock pool for testing; the total comparison is calculated in Equation 7, where N is the number of stocks in the stock pool.

$$N = \frac{\mathrm{N}!}{(2 \times (\mathrm{N} - 2)!)} \tag{7}$$

3.3. The Markowitz Portfolio Optimization Model

A visual graph of the lowest possible variance which could be reached for any given level of expected return is defined as the minimum variance frontier. A portfolio of risk assets having the lowest variance of all risky asset portfolios is defined as the global minimum variance (GMV) portfolio. The efficient frontier is the range of all investments that are within the minimum variance frontier and is above the global minimum variance portfolio. The expected return of a portfolio is calculated as:

$$E(r_p) = \sum_{i=1}^{n} w_i \times E(r_i) \tag{8}$$

The variance of a two-asset portfolio such as a and y is calculated as:

$$\sigma_p^2 = \omega_x^2\sigma_x^2 + \omega_y^2\sigma_y^2 + 2\omega_x\omega_y Cov(r_x, r_y) \tag{9}$$

Generalizing the equation to accommodate more than two assets results in the equation:

$$\sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} \omega_i\omega_j Cov(r_i, r_j) \tag{10}$$

After moving past a two-asset portfolio, it is necessary to use matrix multiplication to determine the optimal asset weights in the portfolio. The expected return for the portfolio is calculated as:

$$E(r_p) = \boldsymbol{W^T R} = [W_1 \cdots W_2] \begin{bmatrix} E(r_1) \\ \vdots \\ E(r_j \end{bmatrix} \tag{11}$$

where **W** is the vector of the weights of the individual assets (1 through j) in the portfolio, and where **R** is the vector of the individual assets (1 through j) in the portfolio.
The variance of the portfolio is calculated as:

$$\sigma_p^2 = W^T S(W) \tag{12}$$

Whereas, the standard deviation of the portfolio is calculated as:

$$\sigma_p = \sqrt{W^T S(W)} \tag{13}$$

where S is referred to as the variance-covariance matrix of the covariances between each of the asset's returns in the portfolio. The covariance of an asset's returns with the returns for the same asset is the variance of the asset's returns. The definition of W remains the same as above. The optimal weights for assets in a portfolio are the ones that maximize the value of Sharpe Ratio for the portfolio.

$$S_p = \frac{E(r_p) - r_f}{\sigma_p} \tag{14}$$

4. DATA AND METHODOLOGY

4.1. Data

A stock pool is created for stock selection by including stocks of BIST-100, BIST-50 and BIST DIVIDEND indexes which are all traded indexes in BIST. Stocks of banks and sport clubs are eliminated in order to provide alignment for fundamental ratio types and annual report timing among selected stocks. Banks have different types of ratios compared with other firms in the industry, and sport club firms reveal their annual reports on different dates compared with other firms.

For SSD and Markowitz tests, daily returns within a one-year period, accounting to around 250 days, are tested. For the ANN model, 19 financial ratios of firms are trained with one year ahead returns. Therefore, SSD and Markowitz tests may be evaluated as technical analyses, and ANN may be considered as a fundamental analysis.

Table 1: Tested Methods and Periods

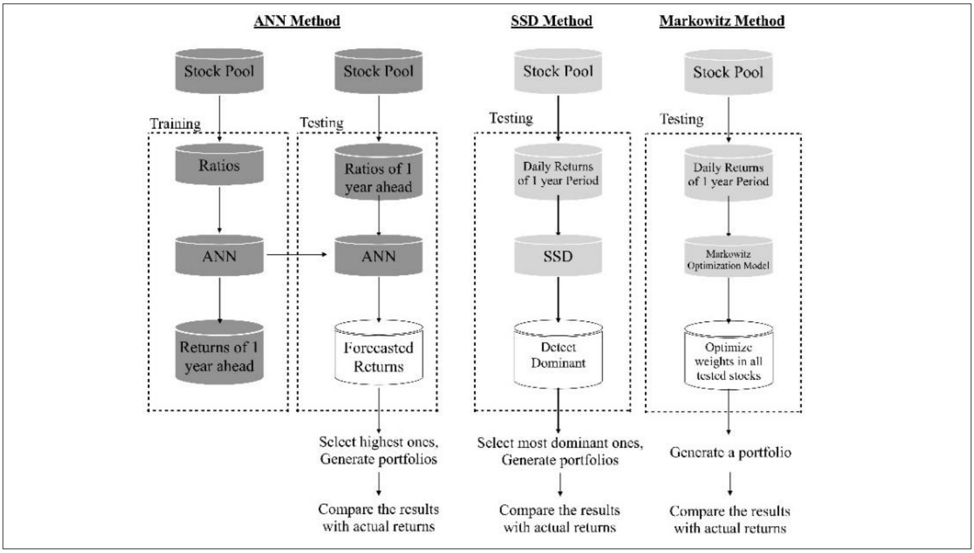
Methods	Tested Periods	Portfolio Periods
SSD, M	Jan 1st, 2000 to Dec-End, 2017	1-to-17 Years
ANN, SSD, M	Mar-End, 2000 to Mar-End, 2018	1-to-17 Years
SSD, M	Mar-End, 2000 to Mar-End, 2018	1-to-17 Years

