EFFECTIVENESS OF TECHNICAL INDICATORS IN PREDICTING BIST100 INDEX RETURNS

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ABSTRACT

This paper presents a logistic regression-based approach for predicting the direction of the Borsa Istanbul (BIST) index's price movements using technical indicators. Historical price data from 2005 to 2021 is utilized, and five thresholds are determined from -2% to 2% based on the daily or weekly returns of the BIST index. Binary variables which utilized in logistic regression as dependent variable are defined according to the thresholds, and logistic regression is applied using annual or semiannual training data. Daily models perform better than weekly models in logistic regression, and On Balance Volume (OBV) and Average Directional Index (ADX) are the indicators within the best statistical results. 0% threshold models are best in accuracy of prediction (approximately half of prediction is accurate). Weekly models are better than daily models, and annual models are better than semiannual models in accuracy. Some of the models outperformed the BIST index in cumulative return (daily cumulative return is 4,84; weekly is 4,48), with two models having approximately three times the cumulative return of the BIST index namely Daily-1% threshold-6 month's cumulative return is 13,35; Weekly-2% threshold-12 month's is 12,96. In summary, the results show that technical indicators can be successful in predicting stock or index returns depending on the training period, time period, and the combination of technical indicators used.

ÖZETÇE

Bu makale, teknik göstergeler kullanarak Borsa Istanbul (BIST) endeksinin fiyat hareketlerinin yönünü tahmin etmek için lojistik regresyon tabanlı bir yaklaşım sunmaktadır. 2005-2021 yılları arasındaki geçmiş fiyat verileri kullanılmıştır ve BIST endeksinin günlük veya haftalık getirilerine dayanarak -2% ila 2% arasında beş eşik belirlenmiştir. Bağımlı değişken olarak kullanılan sinyal değerleri BİST'in tarihsel getirilerine göre tanımlanmıştır ve yıllık veya yarıyıllık verileri kullanılarak lojistik regresyon uygulanmıştır. Günlük modeller, lojistik regresyonda haftalık modellere göre daha iyi performans göstermiştir ve On Balance Volume (OBV) ve Average Directional Index (ADX), en iyi istatistiksel sonuçlara sahip göstergeler arasındadır. %0 modeller, tahmin doğruluğu açısından en iyisidir (tahminlerin yaklaşık yarısı doğrudur). Tahmin performansında haftalık modeller, günlük modellere ve yıllık modeller de yarıyıllık modellerden daha iyidir. Bazı modeller birikimli getiri açısından BIST endeksini geride bırakmıştır (günlük birikimli getiri 4,84; haftalık ise 4,48), Daily-1% model-6 ay birikimli getiri 13,35; Weekly-2% model-12 ay birikimli getiri ise 12,96 olmak üzere, BIST endeksine göre yaklaşık üç katı olan iki model bulunmaktadır. Sonuç olarak, teknik göstergelerin, eğitim dönemi, zaman aralığı ve kullanılan teknik göstergelerin kombinasyonuna bağlı olarak hisse senedi veya endeks getirilerini tahmin etmede başarılı olabileceği gösterilmiştir.

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INTRODUCTION

The Borsa Istanbul (BIST) is the main stock exchange in Turkey and one of the largest in the region, with over 500 listed companies and a market capitalization exceeding $237 billion, as reported by the World Bank database. The number of investors in the BIST market is over 5 million as of May 2023, according to the Central Depository of the Turkish Capital Market. The average daily volume of the index year-to-date is around 3.1 billion TRY, indicating the significance of the market in the Turkish economy, representing approximately 33% of the GDP. The market attracts a significant amount of attention from investors and analysts, as shown by the passion of investors for BIST. According to statistics from the Turkish Statistical Institute, the yearly real return of the BIST index over CPI from May 2022 to April 2023 was 42.2%, while other financial instruments had yearly real returns of less than 0%, such as the US Dollar's return of -8.50% and the Government Domestic Debt Instrument's return of -6.78%. Therefore, predicting the movement of the BIST index has been a topic of great interest for investors and traders as it can provide valuable insights.

The present study aims to utilize logistic regression analysis on technical indicators values of BIST index values to predict its movement direction within a threshold range of -2% to 2%. I determined 15 different indicators for this paper; however, I excluded some of them because of correlation. Utilized indicators in models are Bollinger Bands, Keltner Channel, Parabolic SAR, On Balance Volume, Moving Average Convergence Divergence, Average Directional Index, Relative Strength Index, Stochastic Oscillator, Commodity Channel Index, Chande Momentum Oscillator, Money Flow Index, Moving Averages which are simple, exponential and weighted. These and non-used indicators' explanations are given in Appendix section. The study utilizes data spanning from 2005 to 2021 and considers two different training time periods of 6 months or 12 months. The main objective is to predict the next day or week's BIST index movement direction. To achieve this, the training time period is rolled according to the forecast date and feed into the logistic regression equation.

As mentioned before, the primary objective of this paper is to examine the relationship between technical indicators and stock prices or movement direction. Despite the popularity of technical indicators among investors, there is a scarcity of literature on this topic. This study aims to fill that gap.

Although predicting the exact return of an asset is the ultimate goal in prediction, knowing only the movement direction of the asset is sufficient for investors and portfolio managers to make informed decisions. Directly predicting returns is a challenging task due to the presence of outlier values in the data sample, which may be caused by noisy values in the data. In this study, logistic regression, and ordinary least squares (OLS) regression are applied to the entire data sample. Upon evaluating the p-values of both regressions, the statistical results of logistic regression outperform OLS regression due to the presence of noisy return values in the time horizon. Therefore, logistic regression is chosen as the preferred method for prediction. Logistic regression is typically used to predict binary events, such as whether a company is bankrupt or not. The selection of logistic regression is also due to its simplicity and comprehensibility for the reader. Additionally, prior literature has also employed logistic regression in similar studies.

The prediction of stock prices or movement directions has been the focus of many studies in recent years. As mentioned in the previous paragraph, logistic regression is within the methods to be used in related papers. For example, [1] develops a methodology based on logistic regression to predict the movement direction of companies listed on the Pakistan Stock Exchange (PSX). Similarly, [2] conducts a study on the prediction of movement direction using logistic regression for one company listed on the Bursa Malaysia (KLSE), using technical indicators such as Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and Stochastic Oscillator (SO). Some similarities between our study and these two studies may be the use of logistic regression, conducting the study through technical indicators, and assigning binary values of 0 and 1. Also, some differences can be identified, such as performing the process from scratch every day, conducting a study for a longer period, and working directly on the index.

In addition to logistic regression, [3] utilizes additional penalized logistic regression methods such as least absolute shrinkage and selection operator (LASSO), elastic net, smoothly clipped absolute deviation (SCAD), and minimax concave penalty (MCP) to predict the movement direction of Google's stock prices. Meanwhile, [4] investigates whether intraday trading is feasible using deep learning and machine learning algorithms on technical indicator values of the Borsa Istanbul (BIST) index. The application methods of both studies are like our study. In the [3], the same model is supported by multiple penalized logistic regression models, while in [4], it is attempted to determine whether the same model could be used in intraday trading operations.

Unlike the method used in most of the studies listed in literature review section, some of the indicators is used with their own values, while some is evaluated as -1, 0, or 1 according to general buying and selling rules in the market. For example, in Bollinger Bands, if the closing price of the stock is higher than the Bollinger Up Band, it is evaluated as 1, if it is lower than the Bollinger Down Band, it is evaluated as -1, and in other cases, it will be evaluated as 0. Another difference is that this study is not focus on a specific stock; however, I generally examine the index (Borsa Istanbul). In addition, both prediction and trading strategies are included in this paper, and the regression used in prediction are not created in one go; nevertheless, I apply separately for each period to be predicted which is the most significant difference. Final difference is that, while the signals in the examined papers are given based on a single threshold, the number of models is increased in this paper and the condition for signal generation will be linked to different thresholds.

To assess the effectiveness of the prediction models, I define three parameters: accuracy, specificity, and sensitivity. Accuracy is calculated as the ratio of the number of predicted true signals (called 1) to the total number of predicted signals (also called 1). Specificity was calculated as the ratio of the number of predicted signals called 0 to the total number of actual signals called 0. Sensitivity was the ratio of the number of predicted signals called 1 to the total number of actual signals called 1.

As outputs of prediction results of models, I find that the accuracy ratios of all prediction models with a threshold of 0% above 50%. For the other thresholds, the accuracy level is less than the 0% models. Additionally, thresholds move away from 0% both negative and positive direction, the ratio of 1 signal which means logistic regression gives a signal within the whole population is decreasing. Conversely, the percentage of 0 signal is increasing. Consequently, the return of models converges to repurchase agreement (Repo) return and standard deviation decreases. Moreover, the return difference between the models is not so far because of decreasing both accuracy as I mentioned in the upper rows and the number of signals which indicate the number of transactions over BIST index.

In addition to the statistical significance, I investigate the economic significance of the findings using a simple trading strategy. The trading strategy involves investing in the dedicated index when the model provides a signal of 1 and investing in a repurchase agreement (Repo) on other days when the model signals 0. All positions are opened and closed at specific times, with no positions being carried over to the next day or week. The strategy is then re-evaluated on the next day.

As a consequence of implementing the trading strategy, I detect that several models examined in this investigation outperform the BIST index in cumulative return over the period of 2006 to 2021. Specifically, 4 out of 10 models performs better in the 6-month period, and 5 out of 10 models performs better in the 12-month period. Notably, the 1% model for daily trading over a 6-month period yields a cumulative return of 13,35, while the 2% model for weekly trading over a 12-month period has a cumulative return of 12,96, which is almost three times greater than the cumulative return of the BIST100. Additionally, the daily models of dedicated threshold exhibit superior results compared to their weekly counterparts in both 6-month and 12-month periods. In fact, 9 out of 10 daily models outperforms the corresponding weekly models in terms of cumulative returns. For example, the 2% model for daily trading over a 6-month horizon achieves a cumulative return of 7,02, while the same model for weekly trading has a cumulative return of 4,11. As an opposite example, 2% model for daily in 12-month has the less return than the weekly model in same threshold. Lastly, there is no significant difference in performance between the 6-month and 12-month models, as 5 out of 10 models in the 6-month period outperforms their 12-month counterparts.

