New Challenges in Accounting and Finance

2018(1)1–36

Testing Technical Trading Rules: Evidence from SAARC Countries

Faisal Anees, Shujahat Haider Hashmi*, Muhammad Asad

Piraeus University of Applied Sciences

Received 2 December 2017 **Accepted** 15 June 2018

ABSTRACT

Technical analysis is widely accepted tool in professional place which is frequently used for investment decisions. Technical analysis beliefs that there exist patterns and trends and by capturing trends and patterns one can bless with above average profits. We test two technical strategies: Moving averages and Trading Range to question, either these techniques can yield profitable returns with the help of historical data. Representative daily indices of Four countries namely Pakistan, India, Srilanka, Bangladesh ranging from 1997 to 2011 have been examined. In case of Moving Average Rule, both simple and exponential averages have been examined to test eleven different short term and long term rules with and without band condition. Our results delivered that buy signals generate consistent above average returns for the all sub periods and sell signals generate lower returns than the normal returns. Intriguing observation is that Exponential average generates higher returns than the Simple Average. The results of Trading Range Break strategy are parallel with Moving average Method. However, Trading Range Strategy found not to give higher average higher return when compared with Moving Averages Rules and degree of volatility in returns is higher when compared with moving Average rule. In attempt to conclude, there exist patterns and trends that yield above average and below average returns which justify the validity of technical analysis.

Keywords: *Technical Analysis Strategies, Moving Average, Resistance and Support level, Ranging Trade break, Efficiency of markets*

**Correspond author E-mail address: shujahat@jinnah.edu.pk* *Doi:*

1. Introduction

The formation of prices in financial markets is a central issue in financial economics. Technical analysis or put in other way, charting, is a procedure which makes use of the blueprints of the series of prices of some financial instrument (For instance, stock, currency, commodity or composite average) for the purpose of providing indications on the future presentation of prices. The wide-ranging aim of technical analysis is to find out recurrences in the series of prices by excluding nonlinear trends from noisy data. Implied in this intend is the appreciation that a number of price developments hold water, and add to the construction of a precise trends whereas others are random deviations to be neglected. For several decades people who have compacted with securities are separated into two groups. Speaking for the first group who thinks that a market pays attention how the market take breaths and come to see the market as alive being. To arrive at this believe, they scrutinize past statistics of volumes and prices, depict patterns and trends and finally make indicators. If someone inquires them whether the formation of prices is an accidental development the answer will be emotional and strongly negative. No trader would reach to an agreement that his profession is parallel to throwing a dice.

Most classic empirical studies pertinent to this subject, including Fama and Blume (1966) and Jensen and Benington (1970), document that technical analysis cannot helpful for advancing returns. On the other hand, the other large group supposes that the price discovery is a random development which implies that the game is reasonable and market pursues random walk. Even Weak form of the Efficient Market Hypothesis puts that all germane information which has come to market and has potential to impact the upcoming prices is latest information.

According to Bessembinder and Chan (1995), there exist three distinctive principles/assumptions underlying to rationale of technical analysis. Speaking for first principle, which purports that all relevant information is steadily adjusted in the prices? All the way through the market mechanism the expectations, dreams, believes and hopes, of every investor are mirrored in the prices of securities. A professional technical analyst maintains that the most excellent counselor you could obtain is market itself and hence requires no want to look for the fundamental information. Second principle is that technical analysis undertakes that prices go away in up, downward and sideways trends. For that reason, the majority of technical trading procedures are trend-following instruments. The third and most important supposition is history recurs itself. Under same circumstances traders will respond the similar leading to price trends that can be acknowledged in data. Technical analysts assert that if a pattern is noticed in a premature stage, gainful trades can be prepared with technical trading techniques. Market action is a repetitive thing. This leads to view that a variety of patterns and trends come out over and again in charts of prices. These patterns and trends develop in response to investors' responses to improve in their riches. Therefore, the reappearance of different trends and patterns is a demonstration of inclination for people to act alike.

The believers of technical analysis believe that changes in feelings give birth to certain patterns and trends to take place repetitively in the price charts; for the reason that people react the same in given circumstances. It is assumed that price steadily passes through to latest highs or latest lows and that volume of trading go away with the prevalent development. Thus the most popular technical trading rules/ techniques are trend adopting techniques (For instance, moving averages and filters). Technical analysis aims to harness the forces of changes in investor's feelings in a premature stage and tries to yield from them.

This will not be out of place to mention that in academia it has remained open to discussion that do technical trading relied on trends or patterns of earlier period prices keep any statistically important predicting control? And does it can beneficially be altered, following adjusting transaction costs and risk? As insights provided by Brock et al. (1992) in their influential paper that "term technical analysis is a general heading for a numerous of trading techniques". Followers of technical analysis are of the opinion that variations in demand and supply can be of great value to detect future trends by charts of market action. Or put it differently, the instantaneous direction of prices determined exclusively by the demand and supply of the financial instrument, and variation in demand and supply are normally obvious upon probing current trends of prices. Technical analysis embraces range of methods such as chart analysis, seasonality and cycle analysis, pattern recognition analysis, and computerized technical trading systems.

The philosophy underlying modern technical strategies can be traced back to Charles Dow's works. Charles Dow was of the belief that prospects for the national economy were provided to market orders that results in stock to either increase or decrease in terms of prices - generally in progress of real economic growth. He was of the belief that fundamental economic variables control prices of a stock over a long run. In order to analyze his theory, Charles Dow started to work out averages to examine market activities. This work gave birth to the Dow-Jones Railroad Average (DJRA) in September 1896 and Industrial Average (DJIA) in May 1896. Important findings of his works were that if two averages are increasing it presents buying time and whilst two averages are decreasing it presents a selling time. If both deviate, should deem this as a caution signal. Dow Theory also asserts that volume should go with the prevalent prime development. Further to elaborate this if the primary trend was upward, volume should rise when price increases and if the primary trend was downward, the volume should decrease when price decreases. In due course, this Theory converted to the heart of technical analysis.