Table 1 displays compared methods, tested periods, and total portfolio periods. In the first row of the table, SSD and Markowitz test are implemented for January-to-December periods since it does not compare annual report timings which are generally revealed in March ends of a year. The second row indicates that ANN, SSD, and Markowitz tests are implemented for March-end periods since annual reports are generally published within the month of March. Additionally, some tested stocks in row 1 are eliminated before the row 2 tests since outlier fundamental ratios are dismissed from ANN test and some ratio data are missing in the dataset taken from the database. In row 3, SSD and Markowitz tests are implemented for the March-end periods because some stocks were eliminated when passing from row 1 tests to row 2 tests. Moreover, the number of tested stocks in row 1 and row 3 tests are equal, providing perfect stage for comparison. Results of row 1 tests may be seen in Section 5.1, and results of row 2 and row 3 tests may be seen in Section 5.2.

4.2. Methodology

Figure 2 indicates differences of methods in terms of implementation. As defined in Section 4.1, ANN is considered as fundamental analysis due to usage of financial ratios, and SSD and Markowitz tests are considered as technical analyses due to usage of only daily returns.

Figure 2: Stock Selection Strategy with ANN, SSD, and the Markowitz Portfolio Optimization Models



4.3. Stock Selection Methodology in ANN

Inputs are the financial ratios of firms, and 19 inputs are used for each neural network. These ratios are defined under factors of profitability, DuPont/Earning Power, liquidity, leverage, and operating. From such aspect, more ratios are implemented here than in the study of Quah and Srinivasan (1999). For profitability, EBITDA margin, operating margin, pretax margin, and net margin are used as 4 ratios. For DuPont/Earning Power, asset turnover, x pretax margin, pretax ROA, x Leverages (Assets/Equity), pretax ROE, ROE, and reinvestment rate are used as 7 ratios. For liquidity, quick ratio, current ratio, and cash cycle (days) are used as 3 ratios. For leverage, assets/equity and debt/equity are used as 2 ratios. For operating, A/R turnover, fixed asset turnover, and ROIC are used as 3 ratios.

Outputs are annual returns of stocks. For this study, the training data of the neural network starts from the 2000-March-End ratios as inputs and 2001-March-End (one year ahead) returns as outputs. The testing of the neural network started from 2001-March-End ratios as inputs and gives the 2002-March-End's returns (one year ahead returns) as output prediction results. According to these predicted outputs in March-End of 2001, portfolios are generated as 10, 20, 30, 40, and 50 number of stocks. Stocks are chosen according to their value from biggest returns to smallest returns. In March-End of 2002, real returns can be compared to predicted ones. For each following year, this structure is repeated until the 2018-March-End. This provides from 1 to 17 years portfolio generation periods. Moreover, this structure, which is called the Moving Window Stock Selection System (Figure 3) based on the study of Eakins and Stansell (2003), is also used in this study.