The Sharpe ratio is calculated for 20 models, out of which 7 had a positive Sharpe ratio over the Repo. The range of ratios spanned from 0.40 to -0.96. BIST100's daily and weekly returns have a Sharpe ratio of 0.05 and 0.07, respectively. Notably, the -1% and -2% thresholds showed a negative Sharpe ratio, with 7 out of 8 models exhibiting a negative Sharpe ratio. This was due to the lower returns of the -1% and -2% models in comparison to models with similar accuracy rates. The models with the highest Sharpe ratio also had the highest cumulative return.

In finance, measuring and comparing investment returns are a crucial task for investors, financial analysts, and portfolio managers. When average returns of models for daily and weekly models in 6-month and 12-month and BIST return are compared, standard deviations of models are less than the index because of the Repo investment. A significant finding is that the models outperformed the index in years when the index had negative returns. This implies that the models could potentially help create alpha over the BIST index, providing an advantage for financial analysts, portfolio managers, and real investors in making investment decisions.

LITERATURE REVIEW

Forecasting the future performance of stock markets has long been a challenging task, attracting significant interest from financial analysts and investors alike. Technical analysis is a widely used approach for predicting stock price movements, involving the analysis of historical price and volume data to identify patterns and trends that can be used to anticipate future market movements. However, while technical analysis can provide valuable insights into market trends and patterns, it is not always sufficient to predict the movements of stocks.

In the field of stock price prediction, technical indicators can be used as a tool to predict market movements based on their values and trends. However, the question remains as to whether there is a correlation between technical indicators and the directional movement of shares or indices. To address this question, this paper employs logistic regression, a statistical modeling technique used to examine the relationships between a set of independent variables and a dependent variable, to predict the directional movement of stock prices based on technical indicator values.

[5] analyzes the performance of several trading rules applied to a sample of 149 Nasdaq stock. In this paper, the authors create 4 different filters according to different strategies. They utilize the moving averages of the stocks in their work. The findings reveal that rules based on a stock's historical price were not effective, while rules that rely on past movements in the Nasdaq market index generated excess returns for many specifications. The study also indicates that some subsets of stocks may generate economically significant abnormal returns, albeit not enough to offset the high transaction

costs involved. The research concludes that trend-following trading rules are more profitable when applied to large NYSE stocks rather than small Nasdaq stocks analyzed in the study.

In 2000, [6] conducts a study that built on the work of [5]. The study applies ten technical indicators to stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ) from 1962 to 1996. The data divides into seven sub-periods of five years, and ten random stocks are chosen from each of five sub-categories based on market capitalization. The study finds that the most efficient technical indicator which can be fitted strict pattern was double tops and double bottoms, followed by head-and-shoulders and inverted head-and-shoulders patterns. The authors also observe that technical indicators are more effective for stocks with larger market capitalizations and that stricter patterns could be identified for stocks listed on NASDAQ. The authors suggest that if technical indicators were supplemented with automated algorithms, they could become a profitable tool for investors.

[7] applies different method in 2005. They develop two different trading strategy applied for the stocks in eleven European countries from 1991 to 2000. First rule is the filter rule based on purchase the share when it rises by X% from the previous low and hold it until it declines by X% from the subsequent high. Second rule is based on the moving averages of the shares. The study finds that while some emerging markets exhibited predictability in their share returns, developed markets did not. For example, filter rule strategy has average 197.8% profit yearly included transaction costs in Turkey while buy & hold strategy for the index is -0.3%. Additionally, moving average rule profit is 197.5% yearly, while buy & hold strategy's profit is 82.3%. The same ratio for

Germany in filter rules is 4.7% (buy & hold strategy's profit is 131%), in moving averages is -137.6% (buy & hold strategy's profit is 248.9%). The study also suggests that attempts to group European countries together when testing and formulating trading strategies may be misplaced, as the markets display widely different share price characteristics.

In 2018, [1] focused on examining the relationship between stock returns and various financial ratios, including Earnings Per Share, Price to Book Ratio, Return of Equity, Current Ratio, Debt to Equity, and Percentage Change of Net Sales. Dependent variable of logistic regression is determined whether the stock had a higher return compared to the index. A value of 1 is assigned if the stock return was higher and 0 if it is lower. The study conduct on stocks listed on the Pakistan Stock Exchange (PSX) between 2012 and 2015. The author first identifies the top 200 stocks in terms of market capitalization per year. After that, the authors extract the financial firms from biggest 200 companies; consequently, they apply logistic regression on 109 remaining non-financial companies. The model achieves an overall accuracy level of 88.4% for all predictions, with an accuracy of 87.2% for upside predictions and 89.7% for downside predictions.

[2] conducts seven different technical indicators, including Relative Strength Index (RSI), Moving Average (MA), Exponential Moving Average (EMA), Moving Average Convergence-Divergence (MACD), Stochastic Oscillators (SO), Rate of Change (ROC), closing price, and Volume Trading (VT), are applied to a single company listed in Bursa Malaysia over an eight-month period. The statistical significance of the indicators is assessed, and four of them (MACD, RSI, SO, and ROC) are found to be significant. Logistic regression is then applied using these four indicators, achieving an 86% true signal rate for in-sample predictions. The model is then used to predict the stock movement for seven upcoming days, resulting in five successful signals. These findings

demonstrate the potential of technical analysis indicators and logistic regression in predicting stock market movements.

[3] conducts a study in 2022 using five different penalized logistic regression methods, namely least absolute shrinkage, and selection operator (LASSO), elastic net, smoothly clipped absolute deviation (SCAD), and minimax concave penalty (MCP), with 19 technical indicators to predict stock prices using data from Google's stock market from 2010 to 2019. The training data comprises 80% of the total data while the remaining 20% is used for observation. The results show that logistic regression achieves an accuracy of 72.4% in predicting the stock prices, ranking third among the models tested. The average accuracy of the five penalized logistic regression models and logistic regression is 71.6%. Among the logistic regression models tested, MCP is found to be the best predictor with 73.2% accuracy, 78.1% sensitivity and 67.8% specificity. The authors then compare the MCP model with two other popular machine learning algorithms, namely Support Vector Machine (SVM) and Artificial Neural Network (ANN). Finally, they conclude that the MCP model is the most successful in predicting stock prices.

In 2017, [8] conducts a study aimed at investigating the relationship between the number of training days and the number of predicted days in stock price prediction methods. The study utilizes three different algorithms, namely Support Vector Machine (SVM), Artificial Neural Network (ANN), and k-Nearest Neighbors (kNN), along with ten technical indicators. The authors develop two variables for prediction, one of which was a direct up or down signal, while the other had three sub-categories: up, down, and no move. The sub-categories are determined based on whether the return is greater than, less than, or between negative or positive thresholds. The results of the study show a correlation between the number of training days and the forecast horizon. Specifically, the best results are observed when the training period was 30-days, and the forecast horizon is also 30-days. Furthermore, the SVM algorithm outperform the other two machine learning algorithms in this study.

There exist previous studies on the prediction of stock prices in Borsa Istanbul (BIST). [9] conducts research in 2022 that utilizes various machine learning techniques including Support Vector Machine (SVM), K-Nearest Neighborhood (KNN), Extreme Gradient Boosting (XGBoost), and Random Forest (RF) Regressions. The authors analyze data from 2016 to 2021 and evaluated the performance of each algorithm based on various metrics such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and R^2 correlation. The study finds that XGBoost was the most effective algorithm in predicting stock prices.

Furthermore, [10] utilizes a distinct methodology for analyzing the Borsa Istanbul index. The authors employ a diverse range of data sources including the Public Disclosure Platform (KAP), Bigpara for text-based technical analysis of each stock, and user comments from Twitter and Mynet Finans platforms. Following the cleaning of the news and comments data, the authors label it either positive or negative. Subsequently, a combination of deep learning algorithms such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long-Short Term Memory Networks (LSTM), and word embedding techniques like Word2Vec, Global Vectors (GloVe), FastText, and Bidirectional Encoder Representations from Transformers (BERT) are utilized to process the data spanning from September 2018 to September 2019, with a focus on the banking sector shares. The research findings indicate that Mynet Finans is the most accurate platform, with an average accuracy of 86.39% for 9 banking sector shares using FastText and LSTM. Conversely, Bigpara, employing Word2Vec and RNN, proved to be the least accurate platform with an average accuracy of 77.82%.

In [4], the authors employ machine learning algorithms, such as Deep Neural Network (DNN), Support Vector Machine (SVM), Random Forest (RF), and Logistic Regression (LR), on intraday data of the Borsa Istanbul (BIST) index. The periods for the data are 30-minutes, 1-hour, and 2-hour, and the data is preprocessed with predefined technical indicators. The authors implement a threshold level to avoid the neutralizing effect of transaction costs on profits generated from the models. The methodology is applied to the BIST index from 2008 to 2016. The study's results suggest that the DNN model outperformed the other models. The lower periods and threshold values are found to be the cause of better results in compound return and average return per trade. The study also suggests that although the precision of the models was low, at approximately 60%, the models were still profitable. This is because the correct predictions of the model generated more returns than the losses from false predictions.

After conducting a literature review, I find that most of the examined papers have established a relationship between technical indicators and stock price predictions, as well as the direction of stock price movements. However, there are two different views regarding this relationship. One view suggests that technical indicators may only be useful for certain stocks and time intervals, and that transaction costs can potentially neutralize the additional returns generated by these models. The other view does not express such reservations and indicates that technical indicators can be useful in predicting stock prices. As a second different perspective, [8] highlights the correlation between the training period and the forecast horizon. As a third different perspective, [10] on Borsa Istanbul (BIST) demonstrates that user comments on websites such as Mynet

Finans, where users can express their thoughts, ideas, and feelings about the stocks they invest in, and can also access related news, can be helpful in predicting stock movements.

METHODOLOGY

In this paper, my target is to forecast closing value of BIST 100 Index which is the index contains 100 biggest stocks in Borsa Istanbul with logistics regression by using technical indicators. The formula of used for logistic regression is explained in (1).

$$p = \frac{1}{1 + e^{-(b_0 + b_1 * x_1 + b_2 * x_2)}} \tag{1}$$

p is the probability of increase in index for upcoming day or week. The usage of probability in prediction is explained in a detailed way in prediction chapter. b_0, b_1, … are the coefficients of regression, they symbolize the weight of technical indicators on probability. x_1, x_2, … values are the technical indicators' values. In the calculation of these, historical opening, closing, daily minimum and maximum, volume parameters of the index were used.