The classical theories of financial markets (most prominent is EMH) greatly influenced the academic studies of financial markets. Many efforts have been made to check EMH (see literature review for more elucidation). This prompted to think that the proof for weak form of market efficiency is very well-built and that technical analysts are misleading themselves about their capability to envisage upcoming price developments and movements. Shortly, in the Introduction we have put together a conflict between Technical Analysis and Efficient Market Hypothesis. According to which any pertinent information is already discounted in prices subsequently there is no means to forecast prices from historical data as Technical analysis take for granted. According to Park and Irwin (2004) after the mid-1980s, nevertheless, technical trading studies tried to work upon the shortcomings of earlier studies and by and large employed some of the given approaches and characteristics in their testing methods: (1) the size of trading systems tested increased compare to former studies; (2) returns were corrected mainly for risk and transaction costs; (3) the out-of-sample verification and constraint (trading rule) optimization were tested (4) and statistical tests were carried out with either usual statistical tests or more complicated boot strap methods, or both.

But this is not out of place to mention here that with the advent twenty-first century, the scholarly supremacy of the Efficient Market Hypothesis has emerged far less universal. Numerous financial statistician and economists and have started to think that stock prices are at least somewhat conventional. A latest class of economists has highlighted behavioral and psychological elements that lie at the heart of determination of stock-price, and believes that upcoming stock prices are rather knowable on the premise of earlier period stock price trends and definite "fundamental" valuation metrics.

The literature also observed noteworthy connections among expected returns and fundamental variables, for instance, the market-to-book ratio, price earnings ratio, and support for systematic patterns in stock returns pertinent to a range of calendar periods such as holiday effect, January effect, weekend effect, the turn-of-the-month effect, the and the predictability originating from bid–ask bounces (Gencay, 1997;1999).

This work attempts to examine the profitability of technical trading techniques in developing countries' scenario. Furthermore, to examine trading strategies, stock behaviour, return trends and relationship between the returns based on past market information, lie at the heart of this work. Finally, this study will throw light on availability of arbitrage profit and opportunities for investment management by diversification of portfolios across the markets.

The remaining paper is ordered as follows. Section 2 reviews germane empirical literature. Methodological issues have been highlighted in Section 3 and results and findings have been recorded in Section4.

2. Literature Review

Technical analysis has remained an admired and deeply relied method for decades amongst professionals in financial setting (Gencay, 1997; 1999). Taylor and Allen (1992) carried out a survey on the question of utilization of technical analysis in foreign exchange market of London where dealers were their respondents. The results show that forty percent of respondents were using trading systems like moving averages, oscillators or momentum indicators. Ninety percent respondent answered that they had been using technical trading strategies where 60 percent respondents answered technical analysis as important as fundamental analysis. Lui and Mole (1998) started a survey in 1995 in Hong Kong on the question of utilization of fundamental and technical analysis. The dealers answered that they viewed technical analysis more useful in predicting patterns, trends and turning points when compared with fundamental analysis. Brorsen and Irwin (1987) carried out a survey in 1986 where large public futures funds' advisory groups comprised his sample. In the survey, interesting observation was that about more than half of respondents answered that they heavily employ computer guided systems. So this is evident from aforesaid works that technical analysis is a vibrant tool in connection to capturing future trends. This tool is widely accepted in capital, foreign exchange, future and commodity markets.

But Laurent (1997) noted that "The gulf between academicians and practitioners could hardly be wider on the issue of the utility of technical analysis trends in prices tend to persist". The rules of technical analysis were developed towards the end of nineteenth century and have been adjusted according to growing realities at academia and professional places (see Pring, (1991); Park et al, (2004) and Murphy (1987) for the historical development of technical analysis rules and methods which were emerged across the globe).

Pesaran and Timmermann (1995; 2000) contend that in financial place, the question that carries weight is how we can manage to forecast series of returns rather than on question of forecasting. But in academia, situation remained other way round. The most promising question was if future prices could be forecasted rather than how to forecast them. In against to fundamental analysis, which has happened to be rapidly accepted by the researchers of modern quantitative finance, but speaking for technical analysis, this proved an orphan from very start (Park and Irwin, 2004). Academic view tends to think that markets are informationally efficient and therefore entire on hand information is detained in existing prices (Fama ,1970).

In efficient markets, every effort to create profits by means of at present available information is useless attempt (Angelov, 2009). According to Hamid et al. (2010) academics and professionals have adopted diverse courses in analyzing time series of financial data. Amongst practitioners', fundamental and technical analysis are famous procedures evolved over the years in financial place according to which financial time series should and could be forecasted by these course of actions. These techniques are proposed to give guidelines on what and when to buy or sell respectively. On the other hand, academics put attention on the distinctiveness of financial time series and its performance and endeavor to look at whether there exists some dependence in successive changes of financial time series that can valuably be utilized by a variety of trading techniques.

According to Park and Irwin (2004) a simple trading system usually has one or two factors that play a vital role to fix on the timing of trading signals. Every rule embedded in a trading system is an outcome of factors. For instance, Dual Moving average Crossover average system keeps two factors; one is short term moving average and other is long term moving average. This may comprise of more than hundreds of trading rules that can be altered by changing the combinations of factors in trading system. The most popular trading systems are moving averages, trading range break or resistance and support level, filters, oscillators.

According to Khaled and Islam (2005) highly developed countries markets are markets that can be characterized with high liquidity level, high level of trading activity, considerable level of depth and low asymmetry of information. On the other hand, developing markets that are often emerging markets with weak infrastructure markets and have witnessed to exhibit more information asymmetry, lower trading activity and trivial depth.

Achelis (1995) in his famous book "Technical Analysis from A to Z" documents that from experience of professionals, message is that, shorter the Moving Average, the less this stays behind the developments of market, and it pursues the market more closely. He further observes that when a short Moving Average is employed, the average firmly pursues the index of market, and index of market regularly crisscrosses the short moving average. The aim is to get a suitably responsive average which provides signals at the early phase of a most recent trend, however not much responsive to market noises This approach can have demerits like; a sensitive (short) Moving Average provides several selling and buying signals and produce changes of position, which in turn yields high transactions costs, and comparatively several fake signals.

