Performance of Technical Analysis: A Review of Literature

Dr. Refaat Mohamed Elsagheer Ahmed(*)

ABSTRACT

The purpose of this study is to review the evidence on the performance of technical analysis. To achieve this purpose, the study reviews the important indicators of technical analysis, the main reasons for performance differences in emerging markets and in various studies as a whole, comprehensively reviews survey, theoretical and empirical studies regarding technical trading strategies. The study has investigate the correction of the hypothesis of the study where, the performance of technical analysis is differ owing to theoretical base, tools of the test procedure, data type, data periods, transaction costs, market type and lastly, the studied market considered.

Keywords: Technical analysis indicators, Finance and behavioral theory, efficient market hypothesis, early and modern empirical Studies.

Introduction:

Technical analysis, also known as "charting", has been a part of financial practice for many decades, Lo ct at, (2000). Ft is considered by many to be the original form of investment analysis, dating back to the 1800s (.Japanese Candlestick) Brock et al., (1992). As opposed to fundamental analysis, which is the study of economic, industry, and company conditions in an effort to determine the intrinsic value of a company´ stock (Cutler et al., 1989).

Whereas technical analysis is the study of past market information such as price, volume and open interest, primarily through the use of charts, to forecast future price trends. The security under study can be a stock, future, index, foreign exchange and any other thing traded in the financial market.

Technicians believe that the market price reflects anything that can possibly affect the price. They also believe that securities move in trends. These trends continue until something happens to change them. Until a trend ends, the future prices are detectable from past information of price and volume, it is not necessary to know the fundamental factors that affect the price of a security, such as a company's financial performance and its market condition.

Over the past twenty years or so, international financial economists have increasingly turned their attention to the study of technical analysis in an attempt to understand both the behavior of foreign exchange market participants; so much so, in fact, that quite an extensive literature has developed on this topic.

(*)A teacher of economics in the high institute of management and computer sciences in New Cairo.

Technical analysis includes a variety of forecasting techniques such as chart analysis, pattern recognition analysis, seasonality and cycle analysis, and computerized technical trading systems.

Previous efforts have been made to investigate the performance of technical analysis, but conclusions differ. Although the issue remains unsolved, it is undeniable that technical analysis has been widely adopted among institutional and individual traders, so the popularity of technical analysis, regardless of its true profitability, will have an impact on markets.

A. Problem of the study

While much of the existing literature seeks to provide analytical solutions or empirical evidence concerning the validity of technical analysis as an investment tool, it is only until recent years that studies concerning its market impact have started to emerge. On the empirical side, the investigation on its market impact has been largely impeded by alack of appropriate data, and perhaps more importantly, by the difficulty in correctly identifying the underlying attributes of market phenomena.

The efficient market hypothesis (EMH) has been the key proposition of traditional (neoclassical) finance for almost forty years. From the beginning of the 1980s, and more and more in the 1990s, new empirical studies of security prices have reversed some of the earlier evidence favoring the EMH. The traditional finance school named these observations anomalies, because they could not be explained in the neoclassical framework. In the response to a growing number of puzzles, a new approach to financial markets has emerged - behavioral finance. It focuses on investors[1] behavior and the decision making process. In the contrary to the classical paradigm, behavioral finance assumes that agents may be irrational in their reactions to new information and make wrong in investment decisions. As a result, markets will not always be efficient and asset pricing may deviate from predictions of traditional market models, and the performance of technical analysis will differ.

In 2008 the world economy encountered a global financial crisis, caused by a mix of a global asset price bubble, overwhelming irrational exuberance and systemic mistakes of economic agents and financial market participants. Against this background, the standard financial theory, based on the efficient market hypothesis and rational representative agent paradigm, seems to be losing touch with reality. Unfortunately, there are no satisfactory alternatives yet, but with growing computing power, modeling possibilities expand and new promising frontiers of research emerge, the performance well be captured.

So we can limit the problem of the study in the following questions:

-What are the important indicators (Rules, Strategies, tools) of technical analysis?

-What is the relative importance of technical analysis?

-What are the sources of performance differences?

-Is performance of technical analysis different between countries?

-Is there a theoretical base (background) for the performance technical analysis?

-Have the performance for technical analysis in the empirical studies positive, mixed or negative?

B. Hypothesis

The hypothesis of the study " it's expected that the difference of the theoretical base, the tool of the test procedure (strategies, trading rules and indicators), data type, data periods (short, long run and intraday data), transaction costs (tax, interest rate, spread tripe ride), market type (mature, emerging) and lastly, the studied market considered (exchange rate, stock, futures markets) effect the performance of technical analysis.

C. Aim and importance of the study

The importance of the study represented in that this study is extended for the study of Park & Invin (2004). But it differs from fifth points: first; this study update the period from 1960 to 2009. Second; this study reclassified the theoretical Base to the finance theory and the behavioral theory (Unlike the Park & Irwin study where they emphasized only on the finance theory). Third; this study indicates the sources (reasons that cause differences of the performance of the technical analysis. Fourth; the study indicates that the performance differs from the emerging countries to the developed countries. Fifth; the study indicates and extended in indicating the most popular tools of technical analysis which used (all/one or some of it) in all the empirical studies in literature.

D. range and Space of the study

Technical analysis is not only concerned about prices but also about trading volumes of the stocks exchange rates and other. The range of the study along the period (1960-2009), the range is extended for prior to this date for purposes of historical deduction, the study produce a review of literature for the studies that handling the performance of technical analysis both statistical performance (Which indicates the results of the various models) and economic performance (Which indicates the economic explanations of these results). Both statistical and economic performance are measured by the profitability (return, predictability, value, yields) of the technical trading rules.

E. Methodology of the study

Technical analysis involves the prediction of future exchange rate (or other asset-price) movements from an inductive analysis of past movements, using either qualitative methods (e.g. the recognition of certain patterns in the data for visual inspection of a time-series plot) or quantitative techniques (e.g. based on an analysis of moving averages), or a combination of both.

So the study relied on the deduction approach, by using the historical and analytical style, to explain theoretical revolution. And use the induction approach which indicates various statistical, mathematical and econometric models which chosen in various studies, to explain the empirical revolution of literature.

F. Study plan

The study divided to sixth points besides the conclusions and recommendations, first: indicates the important indicators have been used in the most of literature, Second: Sources which are responsible for the differences of performance of technical analysis, Third: Performance differences in the emerging markets, Fourth: The relative importance of technical analysis, Fifth: Technical analysis in the economic theory, it divided to two main parties, part one, the finance theory, it included the efficient markets hypothesis (random walk & martingale models), part two, technical analysis in the behavioral theory (noisy rational expectations, noise traders and feedback models & other models as, based agent models).

Lastly, the study indicates the performance in empirical studies, it divided early empirical studies (1960-1987) and the modern studies (1988-2009) the study have more focus on the studies comes out in (2004-2009). The modern studies have been classified into seven categories (the same in Park & Irwin), standard studies, model based boot strap studies, genetic programming studies, reality check studies, chart pattern studies, nonlinear studies and other studies.

1. Important indicators of technical Analysis

Oscillators are confined to a fixed numerical range, unlike indicators, Indicators and oscillators have three main functions, a: To assess the strength of any price change with time (momentum), b: To assess whether a market has recently moved too far too fast (overbought / oversold), c: To assess the prevailing type of market: trending or non-trending (market classifier)

Technical indicators may be roughly separated in trend following indicators, oscillators and indicators of the whole market. Trend following indicators are used to smooth out accidental movements of the stock prices in the short run which should make trends recognizable as Achelis (2000) points out. One has to keep in mind that trend followers always follow the trend which implies that they react with a time-lag. Therefore, trend followers are useful in market conditions with long-lasting trends while in volatile sidewards- moving markets lots of erroneous signals are produced.

The Simple Moving Average in time 7* is calculated according to the following formula:

$$SMA_T = \frac{1}{n} \sum_{s=T-n+1}^{T} P_s$$

Ps denotes the stock price in time s which is interpolated from the previous tick. It is commonly calculated for 5 up to 200 trading days, as described in Achelis (2000). In contrast to the Simple Moving Average, the Weighted Moving Average considers more recent price movements as more relevant and gives them a higher weighting as in Bauer & Dahtquist (1999):

$$WMA_T = \frac{\sum_{s=T-n+1}^{T}(s-T+n)\cdot P_s}{\sum_{s=1}^{n} s}$$

Where, n is set to 202, and buy- or sell-signals are generated whenever the stock price crosses the Weighted Moving Average. Since more weight is attributed to the most resent prices, the Weighted Moving Average is more volatile than the Simple Moving Average and yields, therefore, more buy- and sell-signals.

The Exponential Moving Average gives the more recent prices also a higher weighting, but unlike the Weighted Moving Average it takes all available observations into account, it can be calculated according to Achelis (2000):

$$EMA_T = EMA_{T-1} + \frac{2}{n+1}\cdot(P_T - EMA_{T-1})$$

As above, n equals 202, and the stock price crossing the Exponential Moving Average from below (above) is a signal to buy (sell)- All the trend following indicators produce lots of erroneous signals in a volatile sidewards moving market as Achelis (2000) points out

Oscillators are an alternative to trend following indicators. They measure according to Colby & Meyers (1988) the momentum of changing prices. In contrast to the trend followers they perform best in volatile and sideward moving markets as Murphy (1999) states. The Rate of Change indicates the momentum and, therefore, the acceleration or slowing down of a trend as follow:

$$RoC_T = 100\cdot\frac{P_T}{P_{T-n}}$$

According to Murphy (1999) the Rate of Change is usually calculated for ten days, but it is also used for 26 or 50 weeks. The Volume Price Trend (also referred to as VPrice and Volume Trend") combines prices and trading volume:

$$VPT_T = \sum_{s=T-n+1}^{T} ln\left(\frac{P_s}{P_{s-1}}\right)\cdot V_s$$

Where, v, denotes the number of shares traded between time *s* / 1 and 5. Since trading volume is always positive, the sign of the volume price trend depends on the stock returns. A crossing of zero generates signals to trade. But as Achelis (2000) suggests, also the extremes of the volume price trend may yield valuable information, since they show rising or declining momentum. The Relative Strength Index by Wilder (1979) is the most commonly used oscillator.

$$RSI_T = 100 - \frac{100}{1 + RS_T}$$

$$RS_T = \frac{average\ of\ all\ gains}{average\ of\ all\ losses}$$

Where, RS_t denotes the relative strength in time T which is calculated as the average gains in periods with rising prices divided by the average losses in periods with declining markets. Originally, Wilder (1979) suggested calculating the Relative Strength Index for 14 days while in the present article it comprises 202 five minute time spaces. The limits For the buy- and sell-signals are set according to Murphy (1999) whenever the Relative Strength Index crosses 50.

The following two indicators analyze the sentiment of the market as a whole. Therefore, they yield signals to invest in (or sell) the whole market and not a single stock.

The Advance/Decline Ratio compares the number of rising and falling stock prices of a group of stocks. According to Achelis (2000) a broad trend is detected, whenever the majority of stocks follows a certain direction of an index.

$$ADR_T = \frac{ADV_T}{ADV_T + DCL_T}$$

As in Dukas & Park (1995) *ADVT* denotes the number of advancing stocks prices in the 202 five-minute times spaces before time t. DCL_t is the number of declining stock prices in the same time spaces. Usually, the Advance/Decline Ratio is used as a sort of contrarian indicator: Fosback (1991) considers values greater than 0.56 as bearish and values less than 0.43 as bullish. Achelis (2000) calculates the Advance/Decline Ratio as ADV_t / DCL¸ and sets the limits at 1.25 and 0.9. Zweig (1990), states that current strength in the market implies future strength and treats the advance / decline ratio as a momentum i

As well as the Advance/Decline Ratio, the Short-Term Trading Index analyzes the market as a whole. As Dukas & Park (1995) stress, it is the trading volume that is additionally taken into account:

$$STTI_T = \frac{UPVOL_T}{UPVOL_T + DNVOL_T}$$

Where, UPVOLT denotes the trading volume of all rising stocks while DNVOLT is the trading volume of the declining stocks. Buy- and sell-signals are generated whenever the Short-Term Trading Index Crosse 0.5.

