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Nigerian Stock Market Investment using a Fuzzy Strategy

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Abstract

The Nigerian Capital Market though an emerging market, has in recent times been adjudged to be one of the most resilient in the world even in the heat of the global economic meltdown. It offers high returns on investment as compensation for its high risk. In this research, we have investigated the predictive capability of the fuzzy inference system (FIS) on stocks listed on the Nigerian Stock Exchange, within a two-month window. For each selected stock, the technical indicator-based fuzzy expert system developed in Matlab 7.0 provides the buy, sell or hold decision for each trading day. A web-based user interface enables the investor to access the trade forecast for each day. Using the Netbeans IDE, we implemented the user interface with Sun Java. Our results show that the FIS can reliably serve as a decision support workbench for intelligent investments.

Keywords: fuzzy logic, stock market, Forecasting, Decision making, technical indicator

1. Introduction

After the failure of White (1988) in the first novel attempt to predict the stock market (Canadian equities) using neural networks, and his conclusion that "the present neural network is not a money machine"; a lot of innovations and successes have been attained using Soft Computing (SC). The major components of soft computing are Artificial Neural Networks (ANNs), Fuzzy Logic (FL) and Genetic Algorithms (GLs). In recent years, a lot research studies have focused on market forecasting and trading applications using SC.

Traders make predictions based on incomplete vague, imperfect and uncertain information. Tools applied by most professional traders involve the use of technical analysis, which are used to elicit trends from raw stock prices. As stock market forecasting involves imprecise reasoning with complex underlying factors, fuzzy logic is a natural choice for representing such knowledge (Vaidehi, 2008). Our aim in this paper is to combine selected statistical indicators whose heuristics are applied in the construction of mamdani-type fuzzy inference system with buy, hold and sell output membership functions. The objective is to develop a web-based user interface such that (local and foreign) investors in the Nigerian stock market would have a decision support workbench to intelligently trade their stocks.

The research paper is organized as follows. The second unit is a review of related works on stock market analysis using fuzzy logic. The fuzzy inference model and decision support workbench is presented in unit three. While the conclusion and trade forecasts are examined in unit four.

2. Literature Review

Charles Dow in 1884 drew up an average of the daily closing prices of eleven (11) prominent stocks; and published these stock price movements in the Wall Street Journal between 1900 and 1902 (Edwards et al, 2001). The works of Charles Dow marks the beginning of modern technical analysis. However, before the advent of modern technical analysis, some centuries predating Dow's work (about 1730) Japanese traders executed futures contract (in rice) based on technical analysis of the market. In 1869, the government of Japan suspended the forward market due to its high volatility and price hikes (Tvede, 1999). According to Dow, the averages represented the general business economy, and could as such be used for predicting future business conditions. He reasoned that the price fluctuations within the averages represented the combined facts, hopes, and fears of all the investing parties – a kind of combined stock appraisal (Vanstone, 2005). In 1903, S. A. Nelson updated Dow's work in a book titled "The ABC of Stock Speculation". Dow's work was formally formulated as a theory in 1932 by Robert Rhea and published as 'Dow's Theory'.

Today, many of the modern technical indicators in use are directly based on Dow's theory. Vanstone(2005) classified technical indicators as follows: Charting/pattern matching, Indicators and Esoteric approaches. This research will focus on the use of Indicators for technical analysis. Charting patterns are largely interpreted based on subjective judgments even among knowledgeable analysis; while the esoteric approach lacks scientific merits and justification. Hence, charting and esoteric approaches will not be used. The esoteric approach, for instance the Elliot Wave theory was highly criticized by Warnecks (1987). Additional esoteric approaches concern relationships between the length of women's skirts and stock market price movements known as the 'hemline indicator'.

Continuing, Vanstone outlined the main principles of technical analysis as follows: Price move in trends, Volume goes with the trends, and a trend, once established tends to persist. What then is technical analysis? This is the study of past market behaviour to determine the current state or condition of the market (Rottela, 1992).

In the late 80s, full acceptance of Technical Analysis by the academic community was still quite low, so Taylor and Allen (1992) were asked to conduct a survey on behalf of the Bank of England, in November 1988, regarding the acceptance of Technical Analysis by Chief Foreign Exchange dealers in London. Among other findings, they found that at least 90% of respondents placed some weights on technical analysis, with a skew towards greater acceptance at short time horizons (Vanstone, 2005). Clearly, technical analysis had much greater acceptance amongst actual practitioners than academics were prepared to accept.