Figure 3: Moving Window Stock Selection Method

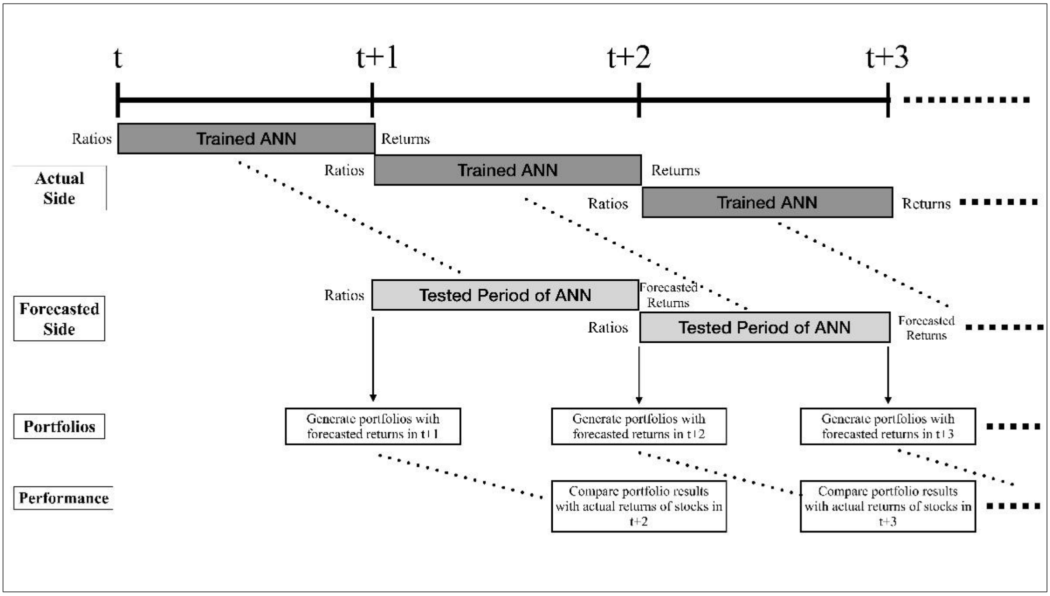


Figure 3 shows the basic approach on how to implement stock selection by using ANN methodology. At (t+1) date, an investor can use (t) date financial ratios to train ANN model with (t+1) date returns and test this model with (t+1) date's financial ratios. The result of this test defines the strategy of the investor in (t+1) date. With the result of this test, the investor can expect returns of (t+2) date in (t+1) date. For the following years, this method may be updated with new ratios and returns.

4.4. Stock Selection in Second Order Stochastic Dominance Method (SSD)

As defined in Guran and Tas (2015), stock selection by the SSD method is based on testing previous year's daily returns with SSD and picking the most dominant stocks for the portfolio of the following year; the steps are repeated each following year.

The process of implementing SSD tests on stocks and picking the most dominant ones for portfolio can be structured as the follows:

(1) Create a stock pool,
(2) Create a column showing returns of all stocks in a smallest-to-largest order, such as -20% to +20%,
(3) Create another column showing the difference between current return and following return,
(4) Create new columns for each stock showing possibilities of giving returns in current row,
(5) The sum of possibilities of the stocks in each column must be given 1,
(6) Create another column sets of each stock showing cumulative sums of each row which must reach 1 due to possibility principle,
(7) Create other columns showing dual comparisons of each stocks,
(8) Rows of these columns show the cumulative sums of multiplication of return difference and cumulative column value's differences,
(9) These latest rows of comparison reveal the dominance in dual stock comparisons, i.e., which one is dominant and which one is weaker, or whether the two stocks share a neutral relationship with no dominant stock between them, and
(10) Pick the dominant stocks.

In this study, after each SSD test, the portfolios generated obtain a certain number of stocks according to their SSD level, from 10 stocks of the most dominant to 20 stocks, 30 stocks, 40 stocks, and 50 stocks accordingly. As explained in Section 4.1, two periods are tested for generating portfolios. The first tested period is January-First to December-End, and the second tested period is from March-End to the next March-End.

According to Table 3, the number of stocks tested with SSD varies from 84 to 146 between 2000 and 2018, meaning the comparison number of stocks on the SSD test varies from 3,486 to 10,585 with Equation 7.

4.5. The Markowitz Portfolio Optimization

Weights of stocks in a portfolio are optimized in the Markowitz model by maximizing Sharpe ratio of a given dataset as returns of stocks, but it means that some stocks may have 0% weight in a portfolio after calculation. Additionally, for this study, a portfolio is arranged to include at least 10 stocks. Therefore, though the optimal stock number in a portfolio as optimized by Markowitz model varies from year to year, it is never lower than 10. Since there is no stable number of stocks for reasons of optimization, the Markowitz model is different from SSD or ANN in that regard.

However, this study uses the same numbers of stocks for the Markowitz tests. Unlike SSD, stocks in a Markowitz portfolio are not fixed, as illustrated in Figure 2. Thus, this becomes an opportunity to compare the performance between the mean-variance model and the SSD model such as implemented in Guran and Tas (2015).

Secondly, the annual simple minimum interest rates of the Central Bank of Turkey are used as risk-free rates in the model by covering each year's rates from 2000 to 2018.

5. RESULTS

Table 2 shows the abbreviations used for columns defined in Section 5.1 and Section 5.2.

Table 2: Definitions of Columns in Section 5.1 and Section 5.2.

Type	Definition
M	Returns of portfolios generated by the Markowitz optimization method with changing stock number (Optimized on all tested stocks).
S10–50	Returns of portfolios generated by SSD method. These portfolios include stocks numbering 10, 20, 30, 40, and 50.
A10–50	Returns of portfolios generated by ANN method. These portfolios include stocks numbering 10, 20, 30, 40, and 50.
A0+	Returns of portfolios generated by ANN method. These portfolios include all forecasted positive stocks (not limited from 10 to 50).
A	Returns of portfolios including all tested stocks.
B	Returns of BIST-100 Index.
NTS	Number of tested stocks.
NTR	Number of stocks trained in ANNs.
20XXE	Years representing performances of portfolios in periods of January first to December end (E is year-end).
20XXM	Years representing performances of portfolios in periods of March end to the upcoming March end (M is March-end).