There are many other indicators such as Money flow index indicates the strength of money flowing out/into a stock. It measures the ratio of positive money flow to negative money flow in a certain number of days. The money flow is "positive" in a day with price closed up; it is "negative" in a day with price closed down.

The Bollinger Bands are plotted as three lines. The middle line is the simple moving average. The upper and low bands a^e plotted two standard deviations away from the moving average. The bands show the range that the stock price should be most possibly located in. If the price is close to the upper band, there is a large possibility that the stock price should decrease. Likewise, if the price is close to the lower band, the stock price will possibly increase.

The resistance level is defined as the local maximum. The support level is the local minimum price. The trading rule related with support and resistance is called trading range break-out (TRB). Here a buy signal is generated when the price penetrates the resistance level. A sell signal is generated when the price penetrates the support level. The local maximum/minimum price can be determined based on the past 50, 150 and 200 days.

2. Sources of performance differences

Several researchers have attempted to explain why technical rules are profitable in terms of their economic contents. LeBaron (1999) claims that much exchange rate predictability is due to central bank intervention, Neely & weller (2001) and Neely (2002) show that trading-rule returns precede central bank interventions.

For reasons of market efficiency, a priori, one would assume that there is no privileged market due to risk aversion investors required a small positive expected return in risky markets. In long-only markets like a stock market—this implies a positive upward drift. In symmetric markets which traders are as likely to be long as they are short, like futures and foreign exchange markets, the implication is that one would expect the price to be predictable to some degree. Kho (1996) shows that time varying risk premium and conditional volatility explain a substantial part of trading-rule returns.

There are sources in the literature affecting the profitability of technical trading rules, e.g. after allowance for transactions costs and interest rate carry is provided by, among others, Cornell and Dietrich (1978), Sweeney (1986), Schulmeister (1987), LeBaron (1999), Saacke (2002) and Neely, weller and Ulrich (2006). Studies supporting the hypothesis that technical trading rules are more profitable for currencies experiencing relatively higher volatility, e.g. Cornell & Dietrich (1978), Dooley & Shafer (1983), Lee & Mathur (1996) and Neely & weller (1999).

Work suggesting that technical trading rule performance is unstable over time, e.g. Logue, Sweeney & Willett (1978), Dooley & Shafer (1983), Menkhoff & Schlumberger (1995), LeBaron (2000), Dueker & Neely (2005) and Neely, Weller & Ulrich (2006). On the other hand, Hansen (2003) points out that loading too many irrelevant rules can reduce the test power.

Furthermore, government intervention in foreign exchange markets may make them more predictable still. So, for theoretical reasons, one may expect that foreign exchange markets should be the most predictable, futures markets intermediate and stock markets the least predictable.

The relationship between trading-rule returns and central bank intervention is important because it might shed light on the source of technical trading-rule profits that seem to contradict the efficient markets hypothesis. The profitability of U.S. intervention operations has been studied primarily because of Friedman's (1953) argument that there is a connection between the profitability of intervention and the ability of intervention to stabilize the market This link is tenuous, however, Salant (1974), Mayer & Taguchi (1983), and De Long, Shleifer, Summers & Waldmann (1989) provide counterexamples.

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Many authors Dooley & Shafer (1983), Corrado & Taylor (1986), Sweeney (1986), Friedman (1988), and Kritzman (1989) have cited the existence of central bank intervention in foreign exchange markets as a potential explanation for the profitability of technical trading rules. The rationale for that theory is as follows: Because intervention is conducted to maintain orderly market conditions or perhaps to achieve macroeconomic goals such as price stability or full employment, rather than to make money, central banks may be willing to take a loss on their trading. LeBaron (1996) found that most trading-rule profits were generated on the day before in-market U.S. intervention.

Szakmary & Mathur (1997) examine the link between trading-rule returns and proxies for central bank intervention in the form of monthly foreign exchange reserves. According to Goodhart & Hesse (1993) and Humpage (1998), most intervention is conducted before noon in New York,before the close of the European markets. [(2)]

Using a nonlinear micro structural model of exchange rate behavior, Reitz & Taylor (2006) find evidence supportive of the existence of a coordination channel of intervention effectiveness. A final piece of evidence on the relation between intervention and technical analysis profitability is provided by Sapp (2004), he finds that market uncertainty, measured by spread and volatility is high before interventions and lower afterwards. This provides an economic rationale for interventions (see also Chaboud & LeBaron (2001) and indicates that profits earned by technical analysis during these periods may be a compensation for risk.

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(1) Friedman (1953) was referring more generally to speculation in foreign exchange and discussed government speculation(intervention) as a special case. Sweeney (1997) reviews research on the profitability of central bank intervention.

(2)Humpage (1994) outlines the institutional aspects of U.S. intervention while Edison (1993) reviews the extensive literature on central bank intervention. The empirical evidence found in Park & Irwin (2004) and James (2006) confirms this theory.

In conclusion time varying risk premium and conditional volatility explain a substantial part of performance differences, There are also sources in the literature affecting the performance of technical trading rules, as transactions costs and interest rate paid, loading too many irrelevant rules can reduce the test power is due to central bank intervention

3 . Performance differences in emerging markets

The majority of US studies find that technical analysis does not add value after transaction costs are accounted for. In a seminal paper, Brock, Lakonishok & LeBaron (hereafter BLL) (1992) test Variable Moving Average (VMA), Fixed Moving Average (FMA) and Trading Rang Breakout (TRB) rules on the Dow Jones Industrial Average and find that statistically significant profits are generated. However, Bessembinder & Chan (1998) show that these profits do not exceed reasonable estimates of transaction costs. Allen & Karjalainen (1999) reach a similar conclusion after applying trading rules selected by genetic algorithms to the US equity market. While there are gross profits available, the profitability is removed once transaction costs are accounted for. Exceptions to the above are the minority but they do exist. For instance Cooper (1999) finds filter rules based on both price and volume generate profits after relatively low estimates of transaction costs are taken into account.

Authors who have tested trading rules on developed markets outside the US generally also find that the profits generated do not offset transactions costs. Hudson, Dempsey & Keasey (1996) apply the BLL (1992) trading rules in the UK equity market and find that they generate profitable signals but these profits are not large enough to offset transaction costs. Precise estimation of the costs incurred in exploiting technical analysis are often difficult to estimate but Bessembinder & Chan (1995) find BLL (1992) trading rules are less profitable in the developed markets of Hong Kong and Japan than they are in emerging markets.

The evidence of profitability over and above transactions costs appears to be the most compelling in emerging markets. Parisi & Vasquez (2000) document large profits to the BLL (1992) trading rules in the Chilean stock market They do not consider transactions costs, however, several other authors do. Bcssembinder & Chan (1995) find BLL (1992) trading rules produce profits in excess of transaction costs in the emerging markets of Malaysia, Thailand, and Taiwan. Ito (1999) also tests BLL (1992) trading rules and finds profitability beyond transaction costs in Indonesian, Mexican and Taiwanese equity indices.

Also, Ratner & Leal (1999) test 10 VMA rules on the emerging markets of India, Korea, Malaysia, Philippines, Taiwan, Thailand, Argentina, Brazil, Chile, and Mexico. They find some evidence of profitability in most markets after transactions costs but most of this is centred in the markets of Mexico, Philippines, Taiwan, and Thailand. It is important to note that none of the studies discussed above formally address the issue of data snooping bias with the technique outlined by Sullivan, Timmcnnaun, & White (1999).

Drawing on the work of White (2000), these authors suggest that rules that are the most profitable are the very rules that are the most likely to be examined over time. This means that it is important to consider the profitability of any rule in the context of the full universe of rules from which it was drawn. We apply the technique advocated by Sullivan, Timmermann & White (1999) to our test of technical analysis profitability in both developed and emerging markets.

Chaudhuri & Wu (2003) find that the random walk hypothesis can be rejected in many emerging markets which implies that technical trading rules may be more profitable in these markets than they are in developed markets. We are unaware of any previous studies that compare profits to the same rules in both developed and emerging markets using data snooping adjusted bootstrap techniques.

The study of Linto (2006), provides a more comprehensive test of technical trading rules on the Asian-Pacific equity markets with more recent data and a different methodology. As such, this study contributes to the overall understanding of the efficiency and price behavior of the Asian Pacific equity markets. The results of this study are consistent with the reasoning that some of the Asian-Pacific equity markets were infomationally inefficient, at least over the period analyzed, as the trading rules were able to earn profits and generate relevant trading information.

The study of Marshall, et,al, (2008), tests data of 49 developed and developing countries, follow the approach of Marshall, Cahan, & Cahan (2008a, b) and apply both the BLL (1992) and STW (1999) bootstrap methodologies. The BLL (1992) methodology involves fitting a null model to the data and estimating its parameters, follow Kwon & Kish (2002) and Marshall. Cahan, & Cahan (2008b) and use the GARCH-M mode(1).

These studies find no evidence that the profits to the technical trading rules considered are greater than those that might be expected due to random data variation, once we take account of data snooping bias. There is some evidence that technical analysis works better in emerging markets, which is consistent with the literature that documents that these markets are less efficient, but this is not a strong result.

4. The Importance of Technical Analysis in survey studies

The importance of survey studies represents in attempting to investigate directly market participants' behavior and experiences, and document their views on how a market works. These features cannot be easily observed in typical data sets.

In the other hand, this importance steam up from the relative importance of financial markets which applied the technical analysis. Study of Menkhoff & Taylor (2006) Comparing spot market turnover yields a ratio of about three in favour of the foreign exchange market compared to

(1)**The** model presented in three equations as fallows' n = a + yo2t **+Pei-l+et o2t = a0 + al et-12+|J at-12 et = at + Zt** equities, where daily spot market turnover was about 480 billion US dollars in foreign exchange versus 160 billion US dollars in equities, both represent more than 75 percent of the respective world markets.

The oldest survey study regarding technical analysis dates back to Stewart (1949), who analyzed the trading behavior of customers of a large Chicago futures commission firm in the 1924-1932 period. The result indicated that in general, traders were unsuccessful in their grain futures trading, regardless of their scale and knowledge of the commodity traded, but Amateur speculators were more likely to be long than short in futures markets, (Long positions generally were taken on days of price declines, while short positions were initiated on days of price rises) Thus, trading against the current movement of prices appeared to be dominant.

The study of Smidt (1965a) surveyed trading activities of amateur traders in the US commodity futures markets in 1961.4 In this survey, about 53% of respondents claimed that they used charts either exclusively or moderately in order to identify trends.

The Group of Thirty (1985) surveyed the views of market participants on the functioning of the foreign exchange market in 1985. The respondents were composed of 40 large banks and 15 securities houses in 12 countries. The survey results indicated that 97% of bank respondents and 87% of the securities houses believed that the use of technical analysis had a significant impact on the market.

Brorsen & Irwin (1987) carried out a survey of large public futures funds' advisory groups in 1986. In their survey, more than half of the advisors responded that they relied heavily on computer- guided technical trading systems.

Frankel & Froot (1990) showed that switching a forecasting method for another over time may explain changes in the demand for dollars in foreign exchange markets. The evidence provided was the survey results of Euromoney magazine for foreign exchange forecasting firms. According to the magazine, in 1978, nineteen forecasting firms exclusively used fundamental analysis and only three firms technical analysis* After 1983, however, the distribution had been reversed. In 1983, only one firm reported using fundamental analysis, and eigftt technical analysis. In 1988, seven firms appeared to rely on fundamental analysis while eighteen firms employed technical analysis.

Taylor & Allen (1992) conducted a survey on the use of technical analysis among chief foreign exchange dealers in the London market in 1988. The results indicated that 64% of respondents reported using moving averages and/or other trend-following systems and 40% reported using other trading systems such as momentum indicators or oscillators. In addition, approximately 90% of respondents reported that they were using some technical analysis when forming their exchange rate expectations at the shortest horizons (in trad ay to one week), with 60% viewing technical analysis to be at least as important as fundamental analysis, the study indicate that the importance of technical analysis appeared to increase across all trading horizons relative to 1988 (the year when Allen & Taylor conducted a survey).