Two popular technical trading rules were tested by Brock et al (1992), namely Moving Average, and trading range breaks (support and resistance breaks). Using data from the Dow Jones Industrial Average (DJIA) from the first trading day in 1897 to the last trading day in 1986, the authors tests combinations of moving averages (and moving average strategies involving fixed and variable length holding periods), as well as the trend-line strategy. Their findings provide support for the use of technical analysis, in particular to the moving average strategy. The authors also discovered that buy(sell) signals generate returns that are higher (lower) than 'normal' returns, and that the differences are not readily explained by risk (Vanstone, 2005). The conclusion is that technical rules have predictive powers. Lee and Swaminathan (2000) investigated both price momentum and trading volume. They find past trading volume predicts the magnitude and persistence of price momentum. They conclude that past volume helps to reconcile intermediate-horizon over-reaction effects. Su and Huang(2003) use combinations of technical indicators (moving average, stochastic Line [KD], Moving average convergence and divergence [MACD], Relative Strength Index [RSI] and moving average exchanged volume [EMA] to determine trend directions with good results. On a final note regarding the legitimacy and credibility of technical analysis, Vanstone(2005) stated that as technical indicators become more widely known, the abnormal returns they attempt to provide will be diminished and its usefulness invalidated.

Stock market indicators are mostly proven statistical functions, some of which are very similar in nature (Agarwala et al., 2002). Analysts are often required to identify indicators that would be useful to them by meticulous screening methods that may be time consuming and may have some undesired financial repercussions. Many technical indicators are available to predict the stock market such as Relative Strength Index (RSI), Moving Average (MA), Guppy Multiple Moving Average (GMMA), etc. The technical indicator gives a good idea of market trends with the help of market price and volume. Volume tells whether there is movement on market or not and price tells in which direction market is going.

Fuzzy logic, originally introduced by Lofti Zadeh in the 1960's, resembles human reasoning in its use of approximate, vague, noisy or imprecise data/information and uncertainty to generate decisions. According to Sriram (2005), fuzzy theory was designed with a specific purpose of mathematically representing vagueness and provides formalized procedures for tackling the impreciseness inherent in many variables in a multitude of problems. In the last decade, fuzzy time series has been widely used for forecasting dynamic and non-linear data. Yu et al(2004) proposed a bivariate fuzzy time series model to forecast the TAIEX. In their study they applied neural networks to fuzzy time series forecasting and proposed bivariate models in order to improve forecasting. The stock index and its corresponding index futures are taken as the inputs to forecast the stock index for the next day. Both in-sample estimation and out-of-sample forecasting are conducted. Teoh et al (2005) used Fuzzy time series model based on probabilistic approach and rough set rule induction for empirical research in stock markets. In their study they proposed a hybrid fuzzy time series model with two advanced methods, cumulative probability distribution approach (CPDA) and rough set rule induction, to forecast stock markets.

Cheng et al (2001) proposed a new fuzzy time-series model which incorporates the adaptive expectation model into forecasting processes to modify forecasting errors. Shiva (2002) presented a computational method of forecasting based on high-order fuzzy time series. Wong et al (2008) proposed traditional time series method (ARIMA model and Vector ARMA model) and Fuzzy Time Series Method (Two-factor model, Heuristic model, and Markov model) for the forecasting problem. Hence, it is more convenient to use the fuzzy time series method in the limited information and urgent decision making circumstance.

3. Methodology

Fuzzy theory attempts to mimic human reasoning in its use of approximate information and uncertainty to generate decisions. Unlike traditional computing (which demands precision inherent in all system variables and domains), fuzzy set theory imparts knowledge to the system in a more natural way using fuzzy sets. This way, our stock trading problem is simplified. In this research, we shall be using the Mamdani-type fuzzy rule model of the form:

R1: If x is A_1 and y is B_1 then z is C_1

R2: If x is A_2 and y is B_2 then z is C_2

Where A_i , B_i and C_i, are fuzzy sets defined on the universes of x, y, z respectively.

3.1 The Fuzzy Stock Prediction System

There are four major units in the system, namely: Technical indicator module, Fuzzification module, Fuzzy processing module, and Defuzzification module. The technical indicators module transforms past historical stock prices into selected indicators (oscillators). These indicators then become inputs to the fuzzification module. The fuzzification module again transforms each crisp technical indicator input into fuzzy values (known as fuzzy indicators). These fuzzy indicators serve as input to the fuzzy processing module, which generates Buy/Sell actions to be taken for the stock in question; based on the embedded fuzzy IF/THEN rules. To finally obtain a crisp value, the defuzzification module maps the fuzzy action value into crisp decision.