5.1. January-to-December Portfolios Representing Comparison of Markowitz

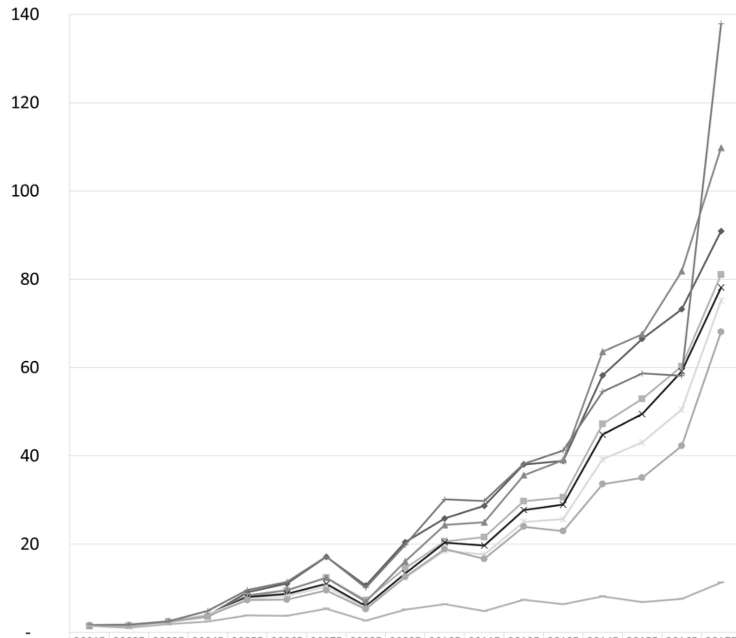
Table 3 indicates the comparison of January-to-December portfolio performances of SSD and Markowitz within a 17-year period. Total return averages of the SSD and Markowitz portfolios within 17 years are higher than BIST-100's average return. However, the return performances of the portfolios of SSD and Markowitz at the end of 2003 and 2012 are lower than BIST-100's returns. Additionally, the 2007, 2009, and 2016 portfolio returns of these methods fall between the BIST-100's returns. In 2008, when the mortgage crisis hit the globe, the portfolios of these methods showed negative returns but they did have positive alpha, meaning their losses in 2008 were at least lower than BIST-100's loss in 2008. Notably, the 2006, 2011, 2013, and 2015 portfolios showed positive returns; whereas, in those years, BIST-100 showed negative returns. Though the total average return of the Markowitz portfolios in the 17-year period is slightly higher than SSD's average return, the first 16 years' total average return of SSD is higher than Markowitz's average return of the same period.

Table 3: Returns (as decimals) of the Annual Portfolios Generated by SSD and Markowitz Tests Structured into January-to-December Periods

Years	NTS	S10	S20	S30	S40	S50	M	A	B
2001E	0.50	0.49	0.52	0.52	0.56	0.70	0.54	0.46	0.50
2002E	0.15	0.05	0.04	0.03	0.03	0.05	-0.04	-0.26	0.15
2003E	0.47	0.49	0.53	0.62	0.60	0.41	0.65	0.76	0.47
2004E	0.51	0.49	0.65	0.59	0.56	0.94	0.53	0.30	0.51
2005E	1.39	1.32	1.11	0.99	0.89	0.96	0.93	0.56	1.39
2006E	0.21	0.17	0.14	0.09	0.09	0.19	0.01	-0.02	0.21
2007E	0.55	0.31	0.29	0.26	0.25	0.50	0.28	0.42	0.55
2008E	-0.38	-0.41	-0.44	-0.46	-0.47	-0.41	-0.44	-0.51	-0.38
2009E	0.93	0.99	1.31	1.25	1.23	0.95	1.38	0.96	0.93
2010E	0.26	0.42	0.51	0.52	0.50	0.52	0.50	0.24	0.26
2011E	0.11	0.05	0.03	-0.03	-0.05	-0.01	-0.12	-0.24	0.11
2012E	0.33	0.38	0.43	0.41	0.42	0.28	0.44	0.52	0.33
2013E	0.02	0.03	0.10	0.04	0.03	0.08	-0.04	-0.13	0.02
2014E	0.50	0.54	0.63	0.55	0.53	0.32	0.46	0.28	0.50
2015E	0.14	0.12	0.06	0.10	0.10	0.08	0.04	-0.16	0.14
2016E	0.10	0.14	0.21	0.20	0.17	-0.01	0.20	0.11	0.10
2017E	0.24	0.35	0.34	0.32	0.49	1.37	0.61	0.48	0.24

Figure 4 indicates 1 Turkish Lira walks. By updating portfolios at the end of each year, 1 TL reaches between 67 TL to 138 TL with the SSD or Markowitz model; whereas, 1 TL with BIST-100 only reaches up to 11 TL. Thus, Figure 4 illustrates the substantially higher performances of the two models than that by BIST-100 in the long run.