Historical data of index as mentioned in the previous paragraph is obtained from Reuters as daily or weekly from beginning of 2005 to end of 2021. Additionally, I use KYD repo index in trading strategy for the days when our models do not give a signal. Consequently, KYD Repo index is obtained from Reuters for the same period. For BIST index, imported historical values contain 5 columns that they are opening, closing, maximum and minimum of period and volume. For repo, I imported only index closing value because I need to calculate only return of repo for our trading strategy.

In this paper, developed models show the dependency between the technical indicators and movement direction of the BIST index. To do this, firstly I calculated the technical indicators' values for index. In this work, I used 10 technical indicators which are Bollinger Bands, Parabolic SAR, Keltner Bands, OBV, MACD, ADX, RSI, Stochastic Fast D, CMO, and WMA. Some of these indicators depend on the closing prices such as Bollinger Bands, Parabolic SAR, Keltner Bands, and WMA; hence, I assigned 0 and 1 value based on the buy or sell signal according to accepted standards in the market for these to use in calculations. For the other ones, I directly used the technical indicators' values in the calculations.

After calculation of technical indicators, I applied logistic regression whose dependent variable is signal created according to return of index which is explained in (2). Threshold in the formula symbolizes the return values of the models used in paper from -3% to 3% by increasing 1%. Finally, forecast was done according to coefficients of regression. In calculation of technical indicators, TTR library was utilized and in forecasting, car library was utilized in RStudio.

$$Prediction = P_t = \begin{cases} 1, if\ Return_t \geq Threshold \\ 0, if\ < Threshold \end{cases} \tag{2}$$

After finishing one day or week's forecasts and taking signal value from the model, beginning and end of learning period are delayed one day, and same procedure was repeated for the prediction of upcoming day or week.

3.1 Calculation of Correlation Matrix

Firstly, 15 technical indicators were determined which are within the most used technical indicators in the market. Correlation matrix was created and examined to avoid any collinearity. 70% was designated as highly correlated. These ones are shown in Table 1 with green highlight. Additionally, blue highlighted ones show the correlation result with themselves.

Table 1: Correlation matrix for technical indicators

	Bollinger	PSAR	Keltner	OBV	MACD	ADX	RSI	Stochastic FastK	Stochastic FastD	CCI	CMO	MFI	SMA20-50	EMA20-50	WMA20-50
Bollinger	1,00	0,40	0,56	0,03	0,28	0,02	0,55	0,55	0,51	0,66	0,49	0,40	0,09	0,15	0,19
PSAR	0,40	1,00	0,52	0,03	0,33	0,00	0,59	0,75	0,77	0,71	0,61	0,50	0,03	0,16	0,16
Keltner	0,56	0,52	1,00	0,06	0,60	0,11	0,81	0,70	0,72	0,75	0,79	0,70	0,25	0,34	0,41
OBV	0,03	0,03	0,06	1,00	0,10	0,11	0,10	0,05	0,06	0,05	0,08	0,08	0,04	0,00	0,05
MACD	0,28	0,33	0,60	0,10	1,00	0,11	0,82	0,51	0,59	0,60	0,70	0,64	0,65	0,68	0,75
ADX	0,02	0,00	0,11	0,11	0,11	1,00	0,18	0,05	0,06	0,06	0,11	0,14	0,08	0,06	0,02
RSI	0,55	0,59	0,81	0,10	0,82	0,18	1,00	0,83	0,84	0,88	0,90	0,78	0,49	0,56	0,62
StochasticFastK	0,55	0,75	0,70	0,05	0,51	0,05	0,83	1,00	0,93	0,90	0,82	0,69	0,14	0,26	0,30
StochasticFastD	0,51	0,77	0,72	0,06	0,59	0,06	0,84	0,93	1,00	0,92	0,87	0,76	0,18	0,31	0,38
CCI	0,66	0,71	0,75	0,05	0,60	0,06	0,88	0,90	0,92	1,00	0,86	0,73	0,23	0,34	0,43
CMO	0,49	0,61	0,79	0,08	0,70	0,11	0,90	0,82	0,87	0,86	1,00	0,87	0,29	0,41	0,51
MFI	0,40	0,50	0,70	0,08	0,64	0,14	0,78	0,69	0,76	0,73	0,87	1,00	0,24	0,38	0,46
SMA20-50	0,09	0,03	0,25	0,04	0,65	0,08	0,49	0,14	0,18	0,23	0,29	0,24	1,00	0,75	0,73
EMA20-50	0,15	0,16	0,34	0,00	0,68	0,06	0,56	0,26	0,31	0,34	0,41	0,38	0,75	1,00	0,71
WMA20-50	0,19	0,16	0,41	0,05	0,75	0,02	0,62	0,30	0,38	0,43	0,51	0,46	0,73	0,71	1,00

According to correlation matrix, within the some of the technical indicators group's correlation such as Stochastic Fast K and Stochastic Fast D, CCI, CMO, and MFI, and simple, exponential, and weighted moving averages with each other was highly correlated. Stochastic Fast D, CMO, and WMA were chosen to be used in the calculations. The comparison of calculations from technical indicators group were compared by adding the technical indicators one by one which do not be chosen one by one in showing the endurance of the model.

3.2 Statistical Regression Results by Thresholds

In addition to correlation matrix, regression statistically results were examined to analyze the importance of technical indicators on the explanation of model's success. Firstly, I examined that the R^2 values of models to evaluate the models statistically. In Table 2**Error! Reference source not found.**, I listed the R^2 values based on the daily and weekly models. The values in the table are much lower than the expected values to be considered statistically significant for the models. This can be attributed to the fact that the period between 2005 and 2021 is too long, resulting in data containing a significant amount of noise. As a result, the noise may have contributed to the low R^2 values.

Table 2: R-squared Values of Daily and Weekly Models

	Daily	**Weekly**
Panels	**R-squared**	**R-squared**
Return Based	0,0044	0,0088
3% Model	0,0239	0,0256
2% Model	0,0298	0,0164
1% Model	0,0147	0,0041
0% Model	0,0047	0,0074
-1% Model	0,0208	0,0124
-2% Model	0,0260	0,0145
-3% Model	0,0232	0,0150

Table 3 and Table 4 were created for both daily, weekly models. In these tables, regression was done for all data from 2005 to 2021. Each panel in Table 4 was created by the thresholds. Regression formulas for the panels are below. Formula of Table 3 is summarized in (3), formula of Table 4 is summarized in (4).

$$Return_{t+1} = b_0 + b_1 * Bollinger_t + b_2 * Parabolic\ SAR_t + b_3 * Keltner_t + b_4 * OBV_t + b_5 * MACD_t + b_6 * ADX_t + b_7 * RSI_t + b_8 * Stochastic\ Fast\ D_t + b_9 * CMO_t + b_{10} * WMA_t \quad (3)$$

$$Prediction_{t+1} = b_0 + b_1 * Bollinger_t + b_2 * Parabolic\ SAR_t + b_3 * Keltner_t + b_4 * OBV_t + b_5 * MACD_t + b_6 * ADX_t + b_7 * RSI_t + b_8 * Stochastic\ Fast\ D_t + b_9 * CMO_t + b_{10} * WMA_t \quad (4)$$

In Table 3 and Table 4, second column shows the estimated coefficients of the predictors in the logistic regression model. Third column shows the two-sided p-value for the null hypothesis that the true value of the corresponding coefficient is zero, based on a standard normal distribution. While the orange highlighted rows are in 95% confidence interval, gold ones are in 90% confidence interval. In Table 3, coefficients shown as multiplied with 10^5.

Table 3: OLS Regression results by technical indicators for daily models

Daily			Weekly		
Return-Based	**Coefficients**	**P-Value**	**Return-Based**	**Coefficients**	**P-Value**
Intercept	-450.7000	0.1686	Intercept	-1,159.0000	0.4954
Bollinger	5.6560	0.9434	Bollinger	17.5700	0.9651
PSAR	-3.3510	0.9344	PSAR	-295.4000	0.1703
Keltner	-138.2000	0.0879	Keltner	-655.2000	0.0995
OBV	0.0000	0.7093	OBV	0.0000	0.6411
MACD	-61.6700	0.0185	MACD	-38.3100	0.5223
ADX	4.1100	0.1048	ADX	-10.1200	0.4646
RSI	8.8850	0.1982	RSI	26.2200	0.4681
StochasticFastD	-0.7858	0.7305	StochasticFastD	10.7900	0.3185
CMO	2.33	0.2099	CMO	5.454	0.5495
WMA	44.75	0.2591	WMA	-34.18	0.8563

Table 4: Logistic Regression results by indicators for daily and weekly models

DAILY

0% Model	Coefficients	P-Value
Intercept	-0,1714	0,6609
Bollinger	0,0777	0,4140
PSAR	0,0339	0,4845
Keltner	-0,1931	0,0456
OBV	0,0000	0,0859
MACD	-0,0590	0,0599
ADX	0,0039	0,2015
RSI	0,0072	0,3846
StochasticFastD	-0,0043	0,1154
CMO	0,0056	0,0122
WMA	0,0388	0,4118

1% Model	Coefficients	P-Value
Intercept	-0,7105	0,1160
Bollinger	-0,1211	0,2775
PSAR	-0,0548	0,3263
Keltner	-0,2185	0,0500
OBV	0,0000	0,0000
MACD	0,0016	0,9638
ADX	0,0166	0,0000
RSI	-0,0136	0,1541
StochasticFastD	0,0005	0,8712
CMO	0,0049	0,0579
WMA	-0,0242	0,6609

-1% Model	Coefficients	P-Value
Intercept	0,3294	0,4935
Bollinger	-0,1667	0,1587
PSAR	-0,0486	0,4072
Keltner	0,2788	0,0182
OBV	0,0000	0,0000
MACD	0,1048	0,0050
ADX	0,0097	0,0077
RSI	-0,0347	0,0006
StochasticFastD	0,0025	0,4550
CMO	-0,0005	0,8431
WMA	-0,1115	0,0527

2% Model	Coefficients	P-Value
Intercept	-0,3622	0,5949
Bollinger	-0,0383	0,8192
PSAR	-0,0110	0,8951
Keltner	-0,0048	0,9770
OBV	0,0000	0,0000
MACD	-0,0103	0,8249
ADX	0,0299	0,0000
RSI	-0,0444	0,0018
StochasticFastD	-0,0022	0,6394
CMO	0,0079	0,0447
WMA	0,0192	0,8180