3.2 Technical Indicators

Here, historical prices of certain selected stocks are used to compute the indicators. The data to be used are Banking stock data from Nigerian stock market. We chose three popular technical indicators (RSI, Trend and MACD) as listed in Table 3.1.

The RSI Indicator: It is a price following indicator which considers whether an asset is over bought or oversold. Its value oscillates between a range of 0 and 100. When the RSI rises above 70, the action of sell will be taken, and when the RSI drops below 30, the action of buy will be taken. (Table 3.1 contains the RSI equation). The crossing boundaries for generating the signals are rather arbitrary, but we have used the following classification rules.

1. IF RSI increases to above 70 THEN BULLISH(Overbought)
2. IF RSI decreases to below 70 THEN BEARISH(Oversold)
3. IF RSI increases to above 30 THEN BULLISH(Overbought)
4. IF RSI decreases to below 30 THEN BEARISH(Oversold)

The MACD Indicator: (Table 3.1 contains the MACD equation). Moving Average Convergence/Divergence is an oscillator intended as an improvement on the simple moving average approach. It generates its signal from the crossing of moving average lines. The MACD line is calculated by taking two exponentially moving averages of closing prices with different periods and subtracts the moving average with the longer period from the one with the shorter period. Usually, 12/26 MACD is used, which computes the difference between the 26-day and the 12-day exponential moving averages.
1. IF MACD is Positive THEN BUY.
2. IF MACD is Negative THEN SELL.

Fuzzification Module
This module transforms the technical indicators to fuzzy values using membership functions. Table 1 contains a description of the input membership functions. These membership functions are chosen based on the intuitive meaning obtained from the trading rules. Table 2 contains a description of the membership functions of the output (buy/sell/hold decision). Figure 1 is the output (Decision) membership functions.

Table 1: Description of Input Membership Functions

Indicator	Membership Function(MF)	Type of Membership Function
RSI	High, Medium, Low	Triangular
MACD	Positive, Negative	Trapezoidal
Trend	Positive, Negative	Trapezoidal
Momentum	Low, Medium, High	Triangular

Table 2: Description of Output membership functions

Output	Membership Function(MF)	Type of Membership Function
Decision	Buy, Hold, Sell	Gaussian

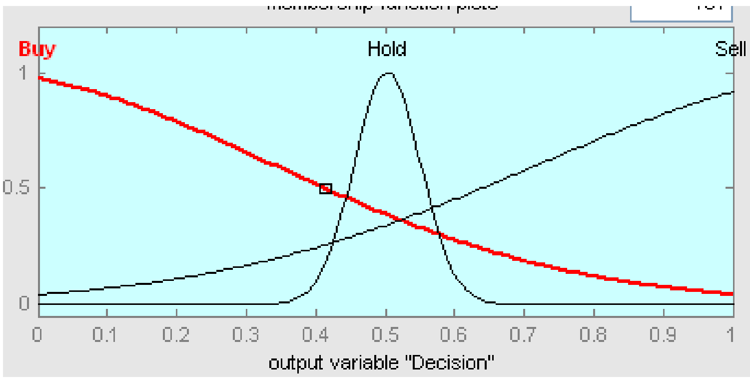

Fig. 1: Plot of Decision (Buy, Hold and Sell) membership functions

3.3 Fuzzy Processing Module

Table 3 contains a summary of the rules for the fuzzy processing module.

Table 3: Fuzzy Logic Rules

If (MACD is Positive) and (RSI is Low) then (Decision is Buy)
If (MACD is Negative) and (RSI is High) then (Decision is Sell)
If (RSI is Medium) then (Decision is Hold)
If (Trend is Positive) and (Momentum is Low) then (Decision is Buy)
If (Trend is Positive) then (Decision is Buy)
If (Trend is Negative) then (Decision is Sell)
If (Trend is Negative) and (Momentum is Low) then (Decision is Sell)

RSI oscillates in [0, 100] range; using fuzzy logic, we can translate this into fuzzy rule:
If RSI is low then the decision will be buy and if RSI is high, then the decision will be sell.