Figure 4: Walks of 1 Turkish Lira Investment on Portfolios from 2000-December-End to 2017-December-End



	2001E	2002E	2003E	2004E	2005E	2006E	2007E	2008E	2009E	2010E	2011E	2012E	2013E	2014E	2015E	2016E	2017E
SSD PORTFOLIO - MOST DOMINANT FIRST 10 STOCKS	1	2	3	4	9	11	17	11	20	26	29	38	39	58	67	73	91
SSD PORTFOLIO - MOST DOMINANT FIRST 20 STOCKS	1	2	2	4	8	10	12	7	15	21	22	30	31	47	53	60	81
SSD PORTFOLIO - MOST DOMINANT FIRST 30 STOCKS	2	2	2	4	8	10	12	7	16	24	25	36	39	64	68	82	110
SSD PORTFOLIO - MOST DOMINANT FIRST 40 STOCKS	2	2	3	4	8	9	11	6	13	20	20	28	29	45	49	59	78
SSD PORTFOLIO - MOST DOMINANT FIRST 50 STOCKS	2	2	3	4	8	8	10	6	12	19	18	25	26	39	43	50	75
ALL TESTED STOCKS	2	1	2	4	7	7	10	5	13	19	17	24	23	34	35	42	68
MARKOWITZ PORTFOLIO - [CHANGING NUMBER OF STOCKS]	2	2	3	5	10	11	17	10	20	30	30	38	41	55	59	58	138
BIST-100 INDEX	1	1	2	2	4	4	5	3	5	6	5	7	6	8	7	8	11

5.2. March-to-Next-March Portfolios Representing the Comparison of ANN, SSD, and Markowitz

Table 4 indicates the comparison of March-End-to-Next-March-End portfolio performances of ANN within the 17-year period. Total return averages of ANN portfolios within 17 years are substantially higher than BIST-100's average return. Only at the end of March 2004 was the return performances of the ANN portfolios lower than that of BIST-100. Additionally, 2007 and 2008 portfolio returns of ANN fall between BIST-100's returns. In the 2008–2009 period, when the mortgage crisis hit the globe, all except the 40-stock portfolio of ANN registered negative returns, however, they did show positive alpha, meaning their loss in 2008M-to-2009M portfolio is lower than BIST-100's loss in 2008M-to-2009M. Moreover, the 2002M-to-2003M portfolios of ANN recorded positive returns when the BIST-100 portfolios of the same year recorded negative returns. Furthermore, by comparing Table 4 and Table 5, it may be calculated that the total average returns of the ANN portfolios within the 17-year period, bar the 10-stock-ANN-portfolio, are quite higher than SSD's and Markowitz's total average returns within the same period.

Table 4: Returns (as decimals) of the Annual Portfolios Generated by ANN Tests Structured within March-End-to-Next-March-End Periods

Years	NTR	NTS	A0+	A10	A20	A30	A40	A50	B
2002M	68	75	0.75	0.43	0.70	0.69	0.67	0.67	0.46
2003M	75	77	0.10	0.07	0.16	0.15	0.11	0.08	-0.19
2004M	77	81	0.86	0.94	1.08	1.01	0.92	0.88	1.13
2005M	81	84	0.32	0.53	0.31	0.32	0.41	0.40	0.27
2006M	84	87	1.03	1.85	1.41	1.16	1.08	1.09	0.68
2007M	87	87	-0.01	0.13	0.09	0.06	0.06	0.06	0.02
2008M	87	93	0.01	-0.12	-0.05	0.11	0.07	0.00	-0.11
2009M	93	92	-0.31	-0.33	-0.30	-0.32	-0.34	-0.31	-0.34
2010M	92	94	1.69	1.49	1.64	1.58	1.59	1.53	1.19
2011M	94	96	0.39	0.55	0.43	0.40	0.39	0.38	0.14
2012M	96	104	-0.02	-0.01	-0.02	0.00	0.02	0.03	-0.03
2013M	104	104	0.50	0.56	0.50	0.47	0.50	0.45	0.38
2014M	104	113	-0.06	-0.14	-0.09	-0.03	-0.04	-0.03	-0.19
2015M	113	116	0.45	0.65	0.58	0.61	0.53	0.48	0.16
2016M	116	117	0.15	0.17	0.17	0.18	0.18	0.18	0.03
2017M	117	117	0.25	0.39	0.34	0.30	0.29	0.31	0.07
2018M	117	118	0.52	1.37	0.92	0.67	0.66	0.60	0.29

Table 5 indicates the comparison of March-End-to-Next-March-End performances of the SSD and Markowitz portfolios within the 17-year period. The number of stocks tested are the same as in ANN's tests, which may be seen in the NTS column in Table 4 and Table 5. Total return average of the SSD and Markowitz portfolios within 17 years are substantially higher than BIST-100's total return average. However, the 2004-March-End period saw the SSD and Markowitz portfolios register lower returns performances than BIST-100's return of the same year. Additionally, the 2006M-to-2007M portfolio returns of SSD and Markowitz fall between the BIST-100 index's return of that year. In the 2008-2009 period, which saw the mortgage crisis devastate the economy, the portfolios of SSD and Markowitz showed negative returns but registered positive alpha, meaning their loss in the 2008M-to-2009M portfolio is lower than BIST-100's loss in the same period. Moreover, the 2002M-to-2003M and 2011M-to-2012M portfolios of SSD and Markowitz showed positive returns when BIST-100's portfolio showed negative returns.