-2% Model	Coefficients	P-Value
Intercept	0,2350	0,7457
Bollinger	-0,0315	0,8583
PSAR	0,0488	0,5786
Keltner	0,1688	0,3340
OBV	0,0000	0,0000
MACD	0,0786	0,1238
ADX	0,0195	0,0002
RSI	-0,0514	0,0007
StochasticFastD	-0,0027	0,5894
CMO	0,0034	0,4059
WMA	-0,1034	0,2267

3% Model	Coefficients	P-Value
Intercept	-2,7980	0,0086
Bollinger	-0,1521	0,5556
PSAR	0,0470	0,7193
Keltner	-0,0393	0,8770
OBV	0,0000	0,0000
MACD	-0,1203	0,0588
ADX	0,0366	0,0000
RSI	-0,0095	0,6636
StochasticFastD	-0,0097	0,1973
CMO	0,0021	0,7311
WMA	0,1211	0,3563

-3% Model	Coefficients	P-Value
Intercept	0,1426	0,8937
Bollinger	-0,0533	0,8352
PSAR	-0,0416	0,7528
Keltner	0,1535	0,5486
OBV	0,0000	0,0008
MACD	0,0402	0,5676
ADX	0,0272	0,0004
RSI	-0,0749	0,0007
StochasticFastD	-0,0011	0,8795
CMO	0,0085	0,1640
WMA	0,0628	0,6218

WEEKLY

0% Model	Coefficients	P-Value
Intercept	-0,3787	0,6860
Bollinger	0,1429	0,5187
PSAR	-0,0296	0,8018
Keltner	-0,5271	0,0161
OBV	0,0000	0,7439
MACD	-0,0248	0,4497
ADX	-0,0056	0,4622
RSI	0,0165	0,4068
StochasticFastD	-0,0007	0,9080
CMO	0,0084	0,0934
WMA	0,0353	0,7332

1% Model	Coefficients	P-Value
Intercept	-0,1783	0,8470
Bollinger	-0,0738	0,7350
PSAR	-0,0719	0,5400
Keltner	-0,2268	0,2950
OBV	0,0000	0,7370
MACD	0,0056	0,8650
ADX	-0,0058	0,4410
RSI	0,0019	0,9230
StochasticFastD	0,0012	0,8360
CMO	0,0044	0,3710
WMA	0,0626	0,5420

-1% Model	Coefficients	P-Value
Intercept	0,7296	0,4638
Bollinger	-0,0846	0,7189
PSAR	0,1767	0,1601
Keltner	0,4767	0,0407
OBV	0,0000	0,6030
MACD	0,0395	0,2567
ADX	0,0038	0,6377
RSI	-0,0288	0,1733
StochasticFastD	-0,0016	0,8035
CMO	-0,0033	0,5309
WMA	0,0012	0,9914

2% Model	Coefficients	P-Value
Intercept	0,0848	0,9320
Bollinger	0,1570	0,5020
PSAR	-0,1372	0,2720
Keltner	-0,3254	0,1600
OBV	0,0000	0,0260
MACD	0,0305	0,3850
ADX	-0,0006	0,9400
RSI	-0,0172	0,4160
StochasticFastD	0,0060	0,3380
CMO	0,0030	0,5790
WMA	0,1229	0,2680

-2% Model	Coefficients	P-Value
Intercept	1,2790	0,2608
Bollinger	0,1769	0,5091
PSAR	0,2497	0,0774
Keltner	0,4411	0,0947
OBV	0,0000	0,4184
MACD	0,0915	0,0201
ADX	0,0127	0,1674
RSI	-0,0494	0,0396
StochasticFastD	-0,0063	0,3776
CMO	-0,0017	0,7840
WMA	-0,0001	0,9996

3% Model	Coefficients	P-Value
Intercept	-1,3560	0,2473
Bollinger	0,1722	0,5332
PSAR	-0,1880	0,1982
Keltner	-0,4668	0,0848
OBV	0,0000	0,0723
MACD	0,0001	0,9988
ADX	0,0137	0,1392
RSI	-0,0142	0,5663
StochasticFastD	0,0119	0,1099
CMO	0,0019	0,7586
WMA	0,0345	0,7931

-3% Model	Coefficients	P-Value
Intercept	-0,3053	0,8167
Bollinger	0,1163	0,7079
PSAR	0,3819	0,0204
Keltner	0,0290	0,9239
OBV	0,0000	0,1777
MACD	0,0551	0,2146
ADX	0,0118	0,2615
RSI	-0,0241	0,3877
StochasticFastD	-0,0073	0,3802
CMO	-0,0021	0,7674
WMA	-0,0094	0,9483

According to Table 3 and Table 4, daily model is more successful as statistically than the weekly model. Moreover, OBV, MACD, ADX are within most important group as statistically than the other technical indicators, especially in daily models. Coefficient of OBV is almost 0 in all of the models. But it is in 95% confidence interval in daily side.

RESULTS

4.1 Prediction

As mentioned in the upper paragraphs, after defining which indicators are used and the calculating the values of technical indicators, logistic regression was applied whose dependent variable is signal values which are 0 and 1, independent variable is technical indicators. The probability of the results was created based on the coefficients of regressions via predict function in car library of RStudio. If the probability is bigger than 50% then the model gives the buy or sell signal depends on the threshold of the model.

In this section, I examine that the prediction results compared to the real results. Table 5 reports that the methodology utilized in comparison. TP is True Positive, FP is False Positive, TN is True Negative, FN is False Negative. I evaluate the results of prediction according to (5), (6), (7).

$$Sensitivity(True\ Positive\ Rate) = \frac{TP}{TP + FN} \tag{5}$$

$$Specificity(1 - False\ Positive\ Rate) = \frac{TN}{TN + FP} \tag{6}$$

$$Accuracy = \frac{TP}{TP + FP} \tag{7}$$

Table 5: Two-class Confusion Matrix

		Real	
		1	0
Prediction	1	TP	FP
	0	FN	TN

Table 6: Model Prediction Results

Daily - 6 Months	0% Model	1% Model	2% Model	-1% Model	-2% Model
Sensitivity	0.6886	0.2566	0.1613	0.1359	0.1340
Specificity	0.3057	0.7872	0.8674	0.8925	0.8943
Accuracy	0.5300	0.2720	0.1013	0.2500	0.0991

Daily - 12 Months	0% Model	1% Model	2% Model	-1% Model	-2% Model
Sensitivity	0.7569	0.1430	0.0616	0.0250	0.0312
Specificity	0.2334	0.9052	0.9530	0.9789	0.9868
Accuracy	0.5289	0.3185	0.1082	0.2386	0.1695

Weekly - 6 Months	0% Model	1% Model	2% Model	-1% Model	-2% Model
Sensitivity	0.5969	0.5515	0.4180	0.3142	0.3064
Specificity	0.3693	0.4362	0.5836	0.6275	0.6556
Accuracy	0.5497	0.4400	0.3036	0.2877	0.1956

Weekly - 12 Months	0% Model	1% Model	2% Model	-1% Model	-2% Model
Sensitivity	0.6520	0.5487	0.4467	0.2797	0.2312
Specificity	0.3011	0.4452	0.6032	0.7339	0.7741
Accuracy	0.5461	0.4427	0.3283	0.3349	0.2186

In the Table 6, the results of prediction outputs are summarized. Columns of Table 6 indicate that models mentioned in the paper. Table 6 states that as the threshold increases, sensitivity decreases. For example, 0% model’s sensitivity is 0.6886 while 1% model’s sensitivity is 0.2566 in Daily – 6 months. On the other hand, as the threshold increases, specificity increases. For instance, 0% model’s specificity is 0.3057 while 1% model’s specificity is 0.7872 in Daily – 6 months. As a summary, 0 signal ratio within all signals increase while 1 signal ratio within all signals decrease as the threshold increase. Moreover, accuracy of the models decreases as the threshold rises generally.

Table 6 reports that 0% threshold has the best results compared to the others. Both daily and weekly models, it has more than 50% accurate forecasts about the index’s return. After 0% model, 1% model is the best successful model compared to others by accuracy. In addition, accuracy is lower in both 2% and -2% models than 1% and -1% models. For instance, 1% model's accuracy is 0.272; however, -1% model's accuracy is 0.25 in Daily – 6 months. Because forecasts might be done in a healthy way if learning data contains 0 and 1 signals in a sufficient number. For instance, 0% model for daily, BIST100 gives signal almost 50% of the period; consequently, model gives more accurate number of signals compared to the other models that give less signal in the period. On the contrary side, learning data has no signals or no sufficient signals for 2% and -2% return level in some of the periods especially in daily models. For this reason, forecasts of these thresholds might not be giving healthy results in evaluation. Furthermore, weekly models have more accuracy than daily models. For example, 0% model's accuracy is 0.5969 in Weekly – 6 months while 0% model's accuracy is 0.53 in Daily – 6 months.

In summary, this section presents four potential outcomes related to the impact of threshold values on the buy, sell, and hold signals generated by the model. Firstly, as the threshold increases, the number of buy and sell signals decreases in both positive and negative directions, leading to a decrease in sensitivity. Conversely, the number of hold signals which is called 0 in the tables increases as the threshold increases, resulting in an increase in specificity. Additionally, the accuracy of the model decreases as the threshold moves further away from 0% for both sides. This may be due to insufficient signal examples in the training data used in the regression analysis. The final finding indicates that weekly models perform better than daily models in terms of sensitivity, specificity, and accuracy.

4.2 Trading Strategy of the Model

The trading strategy utilized for daily model involves allocating the entire investment capital towards either the index or the repurchase agreement (repo). If model gives a signal in the calculation date, the strategy buys the index at the beginning of the next day, then sells the index at the end of the next day. Upon receiving a signal from the model on the designated calculation date, the strategy executes the purchase of the index on the subsequent day and subsequently liquidates the position at the end of the day. In the absence of a signal from the model, the strategy is applied to the repo using a similar process. The weekly trading model follows a comparable strategy to that of the daily model, with the distinction being that transactions are executed on a weekly basis.

The results of the trading strategy described above are presented in Table 7 and Table 8. 6-month or 12-month determines the time interval utilized in logistic regression. Accuracy is the ratio of true signals called 1 given by model within the whole signal called 1 of model. Yearly average return is the average of daily return in annualized version of the model calculated by dividing closing price of next period to closing price of current period. Standard deviations are also annualized. I utilized the standard version of the Sharpe Ratio as proposed in [11], which calculates the ratio as the difference between the portfolio's expected return and the risk-free rate divided by the standard deviation of the portfolio's return. The cumulative return is obtained by multiplying the daily returns with each other in a compound manner. Daily and weekly determines the trading period.