Menkhoff (1997) investigated the behavior of foreign exchange professionals such as dealers or fund managers in Germany in 1992. His survey revealed that 87% of the dealers placed a weight of over 10% to technical analysis in their decision making. The mean value of the importance of technical analysis appeared to be 35% and other professionals also showed similar responses. Respondents believed that technical analysis influenced their decision from intraday to 2-6 months by giving a weight of between 34% and 40%.

Lui & Mole (1998) surveyed the use of technical and fundamental analysis by foreign exchange dealers in Hong Kong in 1995. The dealers believed that technical analysis was more useful than fundamental analysis in forecasting both trends and turning points.

Cheung & Wong (2000) investigated practitioners in the interbank foreign exchange markets in Hong Kong, Tokyo, and Singapore in 1995. Their survey results indicated that about 40% of the dealers believed that technical trading is the major factor determining exchange rates in the medium run (within 6 months), and even in the long run about 17% believed technical trading is the most important determining factor.

Cheung, Chinn & Marsh (2000) surveyed the views of UK-based foreign exchange dealers on technical analysis in 1998. In this survey, 33% of the respondents described themselves as technical analysts and the proportion increased by approximately 20% compared to that of five years ago. Moreover, 26% of the dealers responded that technical trading is the most important factor that determines exchange rate movements over the medium run.

Cheung & Chinn (2001) published survey results for US-based foreign exchange traders conducted in 1998. In the survey, about 30% of the traders indicated that technical trading best describes their trading strategy. Five yeas earlier, only 19% of traders had judged technical trading as their trading practice. About 31% of the traders responded that technical trading was the primary factor determining exchange rate movements up to 6 months.

Oberlechner (2001) reported findings from a survey on the importance of technical and fundamental analysis among foreign exchange traders and financial journalists in Frankfurt, London, Vienna, and Zurich in 1996. For foreign exchange traders, technical analysis seemed to be a more important forecasting tool than fundamental analysis up to a 3- month forecasting horizon, while for financial journalists it seemed to be more important up to 1-month.

The studies of Cheung, Chinn & Marsh (2004) and Gehrig & Menkhoff (2004) asked traders to select the technique which best characterizes their dealing method 54%, 77% respectively. There is not much evidence, even in the practitioner's literature, on what rules technical analysts actually use. Menkhoff & Schmidt (2005) report that 36% of German fund managers surveyed allocating funds using alternative strategies including technical analysis.

Moreover, Covel (2005), citing examples of large and successful hedge funds, advocates the use of technical analysis exclusively without learning any fundamental information on the market Meanwhile the Survey study of Gehrig & Menkhoff (2006) that chief FX dealers who have a typical intraday forecasting horizon give technical analysis a weight of 45% (out of 100% for fundamental, technical and order flow analysis), and the other FX dealers intraday give 37.3% of importance for technical analysis. The study allows an analysis of the implicit relations between the technical and fundamental factors.

A survey by Mizrach & Weerts (2007) about the kind of trade strategies the semi-professional traders in FX markets prefers, suggests that simple rules as moving averages (52%) and chart patterns (56%) are preferred.

In sum, survey studies indicate that technical analysis has been widely used by practitioners in futures markets, foreign exchange markets and stock market traders, and regarded as an important factor in determining price movements at shorter time horizons.

5. Finance theory and technical analysis

Finance Theory must be defined in order to focus the analysis. The following are some definitions provided by classical authors. W. Sharpe (1976) defines Finance Theory as a fairly abstract but rigorous theory, of special interest to portfolio investors. E. Fama (1976) does not provide an explicit definition, but indicates that the objective of his text is to introduce Finance Theory and its empirical verification; Fama considered Finance Theory to be a unique field of economics due to the correspondence between theory and practice. (1)

Huang & Litzenberg (1988) state that Finance Theory deals with individual consumption and portfolio decisions under uncertainty and their implications for financial assets. R. Jarrow (1988) understands Finance Theory to be a theory of portfolios, CAPM, option prices, APT, and models associated with financial economy. T. Copeland & F. Weston (1988) argue

(1)The analysis of a theory's validity and its degree of rigorousness are done according to HemJndez et al. (1994), with respect to the functions that a theory should fulfill, these being: a) to explain the phenomenon: why, how, and when it occurs, b) to systematize and organize knowledge regarding a phenomenon, especially when this knowledge is disperse, and c) to predict the future of the phenomenon, which is the objective of any theory.In terms of its systematization. knowledge existed prior to 1950 as to the prices and models of stocks and interest rates. Fisher (1930), Keynes (1936), Williams (1938), and Schneider (1994) are some of the authors who were working in this area at the same time that technical and fundamental analyses were being developed As of the end of the 1950s, the study of the prices of financial assets was systematized and reoriented with a global approach, generating models with new unknowns and new hypotheses. Prediction is clearly the objective of Finance Theory. Sharpe (1976) indicates that the utility of a normative model rests on its predictive capacity.

that it is a theory that explains how and why individuals and their agents make decisions and choose between different flows, concentrating on assets, portfolio administration, and finance policies. R. Merton (1992) indicates that Finance Theory is a neoclassical theory that covers perfectly defined areas.

Other authors question Finance Theory. W. Buffet (1994) is cited in Hagstrom (1995) as indicating that unlike academics, risk is too complex to be evaluated solely by statistical measurements, as Finance Theory suggests,adding that diversification is a solid principle for average investors, but can be an obstacle. Because this intellectually provocative position comes from a person whose graduate studies are in the area of finance and who has made a fortune in stock investments, it should be considered. Buffet is a true representative of the fundamental analysis approach, which deals with stock prices.

B. G. Malkiel (1996), on the other hand, indicates that Technical Analysis is an anathema in the academic world, because of two considerations: a) the method is clearly false and b) it is easy to criticize. This is a direct, intellectually provocative position with respect to other approaches that are not included in Finance Theory. Despite of technical analysis, deals with the price of the financial *assets* , specifically, the price of stocks, also Technical analysis is very old, both in theoretical approaches and its application to stock prices.

Edwards & Magee (2001), on the other hand, indicate that technical analysis is the science of recording, usually in graphic form, the actual history of trading (price change, volume of transactions, transaction costs etc.) in a certain stock or in .the Average, and then deducting from that pictured history the probable future trend. (1)

Applied Finance, also known as Corporate Finance, concentrates on three main aspects of management: how much and in which assets to invest, how to finance those investments and, finally, how much of the dividends should be distributed among the owners of the stocks. Classical authors such as Brealey & Myers (2002); Weston & Brigham (1993); and Ross, Westerfiel & Jaffe (1995) include this outlook in their works. Although these authors use the value of the financial assets and their prices indistinctly, on markets with incomplete information, value and price are not necessarily the same, then they work also within the hypothesis of inefficient markets as technical analysis work.

5.1. The Efficient Markets Hypothesis

The efficient markets hypothesis has long been a dominant paradigm in describing the behavior of prices in speculative markets. Working (1949, P.160) says that the market expectations must have been defected ; ideal

(1)For details of traditional technical analysis, see Murphy (1999), Achelis (2000), Pring (2002) and Edwards, Aronson (2006), Magee & Bassetti (2007).

market expectations would have taken full account of the information which permitted successful prediction of the price changes.

In later work, he revised his definition of a perfect futures market to "... one in which the market price would constitute at all times the best estimate that could be made, from currently available information, of what •the price would be at the delivery date of the futures contracts (Working. 1962, p.446)." This definition of a perfect futures market is identical to the famous definition of an efficient market given by Fama (1970, p. 383): "A market in which prices always fully reflect available information is called 'efficient'." This definition used as the standard definition in the financial economics metature for fong time.

An another definition of an efficient market is given by Jensen (1978, p.96) who says that: "A market is efficient with respect to information set Q_q if it is impossible to make economic profits by trading on the basis of information set Q_q ." Since the economic profits are risk-adjusted returns after deducting transaction costs, Jensen's definition implies that market efficiency may be tested by considering the net profits and risk of trading strategies based on information set Q_q.[1]

As Blake's text (2000), to consider the Fair Game model, where in the Fair Game Model there is no systematic difference between the actual return on the game and the expected return before the game is played. As in equation (2) the returns in the next period are the expected returns for the next period dependant upon information available in the current period (denoted Qj, plus the prediction error at time $_{1+h}$ as follows:

$$r_{i,t+1} = E(r_{i,t+1}/ \Omega_{t}) + \varepsilon_{it+1} \qquad \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Rather than being ignored, as in some economic theory, the prediction error is integral to this analysis. The error in predicting future returns (ε_{it+1}) is deemed a white noise.[2] As such, this error has three primary statistical properties, consistency, independence and efficiency.

(1)Jensen (1978. p. 97) grouped the various versions of the efficient markets hypothesis into three testable forms based on the definition of the information set Qt First; the Weak Form of the Efficient markets hypothesis, in which the information set Qt is taken to be solely the information contained in the past price history of the market as of time t. Second; the Semi-strong Form of the Efficient markets hypothesis, in which Qt is taken to be all information that is publicly available at time I. Third; the Strong Form of the Efficient markets hypothesis, in which Qt is taken to be all information known to anyone at time t. Timmermann & Granger (2004, p. 25) extended Jensen's definition by specifying how the information variables inQt are used in actual forecasting.

(2)The term white noise refers to a series with an expected value of zero, a variance of ©2 , and an
auto covariance of zero, for more details see: - Blake. D, (2000), "Financial Market Analysis", Second Edition, John Wiley & Sons, Chichester

But what does this mean for the efficient market hypothesis? The data certainly agrees with Malkiel's (1990) suggestion that technical analysis cannot 'consistently outperform a strategy of simply buying and holding a diversified group of securities'. The work on the relative strength index reconfirms the ideas from Lesmond et al. (2001) which found that relative strength rules are rarely profitable, particularly after the inclusion of transaction costs. Overall the research offers strong support for at the very least, weak form EMH.

The claims of technical analysts were initially discounted by the academic community on the grounds that they were inconsistent with market efficiency. But recent work has called into question the extent to which markets are fully efficient. There is now convincing evidence that stock prices display short-term momentum over periods of six months to a year and longer-term mean reversion as; De Bondt & Thaler (1985), Chopra, Lafronishok & Jitter (1992) and Jegadeesh & Titman (1993). This provides support Vr a particular class of technical trading rule that is designed to detect persistent trends. Such rules have been shown to perform profitably in foreign exchange markets as; Dooley & Shafer (1983), Sweeney (1986), Levich & Thomas (1993) and Neely, Weller & Dittmar (1997). There is also evidence of economically significant price reversals over short time horizons of a week to a month as; Jegadeesh (1990), Jegadeesh & Titman (1995), Lehmann (1990) and Gutierrez & Kelley (2007).

Thus, technical analysis provides a weak form test of market efficiency because it heavily uses past price history. Testing the efficient markets hypothesis empirically requires more specific models that can describe the process of price formation when prices fully reflect available information. In this context, two specific models of efficient markets, the random walk model and martingale model are explained next.

5.1.1. Random Walk Models

The idea of the random walk model goes back to Bachelier (1900) who developed several models of price behavior for security and commodity markets. [1] One of his models is the simplest form of the random walk model: if P_t is the unit price of an asset at the end of time/, then it is assumed that the increment $P_{t+1} - P_t$ is an independent and normally distributed random variable with zero mean and variance proportional to T. The random walk model may be regarded as an extension of the martingale model in the sense that it provides more details about the economic environment. The martingale model implies that the conditions of market equilibrium can be stated in terms of the first moment, and thus it tells us little about the details of the stochastic process generating returns. [2]

(1)A French mathematician, Louis BachaJier formulated the random walk (RW) model in 1900 in his Ph.D. thesis.

(2)Working (1934) independently developed the idea of a random walk model for price movements.

Campbell, Lo & MacKinlay (1997) summarize various versions of random walk models as the following three models, based on the distributional characteristics of increments. Random walk model I (RWI) is the simplest version of the random walk hypothesis in which the dynamics of P_t are given by the following equation:

$$P_t = \mu + P_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim IID(0,\sigma^2_t)$$

Where u, is the expected price change or drift, and IID(0,o^2|) denotes that e_t is independently and identically distributed with mean 0 and variance a^2.