Table 5: Returns (as decimals) of the Annual Portfolios Generated by SSD and Markowitz Tests Structured within March-End-to-Next-March-End Periods

Years	NTS	S10	S20	S30	S40	S50	A	M	B
2002M	75	0.60	0.56	0.61	0.63	0.64	0.68	0.63	0.46
2003M	77	0.15	0.15	0.12	0.16	0.15	0.09	0.17	-0.19
2004M	81	0.82	0.76	0.93	0.95	0.93	0.90	0.61	1.13
2005M	84	0.34	0.40	0.42	0.38	0.33	0.38	0.46	0.27
2006M	87	1.22	1.03	0.97	0.92	0.96	0.88	0.95	0.68
2007M	87	0.04	0.03	0.00	0.03	0.02	-0.02	-0.01	0.02
2008M	93	0.07	0.00	-0.06	-0.07	-0.09	-0.02	0.06	-0.11
2009M	92	-0.32	-0.37	-0.35	-0.32	-0.32	-0.31	-0.31	-0.34
2010M	94	1.17	1.32	1.41	1.45	1.37	1.56	1.31	1.19
2011M	96	0.38	0.32	0.40	0.39	0.44	0.38	0.40	0.14
2012M	104	0.14	0.11	0.11	0.06	0.07	0.00	0.11	-0.03
2013M	104	0.40	0.37	0.42	0.43	0.41	0.30	0.17	0.38
2014M	113	0.04	-0.01	-0.02	-0.02	-0.04	-0.11	-0.01	-0.19

2015M	116	0.76	0.71	0.58	0.56	0.58	0.43	0.59	0.16
2016M	117	0.25	0.26	0.18	0.20	0.20	0.15	0.32	0.03
2017M	117	0.10	0.17	0.20	0.20	0.21	0.25	0.07	0.07
2018M	118	0.53	0.41	0.32	0.39	0.36	0.49	0.58	0.29

Table 6 indicates the comparison of March-End-to-Next-March-End performances of the SSD and Markowitz portfolios within the 17-year period. The number of stocks tested are different from that in ANN's tests, as seen in the NTS column in Table 4 and Table 5; however, the number of stocks tested are the same with the other SSD and Markowitz tests in the Section 5.1, as seen in Table 3. Total return average of the SSD and Markowitz portfolios within 17 years are substantially higher than the BIST-100's average return. However, the SSD and Markowitz portfolios registered lower returns at the end of 2004-March than BIST-100's return. Additionally, the 2009M-to-2010M return of the Markowitz portfolio is lower than BIST-100's return of the same year. In 2008–2009, when the mortgage crisis hit the economy, the portfolios of both SSD and Markowitz recorded negative returns but still provided positive alpha, meaning their losses in the 2008M-to-2009M period is at least lower than BIST-100's loss in the same period. Moreover, 2002M-to-2003M and 2011M-to-2012M portfolios of SSD recorded positive returns even when BIST-100 recorded negative returns in the same years.

Table 6: Returns (as decimals) of the Annual Portfolios Generated by SSD and Markowitz Tests Structured within March-End-to-Next-March-End Periods and Aligned with the Number of Stocks Tested in Section 5.1

Years	NTS	S10	S20	S30	S40	S50	A	M	B
2002M	0.53	0.48	0.56	0.57	0.61	0.67	1.02	0.46	0.53
2003M	0.23	0.15	0.15	0.16	0.15	0.05	-0.31	-0.19	0.23
2004M	0.75	0.85	0.92	1.00	1.03	0.98	0.82	1.13	0.75
2005M	0.33	0.40	0.38	0.40	0.42	0.44	0.53	0.27	0.33
2006M	1.30	1.13	1.02	1.00	0.99	0.92	0.80	0.68	1.30
2007M	0.17	0.12	0.06	0.04	0.03	-0.02	0.02	0.02	0.17
2008M	0.29	0.09	0.02	-0.02	-0.04	-0.04	-0.07	-0.11	0.29
2009M	-0.28	-0.30	-0.35	-0.31	-0.30	-0.23	-0.21	-0.34	-0.28
2010M	1.13	1.34	1.39	1.45	1.49	1.53	0.82	1.19	1.13
2011M	0.34	0.27	0.38	0.34	0.31	0.37	0.42	0.14	0.34
2012M	0.14	0.11	0.11	0.07	0.06	-0.02	0.04	-0.03	0.14
2013M	0.40	0.37	0.43	0.40	0.41	0.31	0.23	0.38	0.40
2014M	0.04	0.01	-0.05	-0.04	-0.05	-0.12	-0.04	-0.19	0.04
2015M	0.80	0.74	0.59	0.53	0.52	0.41	0.77	0.16	0.80
2016M	0.26	0.28	0.22	0.19	0.20	0.14	0.28	0.03	0.26
2017M	0.07	0.11	0.17	0.18	0.18	0.23	0.05	0.07	0.07
2018M	0.49	0.45	0.34	0.34	0.39	0.49	0.52	0.29	0.49