3.4 Defuzzification Module

The Mamdani's fuzzy inference scheme (Klir and Yuan, 2002) when given the stock indicators can infer the Decision part at any point in time. The resulting output is a fuzzy value. This is transformed into a crisp decision in the defuzzification module. Our implementation is to use the centre of area (COA)/centroid methods (Klir and Yuan, 2002), a popular technique for defuzzification in the fuzzy logic research and development.

3.5 Fuzzy Control Module Algorithm

The following algorithm outlines the steps required to use the indicators together with the fuzzy inference system:

Function FIS()
{
[1] Input stock closing prices(SP)
[2] MovAve = Calculate(Initial Moving Average)
[3] EMA26 := Calculate(SP, MovAve)
[4] EMA16 := Compute(SP, MovAve)
[5] Calculate MACD: MACD := EMA26 – EMA16
[6] Determine RSI := Calculate(CG, CL)
Where
CG: Gain-stock closing price
CL: Loss-stock closing price
[7] Compute:
PriceChange := *Price Change = [(P(t) – P(t-2))/P(t-2)*]*100
[8] Compute
Momentum := $close_{today} - close_{n\ days\ ago}$
[9] Evaluate Fuzzy inference system
Decision := EvaluateFIS(FIS, MACD, RSI, Trend, Momentum)
[10] If Decision = 0 or Decision < 0.4
[11] then fuzzy_Decision := 'Buy'
[12] Elseif Decision >= 0.4 or Decision <= 0.5
[13] then Fuzzy_Decision = 'No Trade'
Elseif Decision = 1 or Decision > 0.5
[14] then Fuzzy_Decision = 'Sell'
Endif
}
[15] Return (Fuzzy_Decision)

3.6 Forecast Database

The fuzzy forecasts are stored in a MySQL database with following schema/relation:

```
Fuzzy_Forecast(
ffID INT NOT NULL,
stock  VARCHAR(10)
ffDate  DATE,
ffValue  FLOAT,
ffDecision VARCHAR(5)
PRIMARY KEY (ffID)
)
```

3.7 User Interface

With the applet loaded the investor is expected to give a view of the day's prediction in the forecast database using a suitable web-browser with java runtime enabled as shown in figure 2.

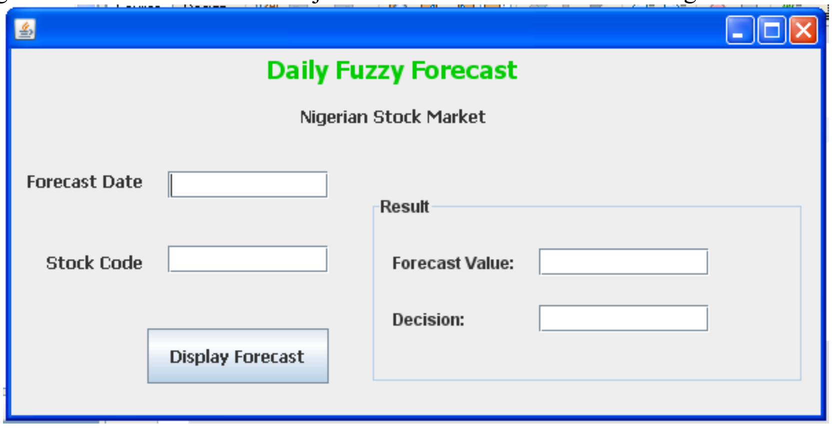

Fig.2: Web Interface for Daily Fuzzy Forecasts

5. Conclusion and Results

The use of technical indicators is a paradigm different from the fundamental approach to market analysis. Technical analysis is based on the assumption that the forces and underlying market factors represented in the historical price patterns. Hence, the use of fuzzy-based technical indicators is an optimal strategy for stock market forecasting. The results of our simulated trades are presented in Appendix A.

The fuzzy system uses at least 30 days (past) stock price data to make forecast, especially the RSI and MACD indicators. What we discovered from the fuzzy system is that the fuzzy inference system is very meticulous in combining all the indicators/rules to give a crisp forecast. Results obtained from testing the fuzzy prediction gave us a 50% of success against the next day.