Random walk model 2 (RW2) relaxes the assumptions of RW1 to include processes with independent but non-identically distributed increments (ε_t).

$$P_t = \mu + P_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim INID(0,\sigma^2_t)$$

RW2 can be regarded as a more general price process in that, for example, it allows for unconditional heteroskedasticity in the £,'s, a particularly useful feature given the time- variation in volatility of many financial asset return series.

While Random walk mode? 3 (RW3) is an even more general version of the random walk hypothesis^ which is obtained by relaxing the independence assumption of RW2 to include processes with dependent but uncorrected increments. For example, a process that has the following properties satisfies the assumptions of RW3 but not of RW1 and RW2: Cov $[\varepsilon_t , \varepsilon_{t-1}]=0$ **for all** $K \neq 0$, but where Cov $[\varepsilon^2_t , \varepsilon^2_{t-1}] \neq 0$ For some K#), this process has uncorrected increments but is evidently not independent because its squared increments are correlated.

Fama & Blume (1966) argued that, in most cases, the martingale model and the random walk model are indistinguishable because the martingale's degree of dependence is so small, and hence for all practical purposes they are the same. Nevertheless, Fama (1970) emphasized that market efficiency does not require the random walk model. From the viewpoint of the submartingale model, the market is still efficient unless returns of technical trading rules exceed those of the buy-and-hold strategy, even though price changes (increments) in a market indicate small dependence.

Most recent studies emphasize the analysis of uncorrected increments using the variance ratio test, as Liu & He (1991) find evidence against the

Although he never mentioned the "random waJk model **• Working suggested that many economic time series resemble a "random-difference series "»which is simply a different label for the same statistical model. He emphasized that in the statistical analysis of time series showing the characteristics of the random difference series in important degree* it is essential for certain purposes to have such a standard series to provide a basis for statistical tests (p. 16). and found that wheat price changes resembled a random-difference series.

random walk hypothesis for five weekly bilateral exchange rates. Similarly, Ajayi & Karemera (1996) find that the random walk hypothesis does not hold well for daily or weekly exchange rate changes in eight Asian Pacific economies.

Anthony & MacDonald (1999) report mixed evidence against the random walk hypothesis for many daily bilateral exchange rates in the European Monetary System. On the other hand by contrast, based on a variance ratio test, Belairie Franch & Opong (2005) reject the random walk hypothesis for Euro exchange rates with the Canadian dollar and Singapore dollar but not with respect to eight other currencies, including several smaller currencies.

5.1.2. The Martingale Model

The martingale model was advocated by Samuelson (1965) and Mandelbrot (1966) as an alternative for the RW model. Samuelson proved the proposition that, with simple properly anticipated prices fluctuate randomly. Then with simple assumptions randomness can be linked with the basic elements of economic equilibria including, preferences and returns* It provides a precise way in which information is reflected in the asset prices. A stochastic process X_t is a martingale within an information set I_t if the best forecast of X_t.1 based on current information I_t would be equal to X_t, then it will be as follows:

Martingale: $E(X_{t+1} / I_t) = X_t$

Samuelson demonstrated that a sequence of prices of an asset is a martingale (or a fair game) if it has unbiased price changes. A martingale stochastic process }P_t is expressed as:

$$E(P_{t+1} / P_t, P_{t-1},\ldots)= P_t ,$$

$$E(P_{t+1}- P_t / P_t, P_{t-1},\ldots)=0$$

where P_t is a price of an asset at time t Equation one states that tomorrow's price is expected to be equal to today's price, given knowledge of today's price and of past prices of the asset. Whereas equation two states that the asset's expected price change (or return) is zero when conditioned on the asset's price history. The martingale process does not imply that successive price changes are independent. It just suggests that the correlation coefficient between these successive price changes will be zero, given information about today's price and past prices.

Thus, the assumptions of the martingale model eliminate the possibility of technical trading rules based only on price history that have expected returns in excess of equilibrium expected returns. Another aspect of the martingale model is that it implicitly assumes risk neutrality. However, since investors are generally risk-averse, in practice it is necessary to properly incorporate risk factors into the model.

As a special case of the fair game model, Fa ma (1970) suggested the sub- martingale model, which means that no trading rules based only on the information set I_q (preferences) can have greater expected returns than ones obtained by following a buy-and- hold strategy in a future period. Fa ma (1970, p. 386) emphasized that "Tests of such rules will be an important part of the empirical evidence on the efficient markets model."

There evidence relevant to earlier works as; Liu & He (1991), Ajavi & Ka remera (1996) and Anthony & MacDonald (1999) that document some (in-sample) predictability of *VS* dollar exchange rates. Some previous studies implemented a model selection approach (e.g.. Swanson & White (1997), rather than the more traditional hypothesis testing approach using the variance ratio test.

Numerous studies have examined the hypothesis that exchange rate changes follow a martingale as the study of Yilmaz (2003), based on 27 years of data, finds that daily exchange rates for seven major currencies follow a martingale most of time, with the exception of periods marked by coordinated central bank interventions. Most of these studies focus on LIS dollar based exchange rates. Unlike these studies, Belairie Franch & Opong (2005) report evidence in favor of the martingale hypothesis for 10 Euro exchange rates (excluding the Canadian dollar and Singapore dollar).

The study of Yang et.al., (2008), attempts to investigate the martingale behavior of seven major Euro exchange rates using out-of-sample forecasts. A number of parametric and nonparametric nonlinear models are employed to capture potential nonlinearity in mean in foreign exchange rates. Traditional statistical criteria fail to reject the martingale hypothesis for all seven Euro exchange rates. However, economic criteria suggest predictability in the direction of daily exchange rate changes as well as trading returns for the three (or possibly four) smaller currencies (i.e., Australian dollar, Canadian dollar, Swiss franc, and perhaps Singapore dollar) but not for the three major currencies (i.e., Japanese yen, British Pound, and US dollar). Hence, the study find little evidence against the martingale behavior for the three major Euro exchange rates but supportive evidence for predictability of the smaller currencies.

Then martingale model assumes risk neutrality but people in general are risk averters. If agents are risk averse they will hold only risky assets if expected returns vary so as to compensate them for these changes in risk. Therefore, one would expect the returns to be partly forecastable (High risk High return). Thus risk aversion will lead to a departure from the martingale model to known as a behavioral theory which will explained next.

6. Technical analysis and Behavioral Theory

In efficient market models technical trading profits are not feasible because, by definition, in efficient markets current prices reflect all available information as in; Working (1949, 1962) and Fama (1970). In addition, according to Jensen (1978) it is impossible to make net risk-adjusted profits of all transaction costs by trading on the basis of past price history. So in efficient markets, therefore, any attempts to make profits by exploiting currently available information are futile.

Theoretically, the efficient markets models rule out the existence of profitable technical trading rules. Contrariwise, models, such as behavioral or feedback as in; De Long et al. (1990a, 1991) and Shleifer & Summers (1990), noisy rational expectations as; Brown & Jennings (1989) and Blume, Easley & O'Hara (1994), agent-based as in; Schmidt (2002), disequilibrium as in; Beja & Goldman (1980), and chaos theory as in; Clyde & Osier (1997), suggest that technical trading strategies may be profitable because they presume that price adjusts sluggishly to new information due to noise, market power, humans irrational behavior, and chaos. In these models, thus, there exist profitable trading opportunities that are not being exploited.

So, the disagreement between the efficient market and the other theoretical models makes empirical evidence a key consideration in determining the profitability of technical trading strategies.

In recent years it has become more and more obvious that psychology plays an ever-more important role in financial markets and also drives back the influence on the rational actions of stock market participants. Behavioral Finance is a young field, with its formal beginnings in the 1980s. It is a new approach into financial markets that has emerged, at least in part, in response to the difficulties faced by the traditional rational paradigm.

Behavioral economics incorporates insights from other social sciences, such as psychology and sociology as indicated Shiller (2003), into economic models and attempts to explain anomalies that defy standard economic analysis. Behavioral economics has to do with complexities of human behavior. In broad terms, it argues that some financial phenomena can be better understood using models in which some agents are not fully rational. Behavioral Finance is showing that in an economy where rational and irrational traders interact, irrationality can have a substantial and long-lived impact on prices.

Behavioral literature shows that sophisticated investors in Finland Stock Market were more likely to follow momentum-trading strategies (Grinblatt & Keloharju 2000, 2001). In addition, Barber & Odean (2000, 2001) and Odean (1999) find that individual investors trade excessively and expose themselves to a high level of risk. Odean (1998a) finds that individual investors are more willing to recognize paper gains than paper losses. Investors who are overconfident believe they can obtain large returns, thus they trade often and they underestimate the associated risks as in; DeLong, Shieifer, Summers & Waldmann (1990), Kyle & Wang (1997), Odean (1998) and Wang (1998, 2001). Coval & Shumway (2002) find that Chicago Board of Trade proprietary traders suffer from a loss due to aversion bias.

As we can see we notice common elements in technical and behavioral theory, So it's natural to split this theory to two models, Noisy Rational Expectations Models And Noise Traders and Feedback Models as a branch of the behavioral theory. Furthermore some studies expand this theory to include other models such as, Chaos, ...etc. [(1)]

(1)Thaier (1993, 2005) edited two collections of most significant papers in ±*i* area of behavioral finance. Books by Shefrin (2000, 2005). Shieifer (2000) **and** Szyszka

As Szyska, A (2007a) refers at the current stage of development behavioral finance is not yet a new unified theory of financial markets. Although a great deal of literature has been published in this area, the character of most of papers is selective and relatively of a narrow scope, explaining usually only one or two effects at the time. Behavioral finance does not substitute neoclassical finance, but rather adds to the traditional view, modifies it, and fills some gaps. However there have been already some attempts to elaborate on this basis more formal and integrated behavioral theory and to create behavioral market models at more general level as in; Shefrin (2005) and Szyszka (2007).

6.1. Noisy Rational Expectations Models

Rational expectation models are important not only to explain trading activities of market participants, but also may be applied to the understanding of price formation in general. For example, these models may give insight into how an exchange rate might be related to fundamental macroeconomic factors in an ecdtiomy such as price indices.

The efficient markets model implicitly assumes that market participants are rational and they have homogeneous beliefs about information. In contrast, noisy rational expectations equilibrium models assume that the current price does not fully reveal all available information because of noise (unobserved current supply of a risky asset or information quality) in the current equilibrium price. Thus, price shows a pattern of systematic slow adjustment to new information and this implies the existence of profitable trading opportunities.

Noisy rational expectations equilibrium models were developed on the basis of asymmetric information among market participants. Working (1958) first developed a model in which traders are divided into two groups: a large group of well* informed and skillful traders and a small group of ill-informed and unskillful traders.

Smidt (1965b) developed another early model in this area and provided the first theoretical foundation for the possibility of profitable technical trading rules by account of the speed and efficiency with which a speculative market responds to new information. Smidt argued that "evidence that a trading system generates positive profits that are not simply the results of following a trend also constitutes evidence of market imperfections" (p. 130).

Grossman & Stiglitz (1976, 1980) developed a formal noisy rational expectations model in which there is an equilibrium degree of disequilibrium. They demonstrated that, in a competitive market, no one has an incentive to obtain costly information if the market-clearing price reflects all available information, and thus the competitive market breaks (hence,

(2007) are also good sources for readers interested to find out more about the behavioral approach to finance they support the weak form of the efficient markets hypothesis and did not supported the strong form).

In contrast to Grossman & Stiglitz, the study of Hellwig (1982) showed that if the time span between successive market transactions is short, the market can approximate full informational efficiency closely, but the returns to the informed traders can be greater than zero. The Grossman-Stiglitz conclusion resulted from the assumption that traders learn from current prices before any transactions at these prices take place, while Hellwig assumes that traders draw information only from past equilibrium prices at which transactions have actually been completed.

Trey nor & Ferguson (1985) showed that if technical analysis is combined with nonpublic information that may change the price of an asset, then it could be useful in achieving unusual profit in a speculative market. Also Brown & Jennings (1989) proposed a two-period noisy rational expectations model in which a current (second-period) price is dominated as an informative source by a weighted average of past (first-period) and current prices.