5.3. Comparison of the Average Returns of All Methods

Table 7 indicates each model's best 1 Turkish Lira walk for the March-End-to-Next-March-End portfolios. By updating the portfolios at the end of each year, 1 TL reaches between 110 TL and 279 TL with ANN or SSD; whereas, BIST-100 reaches only 14 TL. Therefore, the table shows that the performances of ANN and SSD models are substantially higher than BIST-100's performance in the long run. Portfolio generated by ANN model and including the 10 best stocks available shows the best performance by reaching from 1 TL to 279 TL (except dividends).

Portfolios generated by ANN model and including the best 20 and 30 stocks show the second- and third-best performances, respectively. Portfolio generated by SSD model and including the 10 most dominant stocks shows the fourth-best performance by reaching from 1 TL to 187 TL in the long run. However, the 1 TL walk of the Markowitz model could not even reach 100 TL in the March-End-to-March-End portfolios.

Table 7: Best Performances of 1 Turkish Lira Walks on Portfolios from 2001-March-End to 2018-March-End

Years	A10	A20	A30	SD10	A40	S10	SD20	A50	A0+
2002M	1	2	2	2	2	2	1	2	2
2003M	2	2	2	2	2	2	2	2	2
2004M	3	4	4	3	4	3	3	3	4
2005M	5	5	5	4	5	4	4	5	5
2006M	13	13	11	10	10	10	9	10	10
2007M	15	14	12	12	11	10	11	10	10
2008M	13	13	13	15	12	11	11	11	10
2009M	9	9	9	11	8	7	8	7	7
2010M	21	25	23	23	20	16	19	18	18
2011M	33	36	32	31	28	22	24	25	25
2012M	33	35	32	36	28	25	26	26	25
2013M	51	53	47	50	43	35	36	37	37
2014M	44	48	45	52	41	37	37	36	35
2015M	72	75	73	93	63	65	64	54	51
2016M	85	89	86	118	74	81	82	63	58
2017M	118	119	112	125	96	89	92	83	72
2018M	279	228	187	187	159	137	133	133	110

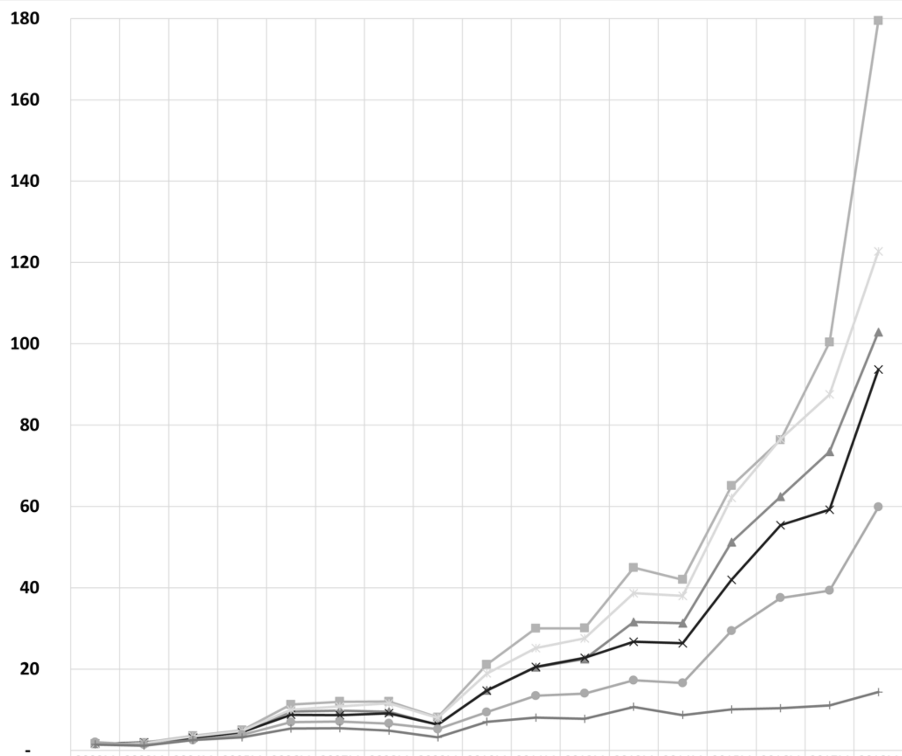
Table 8 indicates the average returns of the March-End-to-March-End portfolios of all three models for each year in the 17-year period.