Table 7: Results of strategy for 6-month model

		6 MONTHS				
		Accuracy	**Yearly Average Return**	**Standard Deviation**	**Sharpe Ratio**	**Cumulative Return**
DAILY	**0% Model**	0.5300	0.1207	0.2133	0.0040	4.7626
	1% Model	0.2720	0.1708	0.1285	0.3966	13.3542
	2% Model	0.1013	0.1270	0.0978	0.0728	7.0183
	-1% Model	0.2500	0.0759	0.1039	-0.4233	3.0759
	-2% Model	0.0991	0.0705	0.1042	-0.0474	2.8227
WEEKLY	**0% Model**	0.5497	0.1123	0.2087	-0.0535	4.0489
	1% Model	0.4400	0.1453	0.1992	0.1095	6.9532
	2% Model	0.3036	0.1066	0.1742	-0.0970	4.1052
	-1% Model	0.2877	-0.0219	0.1518	-0.9578	0.5944
	-2% Model	0.1956	-0.0168	0.1541	-0.9101	0.6408

Table 8: Results of strategy for 12-month model

		12 MONTHS				
		Accuracy	**Yearly Average Return**	**Standard Deviation**	**Sharpe Ratio**	**Cumulative Return**
DAILY	**0% Model**	0.5289	0.1101	0.2179	-0.0447	3.8745
	1% Model	0.3185	0.1275	0.1059	0.0724	6.9825
	2% Model	0.1082	0.1030	0.0681	-0.2474	4.9778
	-1% Model	0.2386	0.1184	0.0533	-0.0274	6.4596
	-2% Model	0.1695	0.1297	0.0391	0.2514	7.8138
WEEKLY	**0% Model**	0.5461	0.1022	0.2224	-0.0957	3.2947
	1% Model	0.4427	0.1065	0.2050	-0.0829	3.7337
	2% Model	0.3283	0.1812	0.1757	0.3283	12.9644
	-1% Model	0.3349	0.0576	0.1306	-0.5041	2.1356
	-2% Model	0.2186	0.0197	0.1121	-0.9254	1.2293

Table 7 and Table 8 indicate that there is no clear superiority between 6-month and 12-month period used in regression or daily and weekly trading period for any of the analyzed variables. Consequently, I computed the column averages to determine which period length in regression is preferable. In summary, the 12-month average outperforms the 6-month average for all variables. In the weekly and daily comparison, the accuracy average for weekly period is better than daily period for both 6-month and 12-month periods, however, the opposite is true for the other variables. Combining the trading and time periods and assessing which combination yields superior results, the combination of weekly trading with a 6-month period is optimal for accuracy, weekly trading with a 12-month period is optimal for yearly average return and Sharpe ratio, and daily trading with a 6-month period is optimal for cumulative return. Standard deviation is optimal for daily trading with 12-month period.

The second finding of the study indicates that there is no significant correlation between high accuracy and high yearly average returns in trading strategies. For example, although daily 1% model for 6 months has 0,272 accuracy rate which is less than 0% model's, its yearly average return is bigger than the 1% model's. This pattern is also observed in the models' standard deviation and Sharpe ratio. For instance, daily 1% model for 6 months has much less accuracy ratio compared to weekly 1% model. On the contrary side, its yearly average return is bigger; additionally, its Sharpe ratio is much bigger.

Apart from the statistical side of trading strategy in trading success can be remarked via cumulative return column. BIST100's cumulative return is 4,8418 for daily models, 4,4809 for weekly models from 2006 to 2021. Most of the models outperform the BIST Index from 2006 to 2021, including daily 1%-2% models, weekly 1% model for 6-month, and all of the models for daily except 0% model and weekly 2% model for 12-month. Therefore, these models can generally be considered successful trading strategies not only compared to the BIST index but also to the investment-only repo. Additionally, daily models have more cumulative returns than weekly models. Final is 6-month models are outperform 12-month models in cumulative return except (-1%)-(-2%)

models for daily, 2%-(-1%)-(-2%) models for weekly. In the next section, I show the performance of predetermined models according to the index by years.

4.3 Trading Performance Comparison of Model by Years

In the preceding section, the study focused on analyzing the predictive outcomes of the models and their influence on the trading success of the strategies. Nevertheless, this alone does not provide sufficient evidence to assess the efficacy of the models in the market. Thus, this section delves deeper into the results of the strategies to ascertain which type of year the model outperforms by comparing it with the performance of the Borsa Istanbul (BIST) index on a yearly basis.

Initially, three models within the highest cumulative returns were selected for all time horizons from 2006 to 2021. For ease of reference, these models were named Model 1, which is a daily 1% model for 6-month, Model 2, which is a weekly 2% model for 12-month, and Model 3, which is a weekly 1% model for 6-month.

In Figure 1, the development of cumulative returns is graphed for both BIST100 Index and Model 1. The divergence between the two began after 2008, which witnessed one of the most significant crises since the 1900s. In Figure 2, a comparison of the yearly averages of the two series is presented. The results indicate that during the years when the BIST100 index experienced negative returns, our model produced positive values. The most considerable difference in favor of the BIST100 index was observed in 2009, which was the year of reaction to the financial crisis in 2008. Out of the 16 years analyzed, the BIST100 index had a higher yearly average return in seven years. The primary reason for the significant difference in cumulative returns is the years in which the BIST100 index recorded negative returns.

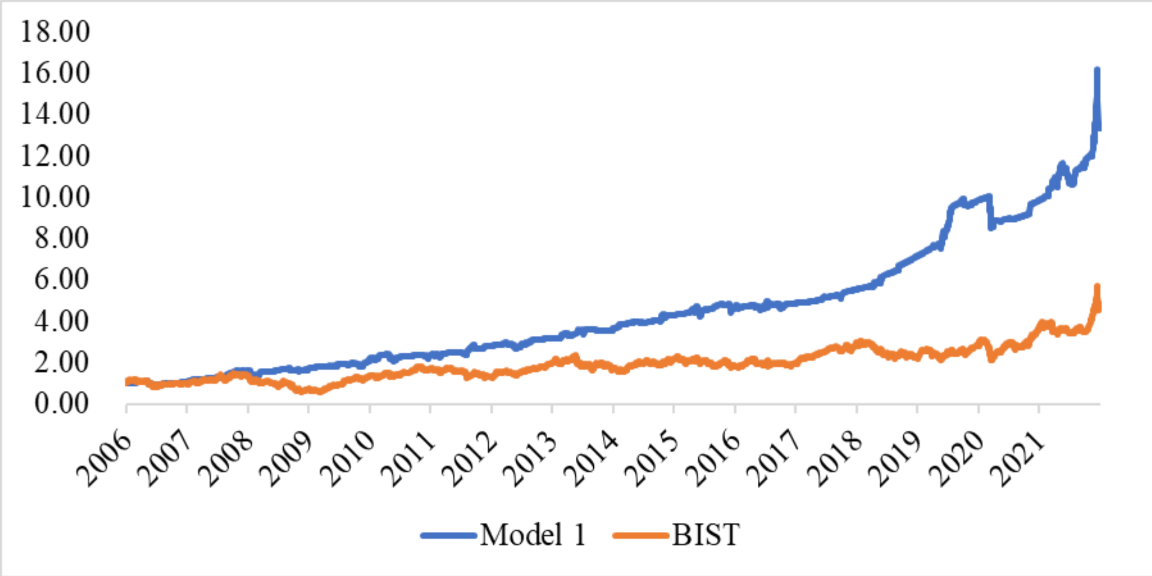

Figure 1: Cumulative Return of BIST100 Index and Model 1

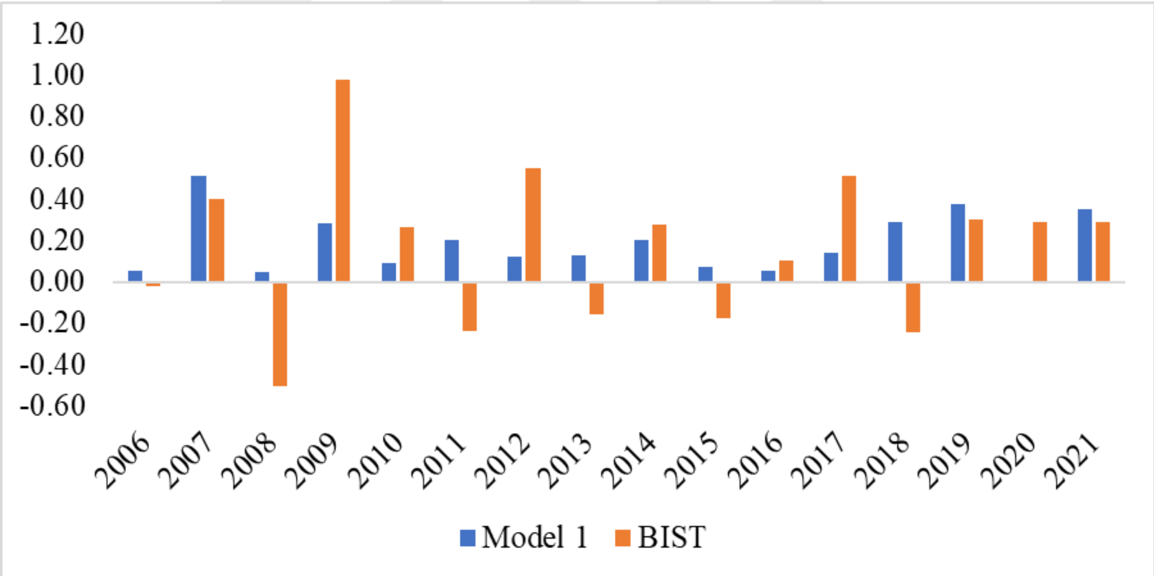

Figure 2: Yearly Average Return of BIST100 Index and Model 1

Figure 3 states that the difference between Model 2 and BIST100 index in cumulative returns. The divergence starts since 2010 in cumulative return. According to Figure 4, Model 2 outperformed the BIST100 index in 2008; nonetheless, although both series have negative returns. 10 of the 16 years, yearly average return of Model 2 is bigger than the index. The average return for these years is 20.52%. For the remaining years' average return is 25.13%. Reason behind the outputs in cumulative returns is the number of the years that model outperforms to index.