Blume, Easley & O'Hara (1994) developed an equilibrium model that emphasizes the informational roles of volume and technical analysis, they argued that "Because the underlying uncertainty in the economy is not resolved in one period, sequences of market statistics can provide information that is not impounded in a single market price" (p. |77).The value of technical analysis depends on the quality of information.

The behavioral finance literature tries to explain what motivates investors to trade. Barber & Odean (2008) emphasize that investors tend to focus on "attention grabbing" stocks. They find abnormal volume and returns attract buyers to a stock. Seasholes & Wu (2007) observe that daily price limits influence trading activity on the Shanghai stock exchange. Experiments by Das & Raghubir (2006) show that stock price trends influence perceived risk.

Heath et al (1999), report that when the stock price is above a 1-year maximum, stock option exercise nearly doubles. This article provides clear evidence that technical indicators stimulate trading. While the study of Bruce & Weerts (2009) find a sharp rise in turnover as a stock crosses an n-day high or low and that turnover is increasing in n .This finding is robust to a number of controls, including market volume^ returns, and news about earnings, dividends and analyst rating changes.

In sum technical analysis can be more profitable if past price and volume data possess higher-quality information, and be less valuable if there is less to be learned from the data. In any case, technical analysis helps traders to correctly update their views on the market.

6.2. Noise Traders and Feedback Models

In the early 1990s, several financial economists developed the Held of behavioral finance, which is "finance from a broader social science perspective including psychology and sociology" (Shiller 2003, p. 83). In the behavioral finance model, there are two types of investors: arbitrageurs (also called sophisticated investors or smart money) and noise traders (feedback traders or liquidity traders). Arbitrageurs are defined as investors who form fully rational expectations about security returns, while noise traders are investors who irrationally trade on noise as if it were information (Black 1986).

Noise traders may obtain their pseudo signals from technical analysts, brokers, or economic consultants and irrationally believe that these signals impound information. The behavioralists' approach, also known as feedback models, is then based on two assumptions. First, noise traders' demand for risky assets is affected by their irrational beliefs or sentiments that are not fully justified by news or fundamental factors. Second, since arbitrageurs are likely to be risk averse, arbitrage, defined as trading by fully rational investors not subject to such sentiment, is risky and therefore limited (Shleifer & Summers 1990, p. 19).

In feedback models, noise traders buy when prices rise and sell when prices fall, like trend chasers. For example, when noise traders follow positive feedback strategies (buy when prices rise), this increases aggregate demand for an asset they purchased and thus results in a further price increase. Arbitrageurs having short horizons may think that the asset is mispriced above its fundamental value, and sell it short. However, their arbitrage b limited because it is always possible that the market will perform very well (fundamental risk) and that the asset will be even more overpriced by noise traders in the near future because they can be even more optimistic "noise trader risU" De Long ct aL (1990a).

As long as there exists risk created by the unpredictability of noise traders[9] opinions, sophisticated investors' arbitrage will be reduced even in the absence of fundamental risk and thus they do not fully counter the effects of the noise traders. Therefore, although ultimately arbitrageurs make prices return to their fundamental levels, in the short run they amplify the effect of noise traders, as indicated in De Long et al. (1990b).

On the other hand, when noise traders are pessimistic and thus follow negative feedback strategies, downward price movement drives further price decreases and over time this process eventually creates a negative bubble. In the feedback models, since noise traders may be more aggressive than arbitrageurs due to their overoptimistic (or over pessimistic) or overconfident views on markets, they bear more risk with higher expected returns. As long as risk-return tradeoffs exist, noise traders may earn higher returns than arbitrageurs. De Long ct al. (1991) further showed that even in the long run noise traders as a group survive and dominate the market in terms of wealth despite their excessive risk taking and excessive consumption.

Hence, the feedback models suggest that technical trading profits may be available even in the long run if technical trading strategies (buy when prices rise and sell when prices fall) are based on noise or "popular models" and not on information such as news or fundamental factors, Shleifer & Summers (1990).

Looking at the informational efficiency of prices, we find that the presence of noise traders increases pricing errors but only when the extent of adverse selection is large. While worsening quality of prices is consistent with the notion expressed by Black (1986), that noise traders "actually put noise into the prices," the more intriguing result of our experiment is that this effect is not observed unless informed traders have very valuable information. The key for explaining this result lies in understanding the way noise traders behave in markets.

Kaniel, Saar & Titman (2006) demonstrates a strong contrarian tendency for the noise traders. This result echoes empirical findings in the U.S. and other countries that individual investors tend to exhibit contrarian trading strategies. Thus, when prices are moving up noise traders are more likely to submit sell orders, and conversely submitting buy orders after the market is moving down.

While the study of Bloom field, O'Hara & Saar (2007) concluded that the noise traders are increasingly taking the other side of the informed traders[9] trades, a behavioral strategy that produces extensive losses for the noise traders and reduced efficiency for the market

6.3. Other Models

Additional models provide support for the use of technical analysis, Beja & Goldman (1980) introduced a simple disequilibrium model that explained the dynamic behavior of prices in the short run. The rationale behind their model was "When price movements are forced by supply and demand imbalances which may take time to clear, a nonstationary economy must experience at least some transient moments of disequilibrium. Observed prices will then depend not only on the state of the environment, but also on the state of the market" (p. 236).

Froot, Scharfstein & Stein (1992) demonstrated that herding behavior of short-horizon traders can lead to informational inefficiency. Their model showed that an informed trader who wants to buy or sell in the near future could benefit from their information only if it is subsequently impounded into the price by the trades of similarly informed speculators. Thus, short-horizon traders would make profits when they can coordinate their research efforts on the same information.

Clyde & Osier (1997) provide another theoretical foundation for technical analysis as a method for nonlinear prediction on a high dimension (or chaotic) system. They showed that graphical technical analysis methods might be equivalent to nonlinear forecasting methods using Takens (1981) method of phase space reconstruction combined with local polynomial mapping techniques for nonlinear prediction, Clyde and Osier conclude that "Technical methods may generally be crude but useful methods of doing nonlinear analysis" (p. 511).

Introducing a simple agent-based model for market price dynamics, Schmidt (1999, 2000, 2002) showed that if technical traders are capable of affecting market liquidity, their concerted actions can move the market price in the direction favorable to their strategy. The model assumes a constant total number of traders that consists of "regular" traders and "technical"traders. (1)

In sum the theoretical literature, the conventional efficient markets models, such as the martingale and random walk models, rule out the existence of profitable technical trading rules because both models assume that current prices fully reflect all available information. On the other hand, other behavioral models, such as noisy rational expectations models, feedback models, disequilibrium models, herding models, agent-basedmodels, and chaos theory, suggest that technical trading strategies may be profitable because they presume that price adjusts sluggishly to new information due to noise, market power, traders 'irrational behavior, and chaos. In these models, thus, there exist profitable trading opportunities that are not being exploited. Such sharp disagreement in theoretical models makes empirical evidence a key consideration in determining the performance (profitability) of technical trading strategies.

7. Performance in empirical Studies

Numerous empirical studies have tested the profitability of various technical trading systems, and many of them included implications about market efficiency. Previous empirical studies are categorized into two groups, "early" studies and "modern" studies based on an overall evaluation of each study in terms of the number of technical trading systems considered, treatments of transaction costs, risk, data snooping problems, parameter optimization and out-of-sample verification, and statistical tests adopted. Most early studies generally examined one or two trading systems and considered transaction costs to compute net returns of 17 trading rules.

However, risk was not adequately handled, statistical tests of trading profits and data snooping problems were often disregarded and out-of-sample verification along with parameter optimization were omitted, with a few exceptions. In contrast, modern studies simulate up to thousands of technical trading rules with the growing power of computers, incorporate transaction costs and risk, evaluate out-of-sample performance of optimized trading rules, and test statistical significance of trading profits with conventional statistical tests or various bootstrap methods.

(1)The regular traders are partitioned into buyers and sellers, and have two dynamic patterns in their behavior, a "fundamentalist" component and a "chartist" component. The former motivates traders to buy an asset if the current price is lower than the fundamental value, and to sell it otherwise, while the latter leads traders to buy if the price increases and sell when price falls. In the model, price moves linearly with the excess demand, which in turn is proportional to the excess number of buyers from both regular and technical traders. Schmidt concluded that if technical traders art* powerful enough in terms of trading volume, they can move price in the direction favorable to their technical trading strategy, this result is similar to those of Beja & Goldman (1980) and Frooi Scharfstein & Stein (1992).

Although the boundary between early and modern studies is blurred, this study follow the study of Park & Irwin (2004), where regards Lukac, Brorsen & Irwin's (1988) work as the first modern study, since it was the first technical trading studies to substantially improve upon early studies in many aspects. Thus, early studies commence with Donchian's (1960) study and include 42 studies through 1987, while modern studies cover (1988-2009) period with 114 studies as shown in tables (1), (2), (3).

7.1. Early Empirical Studies (1960-1987)

In most early studies, technical trading rules are applied to examine price behavior in various speculative markets, along with standard statistical analyses. Until technical trading rules were dominantly used to test market efficiency, previous empirical studies had employed bnly statistical analyses such as serial correlation, runs analysis, and spectral analysis. However, these statistical analyses revealed several limitations.

As Fama & Blume (1966) pointed out, the simple linear relationships that underlay the serial correlation model were not able to detect the complicated patterns that chartists perceived in market prices. Runs analysis was too inflexible in that a run was terminated whenever a reverse sign occurred in the sequence of successive price changes, regardless of the size of the price change (p. 227). Moreover, it was 10 Wilder (1978) originally set the parameter values at n =* 14 and E_T - 30.

Difficult to incorporate the elements of risk and transaction costs into statistical analyses. Fama (1970) argued that "there are types of nonlinear dependence that imply the existence of profitable trading systems, and yet do not imply nonzero serial covariances. Thus, for many reasons it is desirable to directly test the profitability of various trading rules" (P.394). As a result, in early studies technical trading rules are considered as an alternative to avoid such weaknesses of statistical analyses, and are often used together with statistical analyses. Although Jensen (1967) suggested replicating the successful results on additional bodies of data and for other time periods to judge the impact of data snooping, none of the early studies except Jensen & Benington (1970) followed this suggestion.

Second, the riskiness of technical trading rules was often ignored. If investors are risk averse, they will always consider the risk-return tradeoffs of trading rules in their investment. Thus, large trading rule returns do not necessarily refute market efficiency since returns may be improved by taking greater risks. For the same reason, when comparing between trading rule returns and benchmark returns, it is necessary to make explicit allowance for difference of returns due to different degrees of risk. Only a few studies as; Jensen & Benington (1970), Cornell & Dietrich (1978) and Sweeney (1986) adopted such a procedure.

Third, most early studies lacked statistical tests of technical trading profits. Only four studies represented in: James (1968), Peterson <& Leuthold (1982), Bird (1985) and Sweeney (1986), measured statistical significance of returns on technical trading rules using Z- or t-tests under the assumption that trading rule returns are normally distributed.

However, applying conventional statistical tests to trading rule returns may be invalid since a sequence of trading rule returns generally does not follow the normal distribution. Talyor (1985) argued that "the distribution of the return from a filter strategy under the null hypothesis of an efficient market is not known, so that proper significance tests are impossible" (p.727). In fact, Lukac & Brorsen (1990) found that technical trading returns were positively skewed and leptokurtic, and thus argued that past applications of t-tests to technical trading returns might be biased. Moreover, in the presence of data snooping, significance levels of conventional hypothesis tests are exaggerated as in; Lovell (1983) and Denton (1985).

Fourth, Taylor (1986) p.201, argued that "Most published studies contain a dubious optimization". "Traders could not guess the best filter size in advance and it is unlikely an optimized filter will be optimal in the future. The correct procedure is, of course, to split the prices. Then choose using the first part and evaluate this g upon the remaining prices." If the optimal parameter performs well over in- and out-of-sample data, then the researcher may have more confidence in the results. Only three studies used this procedure are; Irwin & Unrig (1984), Taylor (1983) and (1986).

Fifth, technical trading profits were often compared to the performance of a benchmark strategy to derive implications for market efficiency. Benchmarks used in early studies were buy-and- hold returns, geometric mean returns, interest rates for bank deposit, or zero mean profits. However, there was no consensus on which benchmark should be used for a specific market.