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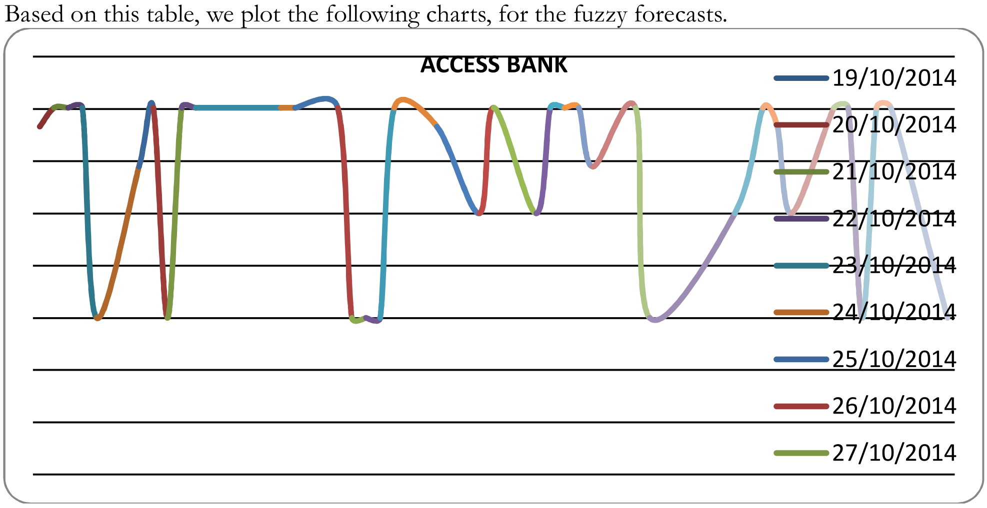
Appendix A

Fuzzy Forecast Buy/Sell/Hold forecast for selected Banks

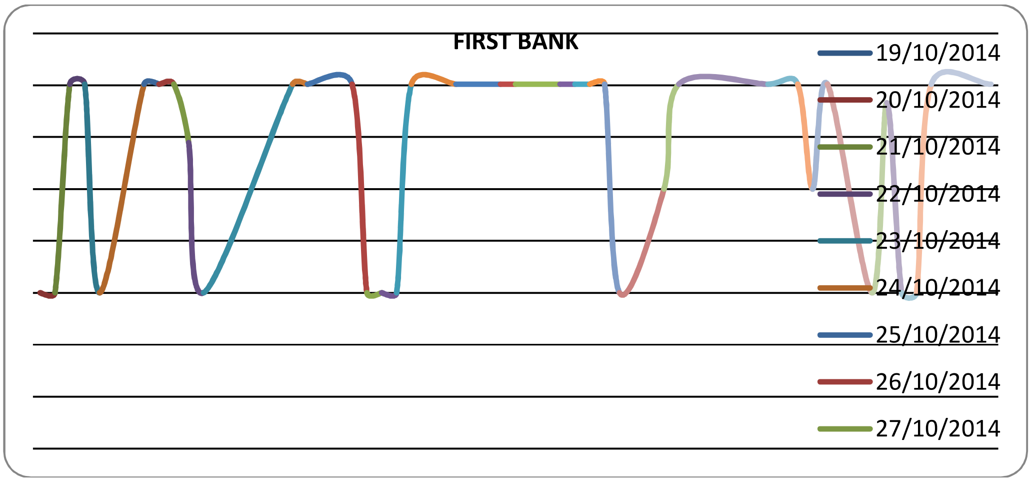
Range (PriceCode)	Fuzzy Forecast			Date
	Access Bank	First Bank	UBA	
1 – 30	0.6661	0.3001	0.3001	10/18/10
2 – 31	0.7020	0.3001	0.7010	10/19/10
3 – 32	0.7020	0.7020	0.7020	10/20/10
4 – 33	0.7020	0.7020	0.7020	10/21/10
5 – 34	0.3001	0.3001	0.5000	10/22/10
6 – 35	0.5894	0.7020	0.7020	10/25/10
7 – 36	0.7020	0.7020	0.7020	10/26/10
8 – 37	0.3001	0.7020	0.7020	10/27/10
9 – 38	0.7020	0.5894	0.5000	10/28/10
10 – 39	0.7020	0.3001	0.7020	10/29/10
11 – 40	0.7020	0.7020	0.7020	11/04/10
12 – 41	0.7020	0.7020	0.7020	11/05/10
13 – 42	0.7020	0.7020	0.3001	11/08/10
14 – 43	0.3001	0.3001	0.3001	11/09/10
15 – 44	0.3001	0.3001	0.6661	11/10/10
16 – 45	0.3001	0.3001	0.6661	11/11/10
17 – 46	0.7020	0.7020	0.7020	11/12/10
18 – 47	0.6661	0.7020	0.7020	11/15/10
19 – 48	0.5000	0.7020	0.6661	11/18/10
20 – 49	0.7020	0.7020	0.7020	11/19/10
21 – 50	0.5000	0.7020	0.7010	11/22/10
22 – 51	0.7020	0.7020	0.7020	11/23/10