In one of the most influential paper germane to technical analysis which is also central to this study, Brock et al. (1992) employ two popular trading rules: moving average and trading range break also tested through bootstrap methods. They compare conditional returns for period 1897 to 1986 of actual Dow Jones Industrial Average Index to returns in simulated series derived from four null models namely the "Random walk, the AR(1)., E-Garch and GARCH-M ". According to them returns derived from buy and sell signals could not be produced with the aid of these popular null models. They find that there are considerable more buying signals than selling signals in examined period. They observethat buy signals tend to generate higher returns when compared with returns generated after selling signals and also found buy returns less volatile than sell returns. They observed that GARCH-M model proved fail to predict returns and also in predicting volatility. Important conclusion is that trade strategies could be workable. Sullivan et al. (1999) in his study started from 1986 where Brock et al. (1992) work ends. He point out that Brock et al. (1992) results are robust to data snooping in examined period of 1896-1986 and he observed that in period 1987-1987 the results of most popular technique are not significant when returns are adjusted to data snooping. They envisage many possible reasons for that like increase in market efficiency on account of lower trading cost, increased level of liquidity and unknown factors of models. Kho (1996) analyzes number of double crossover moving average rule on DEM, SF, BP and JPY future contracts by obtaining weekly data that were traded on IMM for period 1980 to 1991. Results indicate that moving averages rule offer prolific opportunities to be utilized. He reveals that profits measured are enough high to exceed transaction costs and could not be explained solely by serial correlation in returns or models like GARCH-M model. He further introduces a conditional CAPM model that takes into account time-varying price of risk.

Speaking for non linear specification, for instance, the feed forward networks, Gencay (1997; 1998a; 1998b; 1999c) and linear specification examined by conditional mean estimator by employing popular linear null models which were simple autoregressive and GARCH-M. By using simple moving average rule which yields buy and sell returns, he provided the evidence of nonlinear predictability of return series. He documents that nonlinearities in return series of a stock appeared to be very important in forming of conditional mean. Metghalchi, et al. (2009) examines two trading rules for four Asian markets namely South Korea, Singapore, Taiwan and Hong Kong. They observe that moving average rule is profitable and have predictive power concerning price patterns. They put that trading rules can be fruitful to plan a trading strategy that has capacity to outperform buying and hold strategy for all given markets.

In notable study Ahmed et al. (2005) document the profitability of moving average rule in currency markets. They compare the profitability of four Variable Length Moving Average (VMA) rules with buy and hold strategy. The results strongly support the profitability of technical trading rules and implied a serial correlation in return series. They end up with the suggestion that these trading rules can be used as risk management tools where risk management tools are not active in developing markets. Furthermore, Studies conducted in developed countries scenario notably, by Tabell (1964), Treynor and Ferguson (1985), Jegadeesh and Titman (1993), Brown and Jennings (1989) , Blume, et al. (1994), Chan et al. (1996), Lo and MacKinlay (1997) ,Grundy and Martin (1998), and Rouwenhorst (1998) have also given indirect support for technical analysis techniques, and added direct support has been set by Pruitt and White (1988), Neftci (1991), Neely et al. (1997;1998), Chang and Osler (1994;1995), and Allen et al. (1999).

Although , this work is supposed to touch those concepts which are long date back to academic literature. But this work puts fresh insights in variety of ways. This work undertake on those capital markets which termed themselves as developing countries' capital markets. This work presents a opportunity to make comparison these markets under statistical guidance. Speaking for the technical trading rules , a variety of fresh insights have been ensured . No earlier attempt has been made to examine the profitabilty of technical trading rules for given countries . Generally speaking, no earlier work has been witnessed to compare simple moving averages with exponential moving averages. In trading range breakout rule ,latest developments at professional place have been incorporated to yield results. Hypothesis implies that returns should be irrelevant to market patterns and trends, when returns are classified on the basis of buying and selling signals.

3. Data And Methodology

SAARC representative capital markets are Karachi Stock Exchange, Bombay stock Exchange, Colombo Stock Exchange and Dhaka Stock Exchange for Pakistan, India, Srilanka and Bangladesh respectively. All daily closing prices ranging from 1997-2011(divided in three periods) are gathered from yahoo finance except for Dhaka Stock Exchange. DSE prices are taken from its official website land its publications.

$$R_t = \ln (P_t / P_{t-1}) \qquad (1)$$

Where Pt = Market price at time't', Pt-1 = Market price at time't-1'

In this work two of the most widely used technical trading strategies or rules have been examined: moving average rule and trading range break out also known as resistance and support levels. Moving averages rule entails the computation of a moving average implied on price data. Moving averages are also known as running means or rolling averages (Massoud et al ,2009). According to Achelis (1995) buy and selling signals are produced by employing two moving averages of some index under study- short period and long period. A buying signal is generated whenever moving average of short term exceeds moving average of long term and sell signal is generated when moving average of long period exceeds moving average of short.

3.1 Simple Moving Average

This technical analysis procedure aims at to give a decision rule pertaining to the proper investment situation. For instance speaking for popular moving average rule i.e. 1-200, where 1 presents the short term period which is 1 day and 200 is long term moving average. Average for both periods is calculated again and again for every coming time by reducing the most previous data and including the latest fresh data. So with this, the average travels with its data and does not swing majorly. Brock et al (1992) use following equations to calculate short term and long term moving averages

$$M_{t,n} = \frac{1}{n}\sum_{i=t-n+1}^{t} C_i \qquad = \left(C_t + C_{t-1} + \ldots + C_{t-n+2} + C_{t-n+1}\right)/\, n$$

Where $M_{t,n}$ is simple n-day moving average at period t and C_i denotes closing price for period i. According to Brock et al (1992) there are various variations of this rule practised in professional place, we have selected some of the most popular ones: 5-50,1-200,2-200, 5-150, 1-50. They further note that moving average rule is often influenced by introducing a band around the moving average to safe from false signals.

Ahmed (2005) envisage Variable length moving average and Fixed lengthmoving average. Speaking for variable length moving average (VMA), this method give birth to a strategy where traders go long as long as short moving average above the long moving average, for opposite case they go short. This method categorizes all days into either sells or buys if we introduce no brand. Now speaking for Fixed length moving average (FMA), which emphsis that after some crossover ,returns of following days should be different from other normal trading days. So under this strategy guidance , we first record signals than we calculate the returns of next ten days . Ten days returns correspond to two week returns , though selection of ten days can be changed. Other signals occuring during these periods are ignored. We will perform above said strategies : VMA and FMA with and without band.