Early studies used diverse technical trading systems such as filters, stop-loss orders, moving averages, momentum oscillators, relative strength, and channels, to detect the dependence of price changes or to test the profitability of technical trading rules. Filter rules were the most popular trading system. Although many early studies considered transaction costs to compute net returns of trading rules, few studies considered risk, conducted parameter optimization and out-of-sample tests, or performed statistical tests of the significance of trading profits. Moreover, even after Jensen (1967) highlighted the danger of data snooping in technical trading research, none of the early studies except Jensen & Benington (1970) explicitly dealt with this problem.

Among the early studies, three representative studies, Fama & Blume (1966), Stevenson & Bear (1970), and Sweeney (1986), these studies had significant effects on later studies. In addition, these studies contain the aforementioned typical characteristics of early work, but are also relatively comprehensive compared to other studies in the same period.

Early empirical studies examined the performance (profitability) of technical trading rules in various markets. The results varied greatly from market to market as the three representative studies indicated. For 30 individual stock markets, Fama & Blume (1966) found that filter rules could not outperform the simple buy-and-hold strategy after transaction costs. For

July corn and soybean futures contracts, Stevenson and Bear's (1970) results indicated that stop-loss orders and combination rules of filters and stop-loss orders generated substantial net returns and beat the buy-and- hold strategy. For 10 foreign exchange rates, Sweeney (1986) found that small (long) filter rules generated statistically significant risk-adjusted net returns.

Overall, in the early studies, very limited evidence of the profitability of technical trading rules was found in stock markets (e.g., Fama & Blume (1966), Van Home & Parker (1967) and Jensen & Benington (1970), while technical trading rules often realized sizable net profits in futures markets and foreign exchange markets (e.g., for futures markets, as in; Stevenson & Bear (1970), Irwin & Uhrig (1984) and Taylor (1986); for foreign exchange markets, as in; Poole (1967), Cornell & Dietrich (1978) and Sweeney (1986). Thus, stock markets appeared to be efficient relative to futures markets or foreign exchange markets during the time periods examined.

Nonetheless, the early studies exhibited several important features (limitations) in testing procedures. First, most early studies exhaustively tested one or two popular trading systems, such as the filter or moving average. This implies that the successful results in the early studies may be subject to data snooping (or model selection) problems. Indeed, Dooly & Shafer (1983) and Tomek & Querin (1984) proved this argument by showing that when technical trading rules were applied to randomly generated price series, some of the series could be occasionally profitable by chance.

Finally, the results of the technical trading studies in the earlier period seem to be difficult to interpret because the performance of trading rules was often reported in terms of an "average " across all trading rules or all assets (i.e., stocks, currencies, or futures contracts) considered, rather than best-performing rules or individual securities (or exchange rates or contracts). For example, in interpreting their results, Fama & Blume (1966) relied on average returns across all filters for a given stock or across all stocks for a given filter. If they evaluated the performance of the best rules or each individual stock, then their conclusion might have been different. Sweeney (1988) pointed out that "The averaging presumably reduces the importance of aberrations where a particular filter works for a given stock as a statistical fluke. The averaging can, however, serve to obscure filters that genuinely work for some stocks", (p.296).

7.2. Modern Empirical Studies (1988-2009)

As noted previously, "modern" empirical studies are assumed to commence with Lukac, Brorsen, & Irwin (1988), who provide a more comprehensive analysis than any early study. Although modern studies generally have improved upon the limitations of early studies in their testing procedures, treatment of transaction costs, risk, parameter optimization, out-of-sample tests, statistical tests, and data snooping problems still differ considerably among them. Thus, this study is extended for the study of Park & Irwin (2004) which categorizes all modern studies into seven groups by reflecting the differences in testing procedures, so this study update these studies until 2009, and add new procedures tests in these studies.

Modern studies, which are summarized in Table (2), include 114 studies dating from Lukac, Brorsen *&* Irwin (1988) through Sapp (2004). As with the early studies, a representative study from each of the seven categories is reviewed in detail. They are Lukac, Brorsen *&* Irwin (1988), Brock, Lakonishok& LeBaron (1992), Allen & Karjalainen (1999), Sullivan, Timmermann & White (1999), Chang & Osier (1999), Gencay (1998a), and Neely(1997).

First: Standard Studies

Studies in this category incorporate transaction costs and risk into testing procedures while considering various trading systems. Trading rules are optimized in each system based on a specific performance criterion and out-of-sample tests are conducted for the optimal trading rules. In particular, the parameter optimization and out-of-sample tests are significant improvements over early studies, because these procedures are close to actual traders' behavior and may partially address data snooping problems as in; Jensen (1967) and Taylor (1986).

A representative study among the standard studies is Lukac, Brorsen & Irwin (1988). Based on the efficient markets hypothesis and the disequilibrium pricing model suggested by Beja & Goldman (1980), they proposed three testable hypotheses: the random walk model, the traditional test of efficient markets, and the Jensen test of efficient markets. Other studies in this category are summarized in Table (1).

Overall, standard studies indicate that technical trading rules generated statistically significant economic profits in various speculative markets, especially in foreign exchange markets and futures markets. Despite the successful results of standard studies, there still exists a possibility that they were spurious because of data snooping problems.

Although standard studies optimized trading rules and traced the out-of-sample performance of the optimal trading rules, a researcher can obtain a successful result by deliberately searching for profitable choice variables, such as profitable "families" of trading systems, markets, in-sample estimation periods, out-of-sample periods, and trading model assumptions including performance criteria and transaction costs.

Second: Model-based Bootstrap Studies

Studies in this category apply a model-based bootstrap methodology to test statistical significance of trading profits, these studies differ from other studies in that they usually analyzed the same trading rules (the moving average and the trading range break-out) that Brock, Lakonishok, & LeBaron investigated, without conducting trading rule optimization and out-of sample verification. Studies of; Brock, Lakonishok & LeBaron (1992), Levich & Thomas (1993), Bessembinder & Chan (1998) and others, conducted statistical tests for trading returns using model-based bootstrap approaches pioneered by Brock, Lakonishok, & LeBaron (1992). In these studies, popular technical trading rules, such as moving average rules and trading range breakout rules, were tested in an effort to reduce data snooping problems.

The results of the model-based bootstrap studies differed across markets and sample periods tested. In general, technical trading strategies were profitable in several emerging stock markets and foreign exchange markets, while they were unprofitable in developed stock markets (e.g., US markets).

Ratner & Leal (1999) found that moving average rules generated statistically significant annual net returns of 18.2%-32.1% in stock markets of Mexico, Taiwan, Thailand, and the Philippines during the 1982-1995 period. LeBaron (1999), also showed that a 150 moving average rule for the mark and yen generated Sharpe ratios of 0.60-0.98 after a transaction cost of 0.1% per round-trip over the 1979-1992 period, which were much greater than those (0.3-0.4) for buy-and-hold strategies on aggregate US stock portfolios.

However, Bessembinder & Chan (1998) noted that profits from Brock, Lakonishok, & LeBaron's (1992) trading rules for the DJIA index declined substantially over time. In particular, an average break-even oneway transaction cost across the trading rules in a recent period (1976- 1991) was 0.22%, which was compared to estimated one-way transaction costs of 0.24%-0.26%. As pointed out by Sullivan, Timmermann, & White (1999), on the other hand, popular trading rules may have survivorship bias, which implies that they may have been profitable over a long historical period by chance. Moreover, model-based bootstrap studies often omitted trading rule optimization and out-of-sample verification. For other studies see table (2).

The studies of Linto (2006), and Marshall, et.al, (2008), used bootstrap methodologies in exchange markets, and find a little evidence that there are profits to the technical trading rules after take account of data snooping bias in certain countries (emerging markets) such as Bombay, Hong Kong, Indonesia, Korea, Singapore, and Taiwan. Meanwhile these results may have significant economic implications.

Third: Genetic Programming Studies

Genetic programming, introduced by Koza (1992), is a computer-intensive search procedure for problems based on the Darwinian principle of survival of the fittest. In this procedure, a computer randomly generates a set of potential solutions for a specific problem and then allows them to evolve over many successive generations under a given fitness (performance) criterion.

Genetic programming studies as Neely, Weller & Dittmar (1997), Allen & Karjalainen (1999), Ready (2002), and others, attempted to avoid data snooping problems by testing ex ante trading rules optimized by genetic programming techniques. In these studies, out-of-sample verification for the optimal trading rules was conducted together with statistical tests, and transaction costs and risk were incorporated into the testing procedure. Genetic programming studies generally indicated that technical trading rules formulated by genetic programming might be successful in foreign exchange markets but not in stock markets. For example, Allen & Karjalainen (1999), Ready (2002), and Neely (2003) all documented that over a long time period, genetic trading rules underperformed buy-and- hold strategies for the S&P 500 index or the DJIA index.

In contrast, Neely & Weller (2001), obtained annual net profits of 1.7%-8.3% for four major currencies over the 1981-1992 period, although profits decreased to around zero or were negative except for the yen over the 1993-1998 period. The results for futures markets varied depending on markets tested. Roberts (2003), obtained a statistically significant daily mean net profit of $1.07 per contract in the wheat futures market for 1978-1998, which exceeded a buy and- hold return of -$3.30 per contract, but found negative mean net returns for corn and soybean futures markets. The genetic

programming technique may become an alternative approach to test technical trading rules because it provides a sophisticated search procedure.

However, it was not applied to technical analysis until the mid-1990s, and moreover, the majority of optimal trading rules identified by a genetic program appeared to have more complex structures than that of typical technical trading rules. Hence, there has been strong doubt as to whether actual traders could have used these trading rules. Cooper & Gulen (2003) and Timmermann & Granger (2004), indicate that forecasting experiments need to specify the set of forecasting models available at any given point in time, including estimation methods; and the search technology used to select the best (or a combination of best) forecasting model(s).

The study of Papadamou & Stephanides (2005) shows how genetic algorithms, a class of algorithms in evolutionary computation, can be employed to improve the performance and the efficiency of computerized trading systems. By comparing the solutions of the optimization problem conducted by different software tools the Emerging Stock Markets, they found that the GA trade tool can perform better, by providing very fast a set of optimum solutions that present a consistency in all over the evaluation period.

As shown in table (2), (3) there are other genetic programming studies, where genetic trading rules performed well in foreign exchange markets with their decreasing performance over time, but the results were mixed in futures markets.

Fourth: Reality Check Studies

According to White (2000), Data snooping occurs when a given set of data is used more than once for purposes of inference or model selection" (p. 1097). He argued that when such data re-use occurs; any satisfactory results obtained may simply be due to chance rather than to any merit inherent in the method yielding the results. Lo & MacKinlay (1990), also argued that "the more scrutiny a collection of data is subjected to, the more likely will interesting (spurious) patterns emerge " (p. 432).

In the literature, there are basically two different approaches to tackling the data snooping bias. The first approach focuses on data and tries to avoid re-using the same data set. This may be done by testing a model with a different but comparable data set; see e.g., Lakonishok, Shleifer & Vishny (1994) and Chan, Karceski & Lakonishok (1998). When such data are not available, one may adopt a large data set and validate the test using several sub samples; see e.g., Brock, Lakonishok, & Le Baron (1992), Rouwenhorst (1998, 1999), Gencay (1998), and Fernandez-Rodriguez et al. (2000). Such sample splitting is, however, somewhat arbitrary and hence may lack desired objectivity.

Second, is a more formal approach which consider all possible models and construct a test with properly controlled test size (type 1 error). For example, Lakonishok & Smidt (1988) suggested using the Bonferroni inequality to bound the size of each individual test. Unfortunately, this method is not appropriate when the number of hypotheses (models) being tested is large, as In the case of testing the profitability of technical analysis.

More subtle forms of data snooping are suggested by Cooper & Gulen (2003) Specifically, a set of data in technical trading research can be repeatedly used to search for profitable "families** of trading systems, markets, in-sample estimation periods, out-of-sample periods, and trading model assumptions including performance criteria and transaction costs.