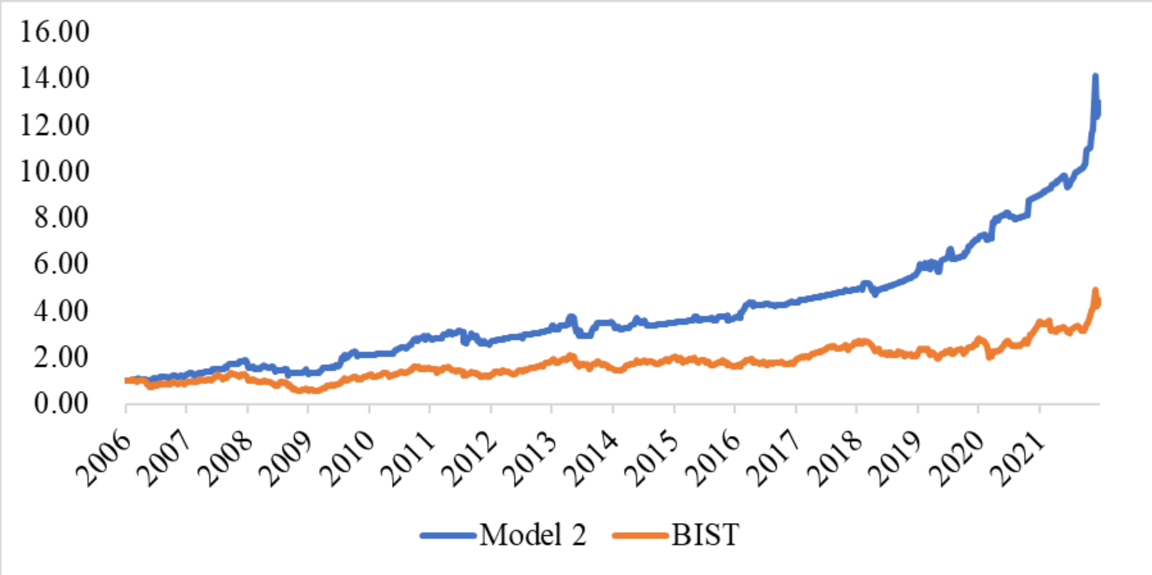

Figure 3: Cumulative Return of BIST100 Index and Model 2

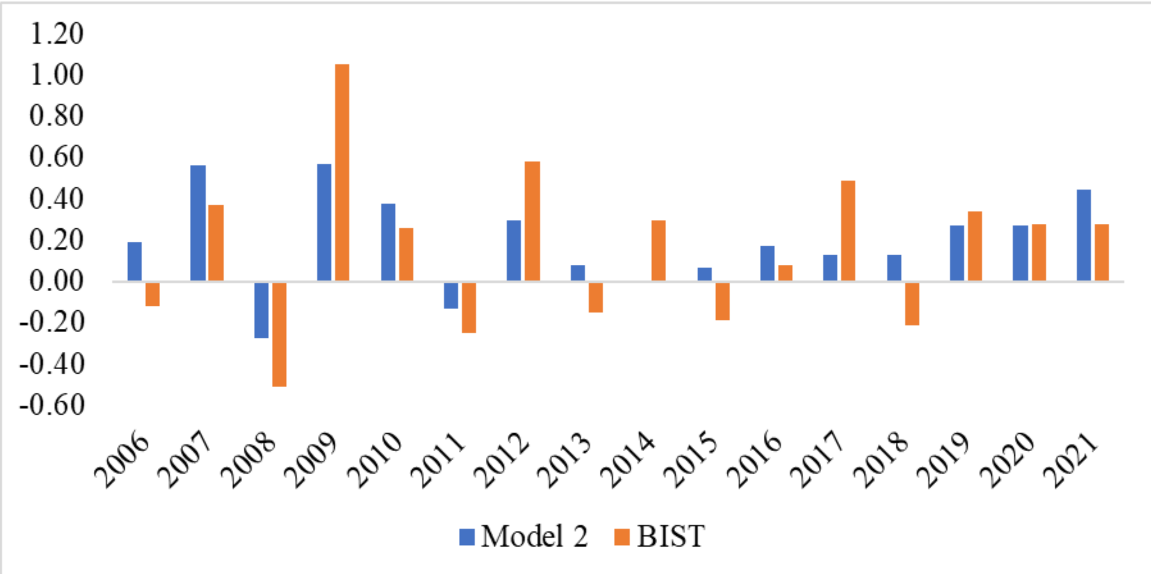

Figure 4: Yearly Average Return of BIST100 Index and Model 2

Figure 5 affirms that the difference between cumulative returns of series. The difference is less than the difference in Figure 1, and Figure 3. Based on Figure 6, Model 3 outperforms the BIST100 Index in most of the years when BIST100 Index have negative value. Most of the difference in cumulative return originates from the years following 2019. Average return of last three years (2018, 2019, 2020, 2021) is 17% for BIST100 index, 40% for Model 3. Unlike the other cases, BIST100 index's average return is bigger than model 6 out of 16 years; however, the average difference for these years is 29.20% bigger than 17.22% that is the average of years when model's average return is bigger than BIST100 index.

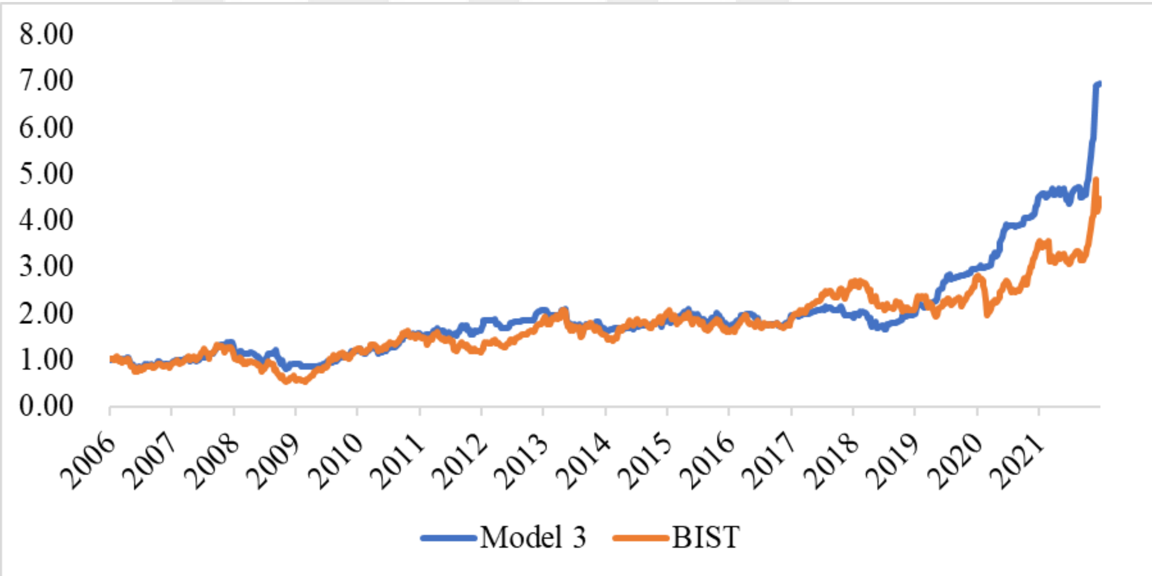

Figure 5: Cumulative Returns of BIST100 Index and Model 3

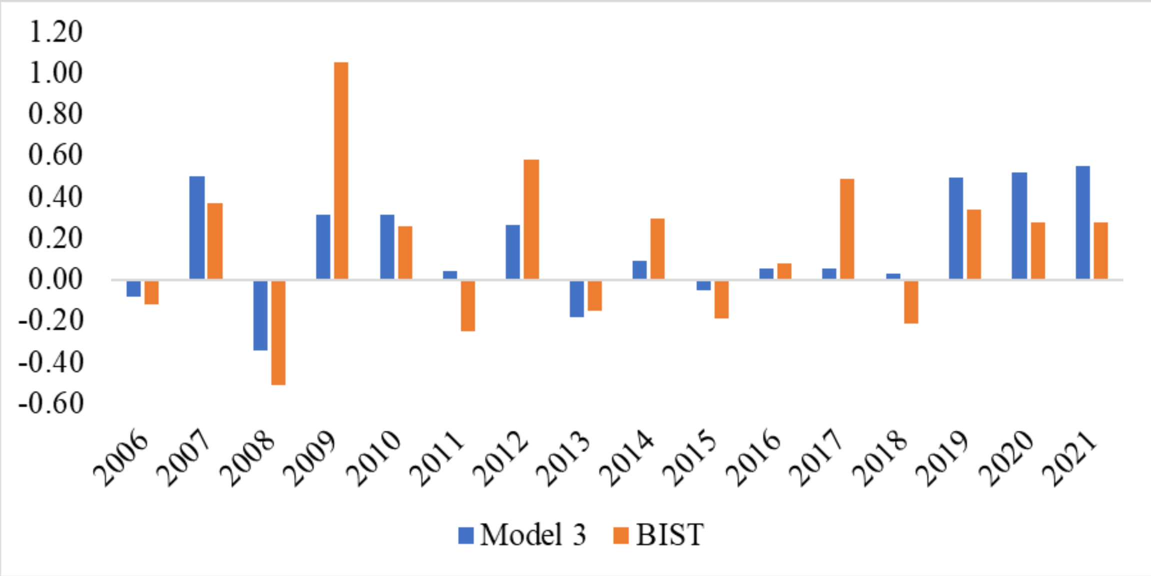

Figure 6: Yearly Average Return of BIST100 Index and Model 3

Model 1 exhibits better performance than the index for the years that BIST100 index's performance is below 0, which can be a useful feature for traders seeking to create alpha on the BIST100 Index. Secondly, Model 2's yearly average return is bigger than Model 1's; nevertheless, standard deviation of Model 2 is bigger than Model 1's. This might be the sign of higher volatility and higher risk of the model. For Model 3, there is not a difference like other two models. Under these circumstances, when I evaluate these models, Model 1 seems most successful and consistent model according to the BIST100 index based on the trading performance and cumulative returns.

ROBUSTNESS

The use of Variance Inflation Factor (VIF) is a common technique to detect multicollinearity among independent variables in regression analysis. When there is high correlation between the predictors, the coefficients in the regression model can become unstable, leading to unreliable and inconsistent results. The VIF calculation is based on the correlation matrix of the predictors and is used to identify the extent to which multicollinearity exists among them. In this study, the VIF values were used to select the technical indicators with the highest correlation in the regression models, allowing for the development of more accurate models.

The VIF function available in car library of RStudio is utilized for this purpose, with a threshold value of 5 being used to identify highly correlated parameters. The VIF values are measured and detailed Table 9.