3.2 Exponential Moving Average

There exist numerous approaches to capture the same trading rule. For example, lagged moving averages, lagged line moving averages, line weighted moving averages, centered moving averages and exponential moving average. Metghalchi (2005) provided that Exponential Moving Averages (also known as exponentially weighted moving average) puts weighting factors which eventually decrease in exponentially manner. Exponential moving averages decrease the lag by putting more weight to recent prices as compared to older prices. Put it differently, the more weight that will be applied to the most recent price. It gives more weight to recent prices so that the calculations can be improvised with respect to prices and previous dates. The Exponential moving average for a series Y is calculated as S1 = Y1 where

$$t > 1 \quad S_t t = \alpha \times Y_t - 1 + (1 - \alpha) \qquad (2)$$

The coefficient α denotes the extent of weighting decline, i.e. a stable smoothing aspect between 0 and 1. A superior α discounts previous observations at faster rate, on the other hand, α can be conveyed in terms of N time periods, where α = 2/ (N+1).

$$S_t = \alpha \times (Y_t - 1 + (1-\alpha) \times Y_t - 2 + (1-\alpha)2 \times Y_t - 3 + \cdots + (1-\alpha)k \times Y_t - (k + 1) + (1-\alpha)k + 1 \tag{3}$$

Y t is the observation at a time period t. St is the p value of them and EMA at any time period t. The above formulation is with reference to Hunter (1986). By frequent appliance of same formula for diverse periods, we can finally engrave S t as a weighted addition of data points Y_t, An alternate approach by Roberts (1999) uses y_t in lieu of Y_{t-1}

$$S_{t\ alternative} = \quad \alpha \times Y_t + (1-\alpha) \times S_t - 1 \tag{4}$$

$$EMA_{today} = \alpha + \alpha \times (price_{today} - EMA_{yesterday}) \tag{5}$$

Expanding out Exponential Moving Average each time results in the following power series, showing how the weighting factor on each data point p_1, p_2, etc., decreases exponentially

$$EMA = \alpha \times (p_1 + (1-\alpha)p_2 + (1-\alpha)^2 p_3 + (1-\alpha)^3\, p_4 + \ \ldots.) \tag{6}$$

$$EMA = \frac{\alpha \times (p_1 + (1-\alpha)p_2 + (1-\alpha)^2 p_3 + (1-\alpha)^3\, p_4 + \ldots.}{1 + (1-\alpha) + (1-\alpha)^2 + (1-\alpha)^3 + \cdots} \tag{7}$$

This is an infinite sum with decreasing terms. The N periods in an N-day Exponential Moving Average only identify the factor. N is not a stopping point for the calculation in the way it is in an Simple Moving Average or Weighted Moving Average.

$$\frac{\alpha \times (1 + (1-\alpha) + (1-\alpha)^2 + \cdots + (1-\alpha)^N}{\alpha \times (1 + (1-\alpha) + (1-\alpha)^2 + \cdots + (1-\alpha)^\infty} = 1\text{-}(1\, \frac{2}{(N+1}))^{N+1} \tag{8}$$

$$\frac{lim}{N \to \infty}(1 - \left(1 - \frac{2}{(N+1)}\right)^{N+1}$$

We have chosen Roberts (1999) approach for its close association with computing averages at professional place. Above stated formula gives a starting value for a day, after which the consecutive day's formula given first can be functional. The question of how far back to go for a first value depends, in the worst case, on the data. Large price values in old data will bring effect on the total even if their weighting is very little. If prices have small variations then just the weighting can be considered.

3.3 Trading Range Break Out (Resistance and Support Level)

Brock et al (1992) called Resistance and Support Level, local maximum and local minimum respectively. Resistance can be defined in number of ways as witnessed in professional technical trading literature, so meeting the soul of definition this is defined in this work as the highest price or price trend at which a stock is trading at present in its trading range; the price that buyers believe the highest valuable price. Resistance occurs when the price of a stock stops going up. This is a level where sellers are expected to come into the market in sufficient numbers to stop further increases in prices, and also a level where the buying interest has/should decreased considerably. Resistance levels happen when the consensus is built that the price will not move higher. Brock et al (1992) went on saying that on the contrary, Support levels specify the price where the greater part of investors considers that prices will move higher. Speaking roughly, this indicates the floor price. Ahmed (2005) observed that Technical traders assume a buying signal when price penetrates the resistance level. In similar lines, a selling signal is generated when price penetrates the support level.

There are various methods of selecting support and resistance exist criteria. For example, Horizontal Price Levels, Trend Lines Moving Averages, Fibonacci Retracement Levels, Round Numbers too, pivot point criteria, Pivot point camarilla's, Pivot points demark, Pivot point Woodiee (Ready, 2003). But pivot point camarilla's method has been employed to determine the support and resistance points in examined period for its adaptation in professional place. This gives four resistance and support levels, where emphasis is given to L3, L4, H3 and H4. Following formulas parallel with Crock (2007) study, have been employed to gauge support and resistance levels with pivot point camarilla's method

R4 = C + RANGE * 1.1/2
R3 = C + RANGE * 1.1/4
R2 = C + RANGE * 1.1/6
R1 = C + RANGE * 1.1/12
PP = (HIGH + LOW + CLOSE)/ 3
S1 = C - RANGE * 1.1/12
S2 = C - RANGE * 1.1/6
S3 = C - RANGE * 1.1/4
S4 = C - RANGE * 1.1/2

There are various varitions of this rule practised in professional place but spirit underlying trading strategy is ensured.

4. Empirical Results

4.1 Results for Variable Length Simple Moving Average (SVMA) Rule

Results for Variable Length Simple Moving Average (VSMA) Rule for all four said indices have been presented in Table1. Different rules covering different periods have been examined to test the validity of technical trading rule. In following table pertain to KSE; there are 11 columns with period as first column and buying returns-selling returns as 11 columns Table 1. For first rule (5,50,.01) , 5 presents short term moving average, 50 presents long term moving average, and .01 is the band which is percentage difference that is required to generate signal. N.Buys denotes total number of buying signals that are generated during examined period.

B.M.Return and S.M.Return presents Buying Mean Returns and Selling Mean Returns respectively, which are calculated by taking average of either said returns for the examined period. Buying days and selling days are those days in which buying signals and sellings signal remain intact. Further, A.B.M.Return and A.S.M.Return present Average Buy Mean Returns and Average Selling Mean Returns respectively, by taking average of all Buying Mean Returns and Selling Mean Returns for each rule. BR-SR is the difference of Average Buy Mean Returns and Average Selling Mean Returns respectively. All buy returns found positive and all selling returns found negative for all examined rules. Total average number of buying and selling signals was 38 for each category, with having 0.00151 and -0.00119 average buying and selling returns respectively. This can also be interpreted as 0.4537 percent and -0.3587 Annual Effective Rate, where, speaking for KSE-INDEX, 0.00055 is one day-unconditional average return and 0.1665 per cent is Annual Effective Rate for whole examined period. Total number of buying days found greater than selling days for all examined rules. To sum up, when returns are classified on the basis of buying and selling signals, buying signals found with followed average positive returns and opposite is observed for selling signals.