White (2000) developed a statistical procedure that, unlike the genetic programming approach, can assess the effects of data snooping in the traditional framework of pre-determined trading rules. The procedure, which is called the Bootstrap Reality Check methodology, tests a null hypothesis that the best trading rule performs no better than a benchmark strategy. In this approach, the best rule is searched by applying a performance measure to the full set of trading rules, and a desired p-value can be obtained from comparing the performance of the best trading rule to approximations to the asymptotic distribution of the performance measure. Thus, White's approach takes account of dependencies across trading rules tested.

Sullivan, Timmermann & White (1999) applied White's Bootstrap Reality Check methodology to 100 years of the Dow Jones Industrial Average (DJIA), from 1897 through 1996. They used the sample period (1897-1986) studied by Brock, Lakonishok & LeBaron (1992) for in-sample tests and an additional 10 years from 1987-1 996 for out-of-sample tests. S&P 500 index futures from 1984 through 1996 were also used to test the performance of trading rules.

"Reality Check" studies as; Sullivan, Timmermann & White (1999, 2003) and Qi & Wu (2002) use White's Bootstrap Reality Check methodology to directly quantify the effects of data snooping. White's methodology delivers a data snooping adjusted p-value by testing the performance of the best rule in the context of the full universe of trading rules. Thus, the approach accounts for dependencies across trading rules tested.

Reality Check studies by Sullivan, Timmermann & White (1999, 2003) provide some evidence that technical trading rules might be profitable in the stock market until the mid-1980s but not thereafter. For example, Sullivan, Timmermann & White (1999) obtained an annual mean return of 17.2% (a breakeven transaction cost of 0.27% per trade) from the best rule for the DJIA index over the 1897- 1996 period, with a data-snooping adjusted p-value of zero. However, in an out-of-sample period (1987-1996),the best rule optimized over the 1897-1986 period yielded an annual mean return of only 2.8%, with a nominal p- value of 0.32.

For the foreign exchange market, Qi & Wu (2002) obtained economically and statistically significant technical trading profits over the 1973-1998 period. They found mean excess returns of 7.2%-12.2% against the buy-and- hold strategy for major currencies except for the Canadian dollar (3.63%) after adjustment for transaction costs and risk. Despite the fact that Reality Check studies use a statistical procedure that can account for data snooping effects.

The simulation and empirical results in Hansen (2003, 2004) indicated that the inclusion of a few poor-performing models severely reduces rejection probabilities of White's Reality Check test under the null, causing the test to be less powerful under the alternative. In the other hand Qi & Wu (2006) introduce evidence on the profitability and statistical significance among 2,127 technical trading rules. The best rules are found to be significantly profitable based on standard tests, so they employ White's (2000) Reality Check to evaluate these rules and find that data-snooping biases do not change the basic conclusions for the full sample. A sub-sample analysis indicates that the data-snooping problem is more serious in the second half of the sample. Profitability becomes much weaker in the more recent period, suggesting that the foreign exchange market becomes more efficient over time.

White's RC test suffers from two drawbacks. First, Hansen (2005) points out that the RC test is conservative because its null distribution is obtained under the least favorable configuration, i.e., the configuration that is least favorable to the alternative. In fact, the RC test may lose power dramatically when many poor models are included in the same test.

To improve on the power property of the RC test, Hansen (2005) proposes the superior predictive ability (SPA) test that avoids the least favorable configuration. Empirical studies, such as Hansen & Lunde (2005) and Hsu & Kuan (2005), also show that the SPA test is more powerful than the RC test. Second, the RC test checks whether there is any significant model but does not identify all such models. Note that Hansen's SPA test shares the same limitation. Romano & Wolf (2005) introduce a RC-based stepwise test, henceforth Step-RC test that is capable of identifying as many significant models as possible. Nonetheless, Romano & Wolfs Step-RC test is conservative because its stepwise critical values are still determined by the leasi favorable configuration, as in the original RC test.

Finally, the study of Po, Yu & Chung (2009) extended SPA test to a stepwise SPA (Step-SPA) test that can identify predictive models in large-scale, multiple testing problems without data snooping bias, it is more powerful than the existing Step-RC test because it avoids a conservative configuration used in the RC test. It is also worth mentioning that the proposed Step-SPA test is readily applicable to other similar, multiple testing problems, such as the performance of mutual funds (hedge funds), the performance of corporate managers, and the forecasting ability of different econometric models.

Fifth: Chart Pattern Studies

Chart pattern studies test the profitability or forecasting ability of visual chart patterns widely used by technical analysts. Well-known chart patterns, whose names are usually derived from their shapes in bar charts, are gaps, spikes, flags, pennants, wedges, saucers, triangles, head and-shoulders, and various tops and bottoms (see e.g. Schwager (1996) for detailed charting discussion). Previously, Levy (1971) documented the profitability of 32 five-point chart formations for NYSE securities.

However, a more rigorous study regarding chart patterns was provided by Chang & Osier (1999), whom evaluated the performance of the head-and-shoulders pattern using daily spot rates for 6 currencies (mark, yen, pound, franc, Swiss franc, and Canadian dollar) during the entire floating rate period, 1973-1994. For the endogenous exit rule, head-and-shoulders rule s generated statistically significant returns of about 13% and 19% per year for the mark and yen, respectively, but not for the other exchange rates. Returns from the exogenous exit rule appeared to be insignificant in most cases.

Other chart pattern studies, Lo, Mamaysky & Wang (2000) examined more chart patterns. They evaluated the usefulness of 10 chart patterns, which are the head-and-shoulders (HS) and inverse head-and-shoulders (1HS), broadening tops (BTOP) and bottoms (BBOT), triangle tops (TTOP) and bottoms (TBOT), rectangle tops (RTOP) and bottoms (RBOT), and double tops (DTOP) and bottoms (DBOT). The goodness-of- fit test compares the quintiles of returns conditioned on technical patterns with those of unconditional returns. If the technical patterns provide no incremental information, both conditional and unconditional returns should be similar.

Caginalp & Laurent (1998) reported that candlestick reversal patterns generated substantial profits in comparison to an average gain for the same holding period (S&P 500 stocks over the 1992-1996 period). While Leigh, Paz & Purvis (2002) and Leigh et al. (2002) also noted that bull flag patterns for the NYSE Composite Index generated positive excess returns over a buy-and-hold strategy before transaction costs. However, Curcio et al. (1997), Guillaume (2000), and Lucke (2003) all showed limited evidence of the profitability of technical patterns in foreign exchange markets, with trading profit* from the patterns declining over time as; Guillaume (2000).

The trading signals generated rom the Asian-Pacific markets can also be further processed by applying a combined signal approach Lento &Gradojevic (2006),

Savin, Weller & Zvingelis (2007) show that a modified version of the algorithm of Lo, Mamaysky & Wang applied to the "head-and-shoulders" pattern has substantial predictive power for U.S. stock returns over periods of one to three months, they have a significant predictive power for future stock returns over horizons of one to three months.

In general, the results of chart pattern studies varied depending on patterns, markets, and sample periods tested, but suggested that some chart patterns might have been profitable in stock markets and foreign exchange markets. Nevertheless, all studies in this category, except for Leigh, Paz & Purvis (2002), neither conducted parameter optimization and out-of-sample tests, nor paid much attention to data snooping problems.

Sixth: Nonlinear Studies

Nonlinear studies attempted to directly measure the profitability of a trading rule derived from a nonlinear model, such as the feed forward networks or the nearest neighbors regressions, or evaluate the nonlinear predictability of asset returns by incorporating past trading signals from simple technical trading rules (e.g., moving average rules) or lagged returns into a nonlinear model.

A single layer feed forward network regression model with hidden layer units and with lagged returns is typically given by Gencay (1998a) who tested the profitability of simple technical trading rules based on a feed forward network using DJ1A data for 1963-1988. Across 6 sub sample periods, the technical trading rules generated annual net returns of 7%-35% after transaction costs and easily dominated a buy-and-hold strategy. The results for the Sharpe ratio were similar.

Moreover, most previous studies do not investigate potential nonlinearity in mean with respect to exchange rates. Hsieh (1989, 1993) argues that most nonlinearity of daily exchange rates arises due to time-varying volatility, which may not imply nonlinear predictability in mean (unless there are significant ARCH-in-mean effects). While no formal forecasting attempt is provided, a state-dependent nonlinear model such as threshold auto regression is considered in Hsieh (1989) and Clements and Smith (2001). They find little evidence for the n on linearity-in-mean in terms of traditional statistical criteria.

Other nonlinear studies as Gencay (1998b, 1999) further investigated the nonlinear predictability of asset returns by incorporating past trading signals from simple technical trading rules, i.e., moving average rules, or lagged returns into a nonlinear model, either the feed forward network or the nearest neighbor regression. Also Reitz & Taylor (2006), Used a nonlinear micro structural model of exchange rate behavior, as evidence supportive of the existence of a coordination channel of intervention effectiveness in exchange markets.

Technical trading rules based on nonlinear models appeared to have either profitability or predictability in both stock and foreign exchange markets. However, nonlinear studies have a similar problem to that of genetic programming studies, such as computational expensiveness, over fitting, data snooping and difficulties interpreting the results. As such, the returns are subject to sophisticated tests of significance. (1)

Seventh: Other Studies

Other studies are ones that do not belong to any categories reviewed so far. In general, these studies are similar to the early studies in that they did not conduct trading rule optimization and out-of-sample verification and address data snooping problems, although several studies as; Sweeney, (1988), Farrell & Olszewski (1993) and Irwin et al. (1997) performed out-of-sample tests.

Other related work studied the market dynamics arising from the interaction and adaptation of heterogeneous agents; these are often referred to as agent-based modeling where agents with varying risk attitudes and beliefs switch between investment strategies according to trading performance as; Brock & Hommes (1997a, 1997b, 1998), Chiarella (1992), Chiarella & He (2001, 2002), Day & Huang (1990), Gaunersdorfer (2000), Hommes (2001, 2002), Lux (1997, 1998), and Lux & Marchesi (1999, 2000). Models with artificial intelligence agents also look into their resulting market behavior as; Arthur et al. (1997), LeBaron et al. (1999).

Researches in this area expanded partly owning to the unsatisfactory assumptions of homogeneous agents and complete rationality in conventional models. Many of these studies have successfully connected their results with some empirical stylized facts, (2)

Table (2) summarizes other studies in this category. As an exceptional case among the studies, Neftci's (1991) work is close to a theoretical study. Using the notion of Markov times, he demonstrated that the moving average rule was one of the few mathematically well-defined technical analysis rules. Markov times are defined as random time periods,whose value can be determined by looking at the current information set, so, Markov times do not rely on future information.

Also, Neely (1997) tested the profitability of filter rules and moving average rules on four major exchange rates (the mark, yen, pound sterling, and Swiss franc) over the 1974-1997 period. The results indicated that trading rules yielded positive net returns in 38 of 40 cases after deducting transaction costs of 0.05% per roundtrip. Specifically, for the mark, 9 of the 10 trading rules generated positive net returns with an annual mean net return of 4.4%. The results for other exchange rates were similar.

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(1)For more details see White (2005), for a thorough discussion of these issue

(2)For further discussions see: Tesfatsion L (2006>. Samanidou, et.al., (2007). LeBaron (2006). Hommes (2006), Epstein (2006), Axelrod & Tesfatsion (2006). Tomas (2009).

The study of Paul et.al., (2007) provide empirical evidence that confirms the prediction that the sequential price jumps in equity prices are positively auto correlated, and he utilized the bi-power variation estimation technique described in Tauchen & Zhou (2006) to identify all statistically significant equity jumps on the individual component stocks of the S&P 100 Index over the sample period 1999- 2005, and find that sequential equity jumps exhibit statistically and economically significant positive autocorrelations.

The tests of the previous study are complement the empirical work of Gutierrez & Kelley (2007), who document negative weekly autocorrelations immediately after extreme information events, but find that momentum profits emerge several weeks after an extreme return and persist over the remainder of the year. This finding is consistent with the predictions of the study of Paul et.al., (2007) that markets react similarly to explicit (public) and implicit (private) news.

In sum, studies in this category indicated that technical trading rules performed quite well in stock markets, foreign exchange markets, and futures markets. As noted above, however, these studies typically omitted trading rule optimization and out-of-sample verification and did not address data snooping problems.