Table 9: VIF Values of Indicators

Daily	Bollinger	PSAR	Keltner	OBV	MACD	ADX	RSI	StochasticFastD	CMO	WMA
0% Model	1,7391	2,6480	3,4357	1,0377	4,6310	1,1355	13,9278	7,3932	7,3161	2,4776
1% Model	1,7325	2,6346	3,4601	1,0412	4,6150	1,1185	14,1195	7,5296	7,5389	2,5208
2% Model	1,7732	2,6266	3,5295	1,0398	4,4312	1,1052	14,1714	7,8093	7,7385	2,5825
-1% Model	1,7660	2,6289	3,4448	1,0261	4,5684	1,0876	13,7402	7,5172	7,3395	2,4860
-2% Model	1,8343	2,6458	3,4045	1,0286	4,2836	1,0962	13,3340	7,6055	7,2050	2,4049

Weekly	Bollinger	PSAR	Keltner	OBV	MACD	ADX	RSI	StochasticFastD	CMO	WMA
0% Model	1,7185	2,9059	4,6564	1,1933	4,8245	1,3726	13,7278	7,8507	6,7616	2,3293
1% Model	1,7403	2,9210	4,6775	1,2058	4,8035	1,3806	13,8676	7,9069	6,8313	2,3179
2% Model	1,7603	2,9200	4,7024	1,1946	4,8048	1,3591	13,7477	7,8952	6,8201	2,3311
-1% Model	1,7055	2,8861	4,6087	1,1753	4,8194	1,3796	13,4950	7,7823	6,6039	2,3359
-2% Model	1,7101	2,8648	4,6108	1,1520	4,9158	1,3851	13,3223	7,7275	6,5022	2,3563

Table 9: VIF Values of Indicators Table 9 indicates that the Variance Inflation Factor (VIF) values of the technical indicators used in the regression models. From Table 9, RSI, Stochastic Fast D, and CMO have VIF values greater than 5. To solve this issue, these indicators were excluded one by one, and the VIF values were recalculated after each exclusion. Upon exclusion RSI and Stochastic Fast D, all remaining indicators had VIF values less than 5. Table 10 presents the VIF values of the indicators after the exclusion of RSI and Stochastic Fast D.

Table 10: VIF Values of Indicators after Exclusion

Daily	Bollinger	PSAR	Keltner	OBV	MACD	ADX	CMO	WMA
0% Model	1,5410	1,7017	3,0810	1,0380	3,3332	1,0420	4,1925	2,3088
1% Model	1,5338	1,7088	3,0974	1,0444	3,3295	1,0348	4,2842	2,3306
2% Model	1,5568	1,7074	3,1634	1,0436	3,2756	1,0570	4,3530	2,3333
-1% Model	1,5531	1,6984	3,0854	1,0296	3,2841	1,0274	4,1934	2,3030
-2% Model	1,5969	1,6925	3,0396	1,0302	3,1077	1,0649	4,0756	2,1948

Weekly	Bollinger	PSAR	Keltner	OBV	MACD	ADX	CMO	WMA
0% Model	1,4820	1,8608	4,0270	1,1404	3,6791	1,2208	4,8722	2,2597
1% Model	1,4909	1,8727	4,0379	1,1467	3,6734	1,2197	4,8948	2,2487
2% Model	1,5090	1,8816	4,0608	1,1412	3,6601	1,2055	4,9372	2,2623
-1% Model	1,4796	1,8487	3,9759	1,1297	3,6801	1,2339	4,7852	2,2644
-2% Model	1,4835	1,8606	3,9578	1,1178	3,7671	1,2559	4,7793	2,2880

The results of the new model are summarized in Table 11, Table 12 and Table 13. When comparing Table 11 and Table 6, it is observed that the majority of the models (14 out of 20) have higher accuracy, and (15 out of 20) have higher specificity. However, only 8 out of 20 models have higher sensitivity than the current model. This suggests that modifying the model based on statistical factors improves the prediction results. Furthermore, Table 12 and Table 7 present the trading strategy results of 6-month models. The excluded model outperforms the current model in most parameters. Specifically, 9 out of 10 models have higher accuracy, 8 out of 10 models have higher yearly average return, Sharpe ratio, and cumulative return, as well as lower standard deviation. In the case of 12-month models, there is no clear superiority between the excluded and current model, as detailed in Table 13 for the excluded model and Table 8 for the current model. As a general observation for 12-month models, the excluded model has better statistical and trading results in daily horizons, while the current model performs better in both statistical and trading results in weekly horizons.

Table 11: Prediction Results of New Model

Daily - 6 Months	**0% Model**	**1% Model**	**2% Model**	**-1% Model**	**-2% Model**
Sensitivity	0,6634	0,2166	0,1408	0,1335	0,1184
Specificity	0,3418	0,8289	0,8986	0,9047	0,9200
Accuracy	0,5341	0,2818	0,1140	0,2699	0,1138

Daily - 12 Months	**0% Model**	**1% Model**	**2% Model**	**-1% Model**	**-2% Model**
Sensitivity	0,7775	0,1220	0,0674	0,0143	0,0218
Specificity	0,2350	0,9143	0,9666	0,9884	0,9881
Accuracy	0,5361	0,3061	0,1575	0,2449	0,1373

Weekly - 6 Months	**0% Model**	**1% Model**	**2% Model**	**-1% Model**	**-2% Model**
Sensitivity	0,6454	0,5515	0,4221	0,3716	0,2948
Specificity	0,3466	0,4474	0,5783	0,6862	0,7188
Accuracy	0,5602	0,4449	0,3029	0,3619	0,2227

Weekly - 6 Months	**0% Model**	**1% Model**	**2% Model**	**-1% Model**	**-2% Model**
Sensitivity	0,6938	0,5515	0,4877	0,2337	0,1965
Specificity	0,2670	0,3691	0,5214	0,7651	0,8136
Accuracy	0,5497	0,4125	0,3067	0,3228	0,2237

Table 12: Trading Strategy Results of 6-month

		6 MONTHS				
		Accuracy	**Yearly Average Return**	**Standard Deviation**	**Sharpe Ratio**	**Cumulative Return**
DAILY	**0% Model**	0,5341	0,1501	0,2126	0,1420	7,6249
	1% Model	0,2818	0,1715	0,1223	0,4222	13,6693
	2% Model	0,1140	0,1207	0,0916	0,0086	6,4047
	-1% Model	0,2699	0,1157	0,1014	-0,0412	5,8305
	-2% Model	0,1138	0,0973	0,0880	-0,2566	4,4354
WEEKLY	**0% Model**	0,5602	0,1349	0,2181	0,0523	5,5568
	1% Model	0,4449	0,1301	0,1946	0,0340	5,5410
	2% Model	0,3029	0,1127	0,1734	-0,0623	4,5236
	-1% Model	0,3619	0,0491	0,1532	-0,4858	1,7811
	-2% Model	0,2227	0,0609	0,1390	-0,4498	2,2135

Table 13: Trading Strategy Results of 12-month

		12 MONTHS				
		Accuracy	**Yearly Average Return**	**Standard Deviation**	**Sharpe Ratio**	**Cumulative Return**
DAILY	**0% Model**	0,5361	0,1380	0,2215	0,0819	5,9695
	1% Model	0,3061	0,0973	0,1058	-0,2138	4,3086
	2% Model	0,1575	0,1234	0,0650	0,0539	6,9107
	-1% Model	0,2449	0,1232	0,0397	0,0840	7,0421
	-2% Model	0,1373	0,1225	0,0365	0,0714	6,9735
WEEKLY	**0% Model**	0,5497	0,0784	0,2299	-0,1958	2,2200
	1% Model	0,4125	0,0491	0,2202	-0,3377	1,4624
	2% Model	0,3067	0,1163	0,1962	-0,0364	4,4826
	-1% Model	0,3228	0,0340	0,1170	-0,7613	1,5307
	-2% Model	0,2237	0,0398	0,1130	-0,7403	1,6783

In summary, the excluded model does not demonstrate significant superiority over the current model in both statistical and trading aspects. However, for 6-month models, the excluded models show better performance compared to the current model. On the other hand, there is no clear advantage between the models for 12-month models.

CONCLUSION

This study presents a novel approach to investigate the direct relationship between technical indicators and stock prices. The proposed method utilizes a training dataset containing technical indicator values from 2005 until the preceding day or week of the predicted period of Borsa Istanbul (BIST). The technical indicators are calculated using opening, closing, maximum, minimum prices, and volumes for a specified time interval. Two types of training data based on the time horizon which are 6-month and 12-month are used to predict the directional movement of the BIST index for the next period using logistic regression. The model determines thresholds ranging from -2% to 2% based on the return of specific days, with a threshold of 2% providing a signal of 1 if the BIST index return is greater than 2%, and 0 otherwise. After the end of the first predicted period, the data from this day is used to forecast the next day. The trading strategy invests in the BIST index on the days when the model gives a signal of 1, and in repurchase agreements (Repo) on other days. The strategy opens positions at the beginning of the session and closes them at the end of the session, with no positions carried over to the next period.

Based on the statistical evaluation of the dataset, it has been found that utilizing logistic regression for predicting the movement direction of stock prices is superior to using Ordinary Least Squares Regression (OLS) to predict the direct return. Additionally, the Average Directional Index (ADX) indicator appears to be the most effective predictor based on the regression analysis results.

The findings of this study reveal that the proposed models achieved an accuracy rate of over 50% for the 0% threshold, which was calculated by dividing the true positive signals by the total number of positive signals. It was observed that the accuracy of the models decreased as the absolute threshold increased. Furthermore, the ratio of positive signals decreased with the increase in the absolute threshold, which led to a convergence of cumulative return towards the Repo line and a decrease in standard deviation.

Regarding the trading strategy employed in this study, two key observations were made. Firstly, it was noted that there is no clear relationship between the accuracy of the models and the return on investment. Although the accuracy decreases with an increase in absolute threshold, there is no discernible trend for the return side. Secondly, the daily models outperformed the index, particularly in years when the index had negative returns. In such years, most of the models yielded positive returns and, therefore, would be beneficial to portfolio managers and real investors who are seeking to generate alpha, especially during difficult market conditions.

Based on the cumulative return of the models from 2006 to 2021, it was observed that almost half of the models (9 out of 20) had outperformed the BIST index. Notably, the daily models exhibited better performance compared to the weekly models.