In Table 2, observations of BSE have been presented. All buy returns found positive and all selling returns found negative for all examined rules. Total average number of buying and selling signals was 39 and 40 respectively, having 0.00140,-0.00102 average buying and selling returns respectively. This can also be interpreted as 0.4220 percent and -0.30837 percent buying and selling average Annual Effective Rate, where, speaking for BSE INDEX, 0.00041 is one day-unconditional average return and 0.1236 is Annual Effective Rate for whole examined period. Total number of buying days found greater than selling days for all examined rules.

In Table 3, observations of CSE have been documented. All buy returns found positive and all selling returns found negative for all examined rules except for period 2002-2006 where rules show some variation. Total average number of buying and selling signals was 33 and 34 respectively, having 0.00194,-0.00125 average buying and selling returns respectively. This can also be interpreted as 0.5826 per cent and , -0.345348 per cent buying and selling average Annual Effective Rates, where, speaking for CSE INDEX, 0.00062 is one day-unconditional average return and 0.1863 is Annual Effective Rate for whole examined period. Total number of buying days found greater than selling days for all examined rules.

In Table 4, observations of DSE have been given. All buy returns found positive and all selling returns found negative for all examined rules. Total average number of buying and selling signals was 32 and 31 respectively, having 0.00161,-0.002573 average buying and selling returns respectively. This can also be interpreted as 0.483000 per cent and , -0.35348 per cent buying and selling average Annual Effective Rates, where, speaking for DSE INDEX, 0.00052 is one day-unconditional average return and 0.1663 is Annual Effective Rate for whole examined period. Total number of buying days found greater than selling days for all examined rules.

4.2. Results for Variable Length Exponential Moving Average

The results of simple Exponential Moving Average have been documented in table.2. For all four indices where different rules covering different periods have been examined to check the validity of technical trading rule.

Speaking for Exponential Moving Average for KSE, all buy returns found positive and all selling returns found negative for all examined rules. Total average number of buying and selling signals reported was 49 for each category, with having 0.001961 and -0.002006 average buying and selling returns respectively. To understand this in terms of Annual Effective Rate, 0.5884,-0.6017 per cents are Annual Effective Rates for buying and selling returns respectively, where, speaking for KSE-INDEX, 0.00055 is one day-unconditional average return and 0.1665 percent is Annual Effective Rate for whole examined period. Exponential Moving Average method reported greater signals, greater buying returns, less selling returns and consequently more ERT, when compared with simple moving average. Speaking for hypothesis, this implies that returns should be irrelevant to market patterns and trends, when returns are classified on the basis of buying and selling signals, buying signals found with followed average positive returns and opposite is observed for selling signals. Therefore, Hypothesis is rejected for KSE-INDEX.see Table 5

In Table 6, observations of BSE have been presented. All buy returns found positive and all selling returns found negative for all examined rules. Total average number of buying and selling signals was 48 and 49 respectively, having 0.001699,-0.001453 average buying and selling returns respectively. To understand this in terms of Annual Effective Rate, 0.5095,-0.4357 per cents are Annual Effective Rates for buying and selling returns respectively, where, speaking for BSE-INDEX, 0.0041 is one day-unconditional average return and 0.1236 per cent is Annual Effective Rate for whole examined period. Exponential Moving Average method generated greater signals, greater buying returns, less selling returns and consequently greater ERT for buying returns, when an effort is made to compare with simple moving average. Speaking for stipulated hypothesis, this implies that returns should be irrelevant to market patterns and trends, when returns are classified on the basis of buying and selling signals, buying signals found with followed average positive returns and opposite is observed for selling signals.

In Table 7, observations of CSE have been presented. All buy returns found positive and all selling returns found negative for all examined rules. Total average number of buying and selling signals was 39 for each category, having 0.002177,-0.001493 average buying and selling returns respectively. To understand this in terms of Annual Effective Rate, 0.6531,-0.4479per cents are Annual Effective Rates for buying and selling returns respectively, where, speaking for CSE INDEX, 0.00062 is one day-unconditional average return and 0.1863 is Annual Effective Rate for whole examined period. Therefore, Hypothesis is rejected.

In Table 8, observations of DSE have been documented. Total average number of buying and selling signals was 38 and 39 for both categories, having 0.001986,-0.00156 average buying and selling returns respectively. To understand this in terms of Annual Effective Rate, 0.5431,-

0.4179 per cents are Annual Effective Rates for buying and selling returns respectively, where, 0.00052 is one day-unconditional average return and 0.1663 for whole examined period. Total number of buying days found greater than selling days for all examined rules. Rule (1,50) documents largest number of buying and selling signals. When an effort is made to compare with Simple Moving Average ,in this method, Exponential Moving Average generated greater signals, greater buying returns, less selling returns and consequently greater ERT for buying returns, greater buying return minus selling return,. So in parallel with above hypothesis, the hypothesis that trading strategies cannot be consistent profitable is rejected on above grounds.

4.3. Results for Fixed –Length Simple Moving Average

In this method, we generate signals by adopting same procedure done in Variable Length Simple Moving average Method. But now we only take into account 10 days returns, after buying and selling signals that are generated by crossing of averages. All signals during these 10 days are ignored. This is meant to capturing most recent returns, after any signal is generated. Here we cannot classify all days into either buying days or selling days. Results for Fixed Length Simple Moving Average (VSMA) Rule for all four said indices have been presented in Table 3.

Speaking for KSE, all buy returns found positive and all selling returns found negative for all examined rules. For the number of signals and type, this cannot be safely said. The size of number of signals varies significantly for different rule. Note worthy observation is that, average mean return of 10 days is much improved when we fix 10 days return after some crossover of averages. For Variable Length Simple Moving Average, 0.00151 and -0.00119 are average buying and selling returns respectively. But when we fix 10 days after crossover of short term and long term averages, 0.001961and -0.002006 are new averages of the returns buying and selling returns respectively. The difference between BR-SR is improved, which is 0.00396 against 0.002708 in case of Variable Length Simple Moving Average. So we reject our hypothesis that there can be no indication of predictability of returns see Table 9.