Table 8: Average Returns (as decimals) of All Annual Portfolios Generated by ANN, SSD, and Markowitz Tests Structured within March-End-to-Next-March-End Periods

Years	NN-AV	SS-AV	MS-AV	SD-AV	MD-AV	BIST-100
2002M	0.65	0.61	0.63	0.55	1.02	0.46
2003M	0.11	0.15	0.17	0.17	-0.31	-0.19
2004M	0.95	0.88	0.61	0.91	0.82	1.13
2005M	0.38	0.37	0.46	0.38	0.53	0.27
2006M	1.27	1.02	0.95	1.09	0.80	0.68
2007M	0.06	0.02	-0.01	0.09	0.02	0.02
2008M	0.00	-0.03	0.06	0.07	-0.07	-0.11
2009M	-0.32	-0.34	-0.31	-0.31	-0.21	-0.34
2010M	1.59	1.34	1.31	1.36	0.82	1.19
2011M	0.42	0.39	0.40	0.33	0.42	0.14
2012M	0.00	0.10	0.11	0.10	0.04	-0.03
2013M	0.50	0.41	0.17	0.40	0.23	0.38
2014M	-0.07	-0.01	-0.01	-0.02	-0.04	-0.19
2015M	0.55	0.64	0.59	0.64	0.77	0.16
2016M	0.17	0.22	0.32	0.23	0.28	0.03
2017M	0.31	0.18	0.07	0.14	0.05	0.07
2018M	0.79	0.40	0.58	0.40	0.52	0.29

Figure 5 indicates the walks of 1 Turkish Lira by the averages of the March-to-March portfolios of all three models. One TL with the models is shown to reach between 60 TL and 179 TL; whereas, 1 TL with BIST-100 reaches only 14 TL. Therefore, the average performances of the ANN, SSD, and Markowitz models are substantially higher than BIST-100's performance in the long run. Average return of the portfolios generated by the ANN model shows the best performance by reaching from 1 TL to 179 TL (except dividends). Average return of the portfolios generated by the SSD model shows the second-best performance. The Markowitz model shows the third-best average return. Thus, in the long run, the ANN model, as a fundamental analysis approach, shows better performance than the SSD and the Markowitz, the two technical approaches here.

Figure 5: Walks of 1 Turkish Lira Investment with the Averages of All Types of Portfolios from 2001-March-End to 2018-March-End



	2002M	2003M	2004M	2005M	2006M	2007M	2008M	2009M	2010M	2011M	2012M	2013M	2014M	2015M	2016M	2017M	2018M
NN-Average	2	2	4	5	11	12	12	8	21	30	30	45	42	65	76	100	179
SSD-Average [Same]	2	2	3	5	10	10	10	6	15	20	22	32	31	51	62	73	103
M [Same]	2	2	3	4	9	9	9	6	15	21	23	27	26	42	55	59	94
SSD-Average [Different]	2	2	3	5	10	11	12	8	19	25	28	39	38	62	77	88	123
M-[Different]	2	1	3	4	7	7	7	5	9	13	14	17	17	29	38	39	60
BIST100	1	1	3	3	5	5	5	3	7	8	8	11	9	10	10	11	14

6. SUMMARY AND CONCLUSION

In this empirical research, four research questions about stock selection methods are examined for the BIST stock market.

Firstly, performances of the portfolios generated by these models are compared with each other in the long run. The results indicate that the ANN model based on fundamental approach shows better performance than the SSD and Markowitz models based on technical approach.

Between the two, the SSD model shows quite a better performance than the Markowitz model. On the other hand, all three models show remarkably better performances than the BIST-100 index and the total market in the long run.

Secondly, during economic crises such as the 2008 mortgage crisis, all three models could not avoid suffering negative returns; however, these models did show positive-alpha performances, meaning they at least had better returns than the BIST-100 index. Hence, these three models appear unable to overcome loss during huge financial crises and neither are they successful during short-run financial crises.

Thirdly, during bear or bull periods (but not during economic crises), these models may be used for stock selection in both long and short run. That is, if stock selection does not intersect with economic crises, these models could be used advantageously for portfolio management.

Fourthly, this empirical research shows that, in the long run, these models yield better performances than fixed assets. Therefore, these models can be used by individual investors instead of considering pension funds, bonds, or derivatives. Such investors can appreciate the flexibility of changing stocks in the long run instead of adapting to termination dates of pension funds.

The results in this study of the performance of ANN portfolios are in agreement with other researches on stock markets such as Quah and Srinivasan (1999), Olson and Mossman (2003), Eakins and Stansell (2003), and Chen et al. (2020). Moreover, this empirical study may be improved by a hybrid approach in parallel with Yang et al. (2019).

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