23 – 52	0.7020	0.7020	0.7020	11/24/10
24 – 53	0.7020	0.7020	0.7020	11/25/10
25 – 54	0.5894	0.3001	0.7020	11/26/10
26 – 55	0.7020	0.5000	0.6661	11/29/10
27 – 56	0.3001	0.7020	0.7020	11/30/10
28 – 57	0.5000	0.7020	0.5894	12/06/10
29 – 58	0.7020	0.7020	0.5000	12/08/10
30 – 59	0.6661	0.5000	0.7020	12/09/10
31 – 60	0.5000	0.7020	0.7020	12/10/10
32 – 61	0.7020	0.3001	0.7020	12/13/10
33 – 62	0.7020	0.6661	0.7020	12/14/10
34 – 63	0.3001	0.3001	0.3001	12/15/10
35 – 64	0.7020	0.3001	0.7020	12/16/10
36 – 65	0.7020	0.7020	0.5000	12/17/10
37 – 66	0.3001	0.7020	0.5000	12/21/10

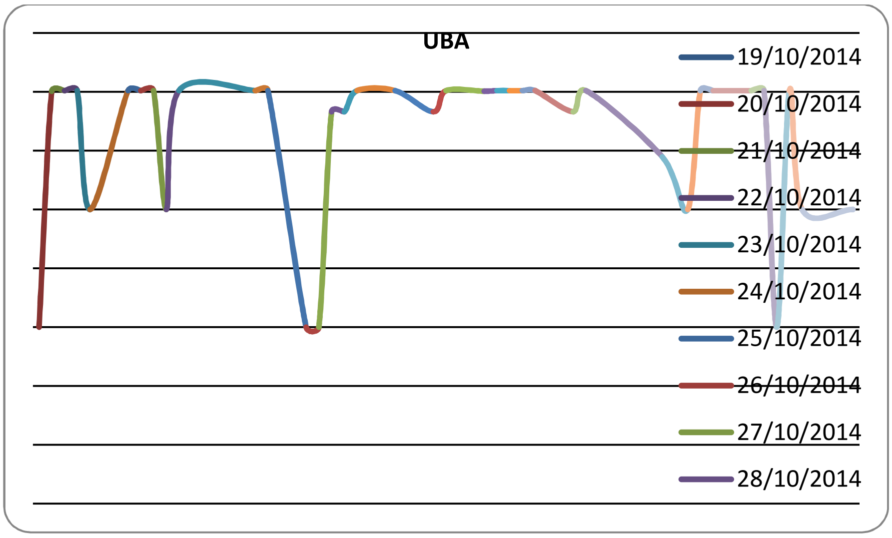
Based on this table, we plot the following charts, for the fuzzy forecasts.



Line Chart of Access Bank Fuzzy Forecast (typically, 0.3 indicates buy and 0.7 indicates sell



Line Chart of First Bank Fuzzy Forecast (typically, 0.3 indicates buy and 0.7 indicates sell



Line Chart of UBA Fuzzy Forecast (typically, 0.3 indicates buy and 0.7 indicates sell

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Appendix B

Table 3.1: Technical Indicators

Indicator	**Equation**
MACD	12-day EMA - 26-day EMA
RSI	$$RSI = 100 - \frac{100}{1 + RS}$$ $$RS = \frac{\sum_{n-17}^{n} D(nT) Gains}{\sum_{n-17}^{n} D(nT)\ Losses}\ , where\ n \geq 17$$
	Where EMA := Exponential Moving Average SMA := Simple Moving Averages D(nT) := Stock Closing Price
*EMA	EMA = (K x (C – P)) + P Where K is a smoothing constant, defined as: $$k = \frac{2}{(1 + N)}$$ And C = Current Close Price; P = Previous Periods EMA (A simple moving average SMA can be used for initialization on the first period) (Also * means the EMA is to formulate other indicators)
Trend	*% Price Change = [(P(t) – P(t-2))/P(t-2)*]*100 Where P (t) refers to the price of the stock today and P (t-2) refers to the price of the stock two periods ago.
Momentum	$momentum = close_{today} - close_{n\ days\ ago}$