The models presented in this paper are updated on a daily basis. However, if data can be gathered at a more frequent interval such as hourly or even minute intervals, intraday trading models could be developed using the same approach. Additionally, further analysis could be conducted to evaluate the use of penalized logistic regression as a method to prevent overfitting issues. It is also important to note that financial markets are dynamic and constantly evolving. As such, new technical indicators or trends may emerge that could be incorporated into these models. As a suggestion for future work, these models should be continuously updated with new and different technical indicators to improve their accuracy and effectiveness in predicting stock prices. Final suggest is this work can be widened by applying to whole stocks in the index; consequently, there will be a different model for all of the stocks. As a result, it can be determined that which stocks can be predicted via technical analysis or which stocks cannot be predicted?

APPENDIX

A. Bollinger Bands

Bollinger Bands were created by John Bollinger in the 1980s and represent trading bands plotted against two standard deviations is above and below a 20-day moving average. [12] The upper and lower bands are plotted two standard deviations away from the middle line, which creates a channel around the price.

The width of the bands expands and contracts according to market volatility. This study proposes a trading strategy using Bollinger Bands. A sell signal, -1, is generated when the current closing price is lower than the previous closing price and the previous closing price is at the upper level of the Bollinger Bands. Conversely, a buy signal, +1, is generated when the previous closing price is at the lower level and the current closing price is higher than the previous closing price. If the price level is above or below the Bollinger Bands, a buy or sell signal is generated, respectively.

$$BOLU = \sum_{i=1}^{n} TP_i + m * \sigma[TP, n] \tag{8}$$

$$BOLD = \sum_{i=1}^{n} TP_i - m * \sigma[TP, n] \tag{9}$$

B. Keltner Channel

Keltner Channels are a technical indicator that utilizes volatility to measure potential price trends in financial markets. Similar to Bollinger Bands, the indicator comprises three lines plotted on a price chart. The middle line is calculated as the exponential moving average of the typical price of the security being analyzed. The upper and lower lines are calculated as a fixed distance from the middle line, which is determined by adding or subtracting twice the Average True Range.

$$True\ Range = Max((Current_{High} - Current_{Low)}), abs(Current_{High} - Close_{PreviosDay}), abs(Current_{Low} - Close_{PreviosDay}) \tag{10}$$

$$ATR = \sum_{i=1}^{n} True\ Range_i \tag{11}$$

$$Keltner\ Channel = Exponential\ Moving\ Average + m * ATR \tag{12}$$

The Keltner Channel can be used to identify market trends, like the Bollinger Bands. A rising angle of the Keltner Channel indicates an upward trend in the price of the security, while a decreasing angle suggests a bearish market trend. In terms of trading strategies used in this paper, Keltner Channels can be utilized to generate buy or sell signals. For example, a breakout above the upper channel may be interpreted as a buy signal, while a breakout below the lower channel may be taken as a sell signal.

Overall, Keltner Channels provide a valuable technical tool for traders and investors to measure volatility and identify potential price trends in financial markets.

C. Parabolic SAR

Parabolic SAR is a technical indicator developed by J. Wells Wilder that aims to identify the direction and changes in direction of price movements. The name "SAR" stands for "Stop and Reversal". The indicator is represented by a series of dots that appear either above or below the price levels on a chart. In trading, a bearish market is signaled when the price levels are below the indicator values, while a bullish market is signaled when the price levels are above the indicator levels.

The calculation of the Parabolic SAR indicator involves a complex formula. At the end of the calculation process, there are two final formulas for the uptrend and downtrend Parabolic SAR values. In (13), "Prior SAR" refers to the Parabolic SAR value from the previous period. "EP" represents the extreme point, which is the highest point for an uptrend calculation and the lowest point for a downtrend calculation. "AF" represents the acceleration factor, which is initially set to 0.02 and increases in rising SAR at each EP change and decreases in falling SAR at each EP change.

$$Parabolic\ SAR = Prior\ SAR \mp Prior\ AF(Prior\ EP - Prior\ SAR) \tag{13}$$

D. On Balance Volume

The On Balance Volume (OBV) indicator posits that volume plays a significant role in price movements. First introduced by Granville in 1963, this technical analysis tool is calculated by adding or subtracting the volume value for a specified date to the current OBV value. When the closing price for a given day is higher than the closing price of the previous day, the volume is added to the OBV value. Conversely, if the closing price is lower than the previous day's closing price, the volume is subtracted from the OBV value [13]. The calculation of this indicator is summarized (14).

$$Current\ OBV = Prior\ OBV\ \mp Current\ Volume \tag{14}$$

E. Moving Average Convergence Divergence (MACD)

The Moving Average Convergence Divergence (MACD) indicator was developed by Appel in 1974. According to [14] the calculation of this technical analysis tool involves subtracting the 26-day exponential moving average (EMA) from the 12-day EMA. The resulting MACD value can provide insights into the momentum of prices over different time frames. Specifically, if the MACD value is greater than 0 and continues to increase, it indicates that price momentum is increasing more in the short term (12-day) than in the long term (26-day). Conversely, if the MACD value is less than 0 and continues to decrease, it indicates that price momentum is moving downward more in the short term (12-day) than in the long term (26-day).

$$MACD = EMA_{26-day} - EMA_{12-day} \quad (15)$$

F. Average Directional Index (ADX)

[15] indicates that this indicator created by Wilder. ADX is the trend following indicator. The ADX is used to determine whether prices are trending upward, downward, or experiencing no significant trend. The indicator consists of two sub-components, namely the Positive Directional Indicator (+DI) and the Negative Directional Indicator (-DI), which are used to calculate the positive or negative movement direction in prices. The primary objective of the ADX is to identify the direction of movement for a security, rather than providing a signal for buying or selling.

G. Relative Strength Index (RSI)

The Relative Strength Index (RSI) is a popular technical indicator developed by J. Welles Wilder in 1978. It is used to determine overbought and oversold conditions of a security or market. RSI is a momentum oscillator that measures the magnitude and velocity of price changes. The indicator ranges from 0 to 100, with readings above 70 generally indicating overbought conditions and readings below 30 indicating oversold conditions. A buy signal is generated when RSI crosses above the oversold threshold of 30, while a sell signal is generated when RSI crosses below the overbought threshold of 70. Calculation is summarized in (16).

$$RSI_t = 100 - \frac{100}{RS_t} \ where \ RS_t = \frac{\sum_{n=1}^{t} \max(0, P_n - P_{n-1})}{\sum_{n=1}^{t} \min(0, P_n - P_{n-1})} \quad (16)$$

H. Stochastic Oscillator

The stochastic oscillator is a technical indicator that enables traders to compare a stock's closing price to its closing prices within a predefined period. According to [16], the purpose of the oscillator is to assist traders in deciding the optimal time to buy or sell stocks. The oscillator consists of two primary lines, the K line and the D line. The D line is calculated as the 3-day simple moving average of the K line, and the details of the calculation are provided in (17), where n represents the designated period for computation, and t represents the current day.

$$\%K = \frac{P_t - \max\,(High_n)}{\max\,(High_n) - \min\,(Low_n)} \tag{17}$$

I. Commodity Channel Index (CCI)

The Commodity Channel Index (CCI) is a technical indicator developed by Donald Lambert to determine whether a financial instrument is overbought or oversold. It is based on the relationship between an asset's price, its moving average, and standard deviation. The CCI is calculated by taking the difference between the asset's typical price and its simple moving average, and then dividing that difference by the mean absolute deviation of the typical price. A high positive CCI value indicates that the asset is overbought, while a low negative value indicates that it is oversold. Details are shown in (18) and (19).

$$TP_t = \frac{High_t + Low_t + Close_t}{3} \tag{18}$$

$$CCI_t = \frac{TP_t - (\sum_{i=1}^{n} TP_{t-i+1})/n}{0{,}015 * (\sum_{i=1}^{n} |\, TP_{t-i+1} - (\frac{\sum_{i=1}^{n} TP_{t-i+1}}{n})|/n} \tag{19}$$

J. Chande Momentum Oscillator (CMO)

The Chande Momentum Oscillator (CMO) is a technical indicator that measures the momentum of a security's price. Developed by Tushar Chande in 1994, it calculates the difference between the sum of gains and the sum of losses over a specified time period. In the paper 14-period is used like the popular usage in the market. The CMO is useful for identifying overbought and oversold conditions and potential trend reversals. When the oscillator value is above a certain threshold, it indicates that the security is overbought and likely to experience a price decline, while a value below the threshold suggests oversold conditions and a possible price increase. Calculation details are shown in (20), (21), and (22).

$$Ups_t = \begin{cases} Price_t - Price_{t-1}, if\ Price_t > Price_{t-1} \\ 0, else \end{cases} \tag{20}$$

$$Downs_t = \begin{cases} Price_{t-1} - Price_t, if\ Price_{t-1} > Price_t \\ 0, else \end{cases} \tag{21}$$

$$CMO = \frac{\sum_{t=1}^{n} Ups_t - Downs_t}{\sum_{t=1}^{n} Ups_t + Downs_t} \tag{22}$$

K. Money Flow Index (MFI)

It is used to measure the buying and selling pressure of a security over a specified period of time. The MFI is based on the principle that price and volume are closely related in the stock market. The MFI is calculated by first calculating the typical price, which is the average of the high, low, and close prices for a given period. Next, the raw money flow is calculated by multiplying the typical price by the volume. The money flow ratio is then calculated by dividing the positive money flow by the negative money flow over a specified period of time. Finally, the MFI is calculated by using the money flow ratio and applying it to a 0-100 scale. The MFI is interpreted in a similar way to the RSI, with readings above 80 indicating overbought conditions and readings below 20 indicating oversold conditions.

L. Moving Averages

Moving averages are one of the most widely used technical indicators in financial analysis. They are used to smooth out price data over a specified time period and help identify trends and potential buy or sell signals. Simple moving averages (SMA) give equal weight to each period's price data, while exponential moving averages (EMA) place more weight on recent prices. Weighted moving averages (WMA) give more weight to the most recent prices, and less weight to older prices. This can make them more responsive to short-term price movements but can also make them more volatile. In this paper, I utilized weighted moving averages as a technical indicator, where a buy signal is generated when the short-term (20-period) weighted moving average crosses above the long-term (50-period) weighted moving average, and a sell signal is generated when the opposite occurs.

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VITA

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His research interests primarily revolve around utilizing technical indicators to predict returns on the BIST100 index. His research paper focuses on exploring the potential of these indicators to provide valuable insights into market trends and investment strategies.

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