In case of BSE, all buy returns found positive and all selling returns found negative for all examined rules. For the number of signals and type, selling signals found greater than buying signals. But the size of number of signals varies significantly for different rule. Average mean return of 10 days is much improved when we fix 10 days return after some crossover of averages. For Variable Length Simple Moving Average, 0.001407 and -0.001028 are average buying and selling returns respectively. But when we fix 10 days after crossover of short term and long term averages, 0.004386,-0.006382 are new averages of the returns buying and selling returns respectively. The difference between BR-SR is improved, which is 0.01768 against 0.00396 in case of Variable Length Simple Moving Average. So we can safely reject our hypothesis that there can be no indication of predictability of returns in presence of patterns see Table 10.

In case of CSE, all buy returns also found positive and all selling returns found negative for all examined rules. For the number of signals and type, selling signals found lesser than buying signals (see Table 11). For Variable Length Simple Moving Average, 0.00217 and -0.00149 are average buying and selling returns respectively. But when we fix 10 days after crossover of short term and long term averages, 0.005107,-0.003380 are new averages of the returns buying and selling returns respectively. The difference between BR-SR is improved, which is 0.008487 against 0.003670 in case of Variable Length Simple Moving Average.

In case of DSE, all buy returns also found positive and all selling returns found negative for all examined rules. For the number of signals and type, selling signals found lesser than buying signals (see Table 12). So we can safely reject our hypothesis that there can be no indication of predictability of returns in presence of patterns.

4.4. Results for Fixed –Length Exponential Moving Average

The results of simple Exponential Moving Average have been documented in table 4. Same procedures have been adapted to generate signals. But Exponential Moving Average has been employed, to generate signals and to capture 10 day returns, in response to crossover of short term and long term moving averages.

The results of KSE have been given in Table 13. There were average 23 buying signals for both categories. Note worthy observation is that, average mean return of 10 days is much improved when we fix 10 days return after some crossover of averages. For Variable Length Exponential Moving Average, 0.001961 and 0.001961 are average buying and selling returns respectively. But when we set 10 days after crossover of short term and long term averages, 0.005250 and -0.005270 are new averages of buying and selling returns respectively. The difference between BR-SR is improved, which is 0.01051 against 0.003967 in case of Variable Length Exponential Moving Average. So this leads us to reject our hypothesis that there can be no indication of predictability of returns in presence of patterns.

The observations of BSE have been given in Table 14. There were average 23 buying signals and 21 selling average signals derived from all rules. Earlier we observed that, average mean return of 10 days is much improved when we fix 10 days return after some crossover of averages. For Variable Length Exponential Moving Average, 0.001699 and -0.001453 are average buying and selling returns respectively. But when we set 10 days after crossover of short term and long term averages, 0.003828 and -0.004826 are new averages of buying and selling returns respectively. The difference between BR-SR is improved, which is 0.008628 against 0.003151 in case of Variable Length Exponential Moving Average. This leads us to reject our hypothesis.

The observations of CSE have been given in Table 15. All buy returns found positive and all selling returns found negative for all examined rules. There were average 20 signals for each category. Earlier we noted that, average mean return of 10 days is much improved when we fix 10 days return after some crossover of averages. For Variable Length Exponential Moving Average, 0.002177and -0.001493 were average buying and selling returns respectively. But when we set 10 days after crossover of short term and long term averages, 0.005128 and -0.003328, average are new averages of buying and selling returns respectively. The difference between BR-SR is improved, which is 0.008455 against 0.003670 in case of Variable Length Exponential Moving Average.

The observations of DSE have been given in Table 16. All buy returns found positive and all selling returns found negative for all examined rules. There were average 22 signals for buying returns and 21 selling signals. Earlier we noted that, average mean return of 10 days is much improved when we fix 10 days return after some crossover of averages. For Variable Length Exponential Moving Average, 0.001677and -0.001359 were average buying and selling returns respectively. But when we set 10 days after crossover of short term and long term averages, 0.003128 and -0.003428, averages are new averages of buying and selling returns respectively. The difference between BR-SR is improved, which is 0.006435 against 0.001640 in case of Variable Length Exponential Moving Average. In case of Variable Length Simple Moving Average, 0.00117 and -0.00129 were average buying and selling returns respectively. So this can be observed when we employ Fixed Variable Length Exponential moving average, this documents greatest buying returns and least selling returns. Speaking for hypothesis involved, above mentioned observations leads us to reject our hypothesis that there can be no indication of predictability of returns in presence of patterns.

4.5. Results for Trading Range Break

Results of trading range break have been given in table 5 for all four indices where different rules covering different periods have been examined to check the validity of technical trading rule. We earlier mentioned that this strategy generates signal when prices penetrates resistance and support levels. To test this strategy two rules have been employed. For determination of returns Fixed Variable Length Rule has been employed because in this rule this is not possible to identify all days as buying or selling.

Documenting the observations for KSE Table 17, total average of 26 buying signals was observed against 16 average selling signals. So there are buying signals in greater strength. All average buying returns turned out positive and all average selling returns turned out to be negative. Average buying returns found .00309 and average selling returns observed -.00469. though all average mean buying returns turned out to be positive and all average selling returns turned out to be negative, but at places buy mean returns varies for different periods. The difference of average mean buying returns and average mean selling returns were .00777. So this leads to reject our hypothesis.

The observations of BSE have been given in Table 18 All buy returns found positive and all selling returns found negative for all examined rules. There were average 27 buying signals and 26 selling average signals derived from all rules. Rule (1,100) gives the maximum signals and other rule gives lower signals. Average buying returns found .00309 and average selling returns observed -.00469. though all average mean buying returns turned out to be positive and all average selling returns turned out to be negative, but at places buy mean returns varies for different periods. The difference of average mean buying returns and average mean selling returns were .00777. So this leads to reject our hypothesis that myth of seasonality effect cannot be rejected.

The observations of CSE have been given in Table 19. Consistent with previous observations all buy returns found positive and all selling returns found negative for all examined rules. There were average 25 buying signals and 18 selling average signals derived from all rules. Rule (1,100) gives the maximum signals of selling while other rule gives maximum buying signals. Average buying returns found .004260 and on the other hand average selling returns observed -.001544. The difference of average mean buying returns and average mean selling returns found to be .001797.So we can reject our hypothesis that there exist no patterns or trends in a market. Intriguing result found in case of Fixed Variable Length Rule, when we set 10 days after crossover of short term and long term averages, 0.00512 and -0.00332 were averages of buying and selling returns respectively, which are greater than trading range break strategy.

The observations of DSE have been documented in Table 20. There were average 25 buying signals and 22 selling average signals derived from all rules. Rule (1,100) gives the maximum signals of buying while other rule gives maximum selling signals. Average buying returns found .004535 and on the other hand average selling returns observed -.001763. The difference of average mean buying returns and average mean selling returns were .006297. So parallel with above observations, we can reject our hypothesis that there exist no patterns or trends in a market. Intriguing result found in case of Fixed Variable Length Rule, when we set 10 days after crossover of short term and long term averages, 0.00512 and -0.00332 were averages of buying and selling returns respectively, which are greater than trading range break strategy.

5. Conclusion and Discussion

To examine the profitability of technical trading strategies, we employed two very popular and widely used rules: Moving Averages and Trading Range Break. Moving Averages strategy was examined with simple and exponential averages. Two methods were adopted in Moving Averages rule. Firstly, we examined the whole returns called Variable Length Moving Average rule, and secondly fixed ten days returns followed by a signal called Fixed Length Moving Average rule. Trading Range Break strategy was observed with Fixed Length Moving Average rule. We have engendered various null hypotheses revolving around Efficient Market Hypothesis. Speaking for seasonality's effects which run against Efficient Market Hypothesis, and in given scenario, our primary-focused null hypothesis was that there cannot be persistent trends and patterns in a given market. Technical analysis inspires from the belief that there exist persistent patterns and trends that investor can utilized to earn above average returns. The results of technical trading rules are as follow

Overall our results of technical trading rules provide strong support for the technical trading strategies. Our results found that buy signals generate consistent above average returns for the all sub periods and sell signals generate lower returns than the normal returns. Or put it differently, buy returns generate higher returns than the one day unconditional return. Intriguing observation was that Exponential average generates higher returns than the Simple Average and on the other side; Exponential average gives lower returns than the Simple Average method.

It was found that rules with lower days generate much higher return than the rules with higher number of days. Induction of band although, reduced the number of signals but average buying return and selling return do not vary very significantly. There was consistent large number of buying days than the selling days except for first sub period sample were capital markets found to be its initiation age. Buy returns in second sub sample found to be highest were rapid growth was observed in all capital markets.

It was also found that 10 day fixed returns give an average of 1.5 per cent more predictability while comparing with VMA. CSE gives highest average return, when returns were derived from technical rules. Trading Range Break strategy does not give higher average higher return when this was compared with Moving Averages Rules. And degree of volatility in returns is higher when compared with moving Average rule. Though this is suggested that to take lower days while determining the support and resistance levels. Findings of this work also do second this proposition, and speaking for our findings, buy returns found less volatile in both methods of VMA and FMA when compared with sell returns.

This indicates that there exists utility for technical analysis, availability of arbitrage profit and opportunities for investment management by diversification of portfolios across the markets. Finally speaking for the constraints of study, gross returns have been provided rather net profits and data snooping tests have not been incorporated assuming that scope of study is reasonably wide .

6. Bibliography

Achelis, S. (1995). *Technical Analysis from A to Z.* New York: McGraw-Hill.

Allen, H. L. (1990). Charts, noise and fundamentals in the London foreign exchange market. *Economic Journal, 100*, 49-59.

ARONSON, D. R. (2006). *Evidence-Based Technical Analysis: Applying the Scientific Method and Statistical Inference to Trading Signals.* Hoboken: NJ:Wiley.

Bessembinder, H. C. (1995). The profitability of technical trading strategies in the Asian stock markets. *Pacific-Basin Finance Journal, 3*, 257-284.

Brock W., L. J. (1992). Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *Journal of Finance, 47*, 1731-1764.

Brock, W. L. (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance, 47*, 1731–1764.

Brooks, C. (2004). *Introductory econometrics for finance.* Cambridge: Cambridge University Press.

Caginalp, G. A (2003). A Theoretical Foundation for Technical Analysis. *journal of Technical Analysis*, 5-21.

Campbell J.Y., L. A. (1997). *The Econometrics of Financial Markets.* New Jersey: Princeton University Press.

CESARI, R. a. (2003). Benchmarking, Portfolio Insurance and Technical Analysis: A Monte Carlo Comparison of Dynamic Strategies of Asset Allocation. *Journal of Economic Dynamics and Control, 27* (6), 987–1011.

Choudhry, T. (1994). Stochastic trends and stock prices: an international inquiry. *Applied Financial Economics, 4*, 383-390.

Cowles. (1993). Can Stock Market Forecasters Forecast? *Econometrica, 1*, 309-324.

Dickinson, J. P. (1994). Market Efficiency in Developing Countries. *Journal of Business Finance & Accounting , 21*, 133–150.

Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Business, 39*, 226-241.

Fama, E. F. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics, 22*, 3-25.

Fama, E. (1965a). The behavior of stock market prices. *Journal of Business, 38*, 34-105.

Gencay, R. (1998). The predictability of security returns with simple technical trading rules. *Journal of Empirical Finance, 5*, 347–359.

Hansen, P. (2005). A Test for Superior Predictive Ability. *Journal of Business and Economic Statistics, 23*, 365-380.

Hassan, S. a. (2007). Testing of Random Walks and Efficiency in an Emerging Market. *The Business Review Cambridge, 9*.

Jagadeesh, N. (1990). Evidence of Predictable Behavior of Security returns. *Journal of Finance, 45*, 881–908.

K., B. Hoom. (1995). The Profitability of Technical Trading Rules in the Asian Stock Markets. *Pacific-Basin Finance Journal , 3*, 257-284.

Kho, B. (1997). Time-varying risk premia, volatility, and technical trading rule profits:Evidence from foreign currency futures markets. *Journal of Financial Economics, 41*, 249-290.

Lakonishok, J. a. (1988). Are Seasonal Anomalies Real? A Ninety Year Perspective. *Review of Financial Studies, 1*, 402–425.

Lakonishok, J. S. (1998). Are Seasonal Anomalies Real? A Ninety Year Perspective. *Review of Financial Studies, 1*, 402–425.

LeBaron, B. (1998). *An evolutionary bootstrap method for selecting dynamic trading strategies.In Decision Technologies for Computational Finance.* Amsterdam: Kluwer Academic Publishers.

LeBaron, B. (1990's). Technical Trading Profitability in Foreign Exchange Markets in the 1990's. *Brandeis University*, working paper.

Lo, A. M. (1997). Maximizing predictability in the stock and bond markets. *Macroeconomic Dynamics, 1*, 102-134.

M, Red. (2002). Profits from Technical Trading Rules. *Financial Management*, 43-61.

Malkiel, B. G. (2003). The Efficient Market Hypothesis and Its Critics. *Princeton University*, CEPS Working Paper No. 91.

Massoud Metghalchi, J. D. (2009). Validation of Moving Average Trading Rules: Evidence From Hong Kong, Singapore, South Korea, Taiwan. *Multinational Business Review, 17* (3), 101 - 122.

Metghalchi, M. Y. (2008). Is the Swedish Stock Market Efficient? Evidence From Some Simple Trading Rules. *International Review of Financial Analysis, 17*, 475-490.

MURPHY, . J. (1999). *Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications.* New York: New York Institute of Finance.

Park (2004). The Profitability of Technical Analysis: A Review. *AgMAS Project Research Reports*.

Parvez Ahmed, K. B.(2005). Moving average technical trading strategies for currencies of emerging economies. *Managerial Finance, 31* (5), 14 - 27.

Pesaran, M. T. (1995). Predictability of Stock Returns: Robustness and Economic Signficance. *The Journal of Finance, 50*, 1201-1228.

R, Gardon. (1998a). Optimization of Technical Trading Strategies and Profitability in Security Markets. *Economics Letters, 59* (2), 249-254.

R, K. Kalov. (2002). Technical Trading Strategies and Return Predictability: NYSE. *Applied Financial Economics, 12*, 639-653.

R, P. Sajeev. (1998). The CRISMA Trading System: Who Says Technical Analysis Can't Beat the Market. *Journal of Portfolio Management, 14*, 55-58.

Ready, M. (1997). Profits from Technical Trading Rules, working paper. *University of Wisconsin-Madison* .

Reilly, F. A. (2003). *Investment Analysis and Portfolio Management* (7 ed.). Mason, Ohio: South-Western: Thomson.

Samuelson, P. (1965). Proof that Properly Anticipated Prices Fluctuate Randomly,. *Industrial Management Review, 6*, 41-49.

Table 1.

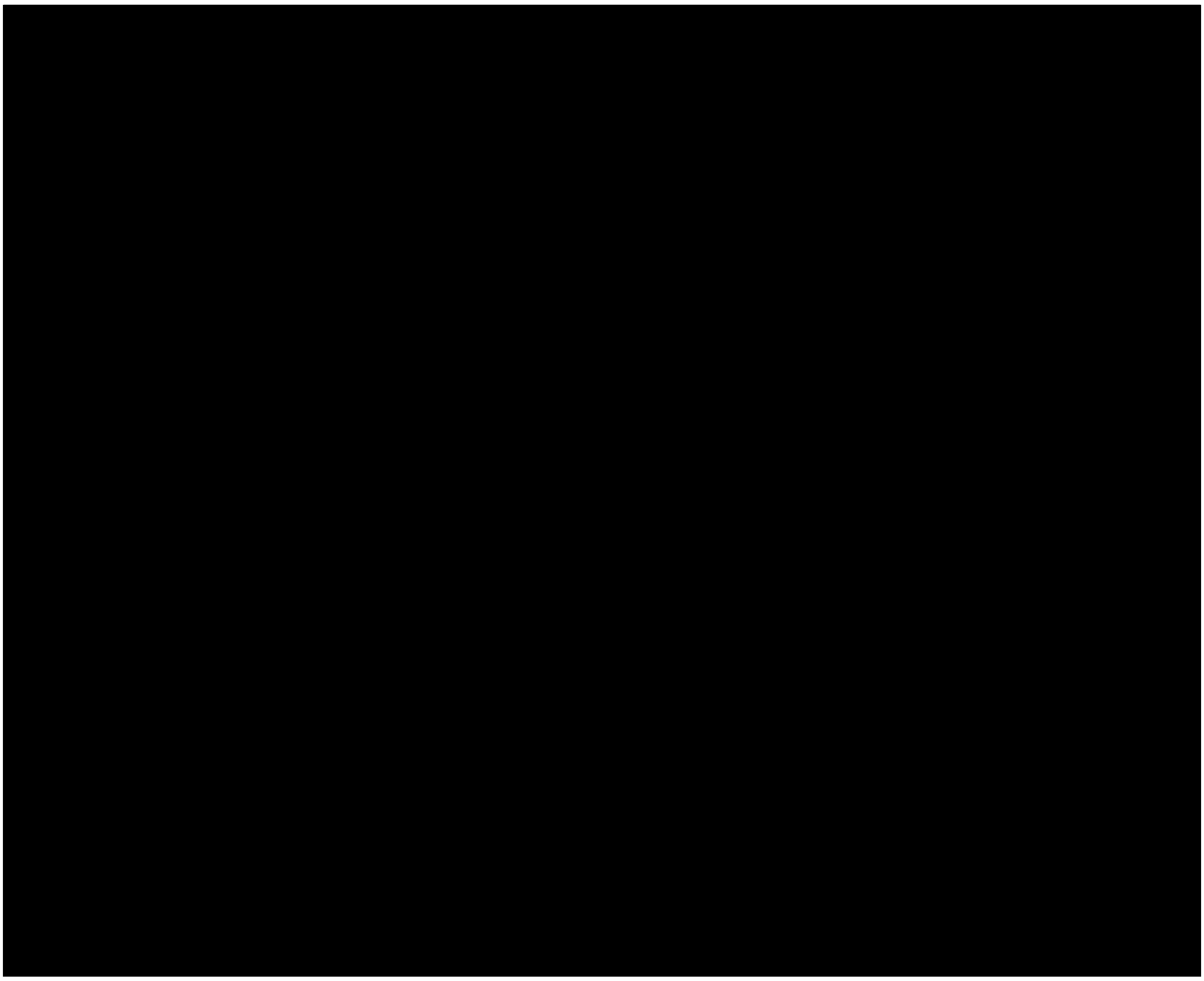

Table 2

[redacted]

Table 3

[redacted]

Table 4

[redacted]

Table 5

[redacted]

Table 6

[redacted]

Table 7

[redacted]

Table 8

[redacted]

Table 9

[redacted]

Table 10

[redacted]

Table 11

[redacted]

Table 12

[redacted]

Table 13

[redacted]

Table 14

[redacted]

Table 15

[redacted]

Table 16

[redacted]

Table 17

[redacted]

Table 18

[redacted]

Table 19

[redacted]

Table 20

[redacted]