Conclusions

1- Survey studies indicates that there are exist a big relative importance for the technical analysis in financial sector as a whole, between the traders, dealers, executive managers, small and big financial companies (brokers, mutual funds, insurance companies, banks, .etc), in futures markets, foreign exchange markets and stock market traders, and regarded as an important factor in determining price movements at shorter time horizons.

2- Several studies found economic profits in emerging (stock) markets, regardless of sample periods considered, for foreign exchange markets over the last few decades, although some studies suggested that technical trading profits have declined or disappeared in recent years as; Marsh (2000), Neely& Weller (2001) and Olson (2004), but for futures markets, technical trading strategies appeared to be profitable between the mid-1970s and the mid-1980s, most of the studies indicate that the reason of the good performance in the emerging countries is due to immature markets and no financial deepness (small markets). On the other hand, studies indicated that technical trading strategies had been able to yield economic profits in US stock markets until the late 1980s, but not thereafter as; Bessembinder & Chan (1998), Sullivan, Timmermann & White (1999), Ready (2002) and Marshall, et.al, (2008,2008a).

3- There are three topics considered the main causes of difference performance; Central Bank intervention, Behavioral Finance and the Paradox of Efficient Markets as indicated in Grossman & Stiglitz (1980). Other studies refers to the data (the length, type of data set), also technological advances will undoubtedly improve information dissemination and as such improve market efficiency, also refers to the problem involves the measurement of risk, the nature of the tests (however it could be said that technical analysis is profitable when conducted by a skilled technician), It has also been noted that 'many predictable patterns seem to disappear after they are published in the finance literature.

4-The performance (Profitability) of theoretical studies as follows:

In efficient market models, such as the martingale model and random walk models, technical trading profits are not feasible when the markets work efficiently, so the performance will be positive in sub-martingale model and weak random walk model.

In contrast, other models (behavioral models) such as noisy rational expectations models, feedback models, disequilibrium models, herding models, agent-based models, and chaos theory, postulate that price adjusts sluggishly to new information due to noise, market frictions, market power, investor's sentiments or herding behavior, or chaos. In these models, therefore, the performance must be positive, there exist profitable trading opportunities.

On the other hand behavioral theory does not substitute neoclassical finance, but rather adds to the traditional view, modifies it, and fills some gaps. As Shefrin (2005) and Szyszka (2007) refers that this theory is more formal and integrated theory and create behavioral market models at more general level.

5- The rapidly growing empirical literature on the performance (profitability) of technical analysis especially in the foreign exchange market has:

A: appeared since the late 1990s has a number of developments among the more recent literature as follows:

First, a major methodological innovation has been the introduction of the bootstrap approach addressing the problem of insignificant evidence as; Levich & Thomas (1993), LeBaron (1999, 2000), and Osier (2000, 2003) and, more recently, the introduction of methods for testing for potential data-snooping bias as; Park & Irwin (2005) and Qi & Wu (2006).

Second, the range of technical analysis tools and trading rules considered has been increased far beyond filter rules, moving averages or point-and-figure indicators, and now includes the possible psychological barriers of round figures, the closely related issue of support and resistance levels such as; De Grauwe & Decupere (1992), Curcio & Good hart (1992) and Osier (2000, 2003, 2005), or of momentum-based strategies as; Okunev & White (2003).

Third, the longer span of data available for the floating rate period since the early 1970s has stimulated the question as to whether profits from technical analysis are declining over time? There is indeed evidence that the foreign exchange market has become more efficient over time in the sense that the application of traditional moving average rules, that was shown to be profitable for the 1970s, e.g. Logue & Sweeney (1977), Cornell & Dietrich (1978), Dooley & Shafer (1983) and Sweeney (1986), became much less profitable in the 1990s as; LeBaron (2000) and Olson (2004), even after allowing for a reduction in transactions costs over time as the study of Neely, Weller & Ulrich (2006). Although significant evidence of profitability albeit on a reduced level, remains and may even have been increasing during recent years in euro-dollar trading as; Park & Irwin (2005), Schulmeister (2005).

Also, there may be more complex forms of technical analysis that did not become less profitable over time e.g. Okunev & White (2003), Neely, Weller & Ulrich (2006). Similar results are reported by Hsu & Kuan (2005) for stock markets, providing support to the interpretation of Neely, Weller & Ulrich (2006) that markets may need time to become aware of and then to arbitrage away profit opportunities generated by technical trading rules.

Fourth, there have been attempts to avoid potential selection bias by letting actors state their preferred rules prior to any profitability analysis Allen & Taylor (1990), Curcio & Goodhart (1992,1993) and Osier (2000).

Finally, some studies such as; Curcio et aL, (1997), Osier (2000, 2003), Neely & Weller (2003) and Kozhan & Salmon (2006), have examined the profitability of technical analysis on a very high-freqency (intra-day) basis, with mixed results.

B: There are some general conclusions related the performance of technical analysis in the all markets, and the performance of some tools as follows:

-There is evidence in support of the usefulness of moving averages, momentum, support and resistance and some patterns.

-Performance of technical analysis works best on currency markets, intermediate on futures markets, and worst on stock markets.

-Performance of chart patterns work better on stock markets than currency markets.

-Non-linear methods work best overall. This is not at all surprising in light of the non-linearities found in markets as; Hsieh (1989), Scheinkman & LeBaron (1989), Frank & Stengos (1989), Brock, Hsieh & LeBaron (1991), Abhyankar, Copeland & Wong (1995, 1997), Brooks (1996), Barkoulas & Travlos (1998), Ammermanna & Patterson (2003), Kilian & Taylor (2003) De Grauwe & Grimaldi (2006, 2006a); Reitz & Taylor (2006).

-Technical analysis doesn't work as well as it used to, as transaction costs decrease, available computing power increases and the number of market participants increases, one would expect markets to become increasingly efficient and thus it is not surprising that the efficacy of technical analysis should diminish.

-Technical trading rules formulated by genetic programming might be successful in foreign exchange markets but not in stock markets.

-Studies on technical trading strategies under Model-based bootstrap were profitable in several emerging (stock) markets and foreign exchange markets, while they were unprofitable in developed stock markets, -Other studies indicated that technical trading rules performed quite well in stock markets, foreign exchange markets and futures markets. As noted above, however, these studies typically omitted trading rule optimization and out-of-sample verification and did not address data snooping problems.

At last As shown in table (3), the number of studies that identified profitable technical trading strategies is far greater than the number of studies that found negative results. Among a total of 114 modern studies, 76 studies found profitability (or predictability) in technical trading strategies, while 24 studies reported negative results. The rest (14 studies) indicated mixed results. In every market, the number of profitable studies is more than triple that of unprofitable studies.

Recommendations

The study introduces humbly some recommendations for policy maker, researchers and all considered and practitioners of technical analysis:

-It must teach the basis of technical analysis in the colleges especially of commerce, side by side to the fundamental analysis as the literature appointed that they are complemented.

-As technical analysis is considered a content and existed phenomenon of the formal economy, and a factor of leading prices (when it featured by efficiency), so it must pay great attention to the performance of technical analysis as it a tool of economic policy especially when its effectiveness is proved.

-It must deregulate technical analysis and encourage economic researchers to formulate theoretical base of it

It must decrease the transactions costs (interest rate, taxes, commissions ...etc), to improve the performance of technical analysis strategies (tools).

-Monetary policy maker should timing the interventions of central bank and any other actions which effect the performance of technical analysis especially in financial cycles.

-It must doing empirical researches which indicates the performance of technical analysis in the Egyptian economic, especially there is a great shortage in the studies of this field.

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Table (1)
Summary of early and standard studies of technical analysis

Studies of early technical analysis studies in period (1961-1987)	Studies of Standard Technical Analysis in period (1988-2009).
-Donchian (1960), Alexander (1961), Houthakker (1961), Cootner (1962), Gray & Nielsen (1963), Alexander (1964), Smidt (1965a), Fama & Blume (1966), Levy (1967a), Levy (1967b), Poole (1967), Van Home & Parker (1967), James (1968), Van Home & Parker (1968), Jensen & Benington (1970), Stevenson & Bear (1970), Dryden (1970a), Dryden (1970b), Levy (1971), Leuthold (1972), Martell & Philippatos (1974), Praetz (1975), Martell (1976), Akemann & Keller (1977), Logue & Sweeney (1977), Cornell & Dietrich (1978), Logue, Sweeney, & Willett (1978), Arnott (1979), Dale & Workman (1980), Bohan (1981), Solt & Swanson (1981), Peterson & Leuthold (1982), Dooley & Shafer (1983), Brush & Boles (1983), Irwin & Uhrig (1984), Neftci & Policano (1984), Tomek& Querin (1984), Bird (1985), Brush (1986), Sweeney (1986), Taylor (1983, 1986), Thompson & Waller (1987).	Lukac, Brorsen & Irwin (1988), Lukac & Brorsen (1989), Sweeney & Surajaras (1989), Taylor & Tari (1989), Lukac & Brorsen (1990), Taylor (1992), Farrell & Olszewski (1993), Silber (1994), Taylor (1994), Menkhoff & Seniumberger (1995), Lee & Mathur (1996a), Lee & Mathur (1996b), Szakmary & Mathur (1997), Goodacre, Bosher & Dove (1999), Kwan, Lam, So, & Yu (2000), Maillet & Michel (2000), Taylor (2000), Goodacre & Kohn-Spreyer (2001), Lee, Gleason & Mathur (2001), Lee, Pan, & Liu (2001), Martin (2001), Skouras (2001), Olson (2004).

Table (2)
Summary of model-based bootstrap technical analysis
Studies in the period (1988 - 2009)

Category	**Studies**
Model-based Bootstrap	Brock, Lakonishok, & LeBaron (1992), Levich & Thomas (1993), Bessembinder & Chan (1995), Hudson, Dempsey & Keasey (1996), Kho (1996), Raj & Thurston (1996), Mills (1997), Bessembinder & Chan (1998), lto (1999), LeBaron (1999), Ratner & Leal (1999), Coutts & Cheung (2000), Parisi & Vasquez (2000), Raj (2000), Gunasekarage & Power (2001), Day & Wang (2002), Kwon & Kish (2002), Neely (2002), Saacke (2002), Fang & Xu (2003), Sapp (2004), Linto (2006) and Marshall, etal, (2008،(
Genetic programming	Neely, Weller, & Dittmar (1997), Allen & Karjalainen (1999), Fyfe, Marney & Tarbert (1999), Neely & Weller (1999), Wang (2000), Neely & Weller (2001), Korczak & Roger (2002), Ready (2002), Neely (2003), Neely A Weller (2003), Roberts (2003), Cooper & Gulen (2003), Timmermann & Granger (2004), Papadamou & Stephanides (2005).
Reality Check	Sullivan, Timmermann & White (1999), Qi & Wu (2002), Sullivan, Timmermann & White (2003), Hansen (2003, 2004, 2005), Hansen & Lunde (2005) and Hsu & Kuan (2005), Romano & Wolf (2005), Qi & Wu (2006), Po, Yu & Chung (2009).
Chart Pattern	Curcio, Goodhart, Guillaume & Payne (1997), Caginalp & Laurent (1998), Chang & Osier (1999), Guillaume (2000), Lo, Mamaysky &

	Wang (2000), Osier (2000), Leigh, Paz & Purvis (2002), Leigh, Modani, Purvis & Roberts (2002), Dawson & Steeley (2003), Lucke (2003), Zhou & Dong (2004), Lento & Gradojevic (2006), Weller and Zvingelis
Nonlinear Studies	Gen^ay (1998a), Gencay (1998b), Gen?ay & Stengos (1998), Gencay (1999), Rodriguez, Martel & Rivero (2000), Rivero, FeTix & Rodriguez (2002), Rodriguez, Rivero & F6lix (2003), Reitz & Taylor (2006), De Grauwe & Grimaldi (2006,2006a); Reitz & Taylor (2006).
Other Technical Analysis Studies	Pruitt & White (1988), Schulmeister (1988), Sweeney (1988), Taylor (1988), Pruitt & White (1989), Neftci (1991), Corrado & Lee (1992), Pruitt, Tse & White (1992), Wong (1995), Cheung &Wong (1997), Irwin, Zulauf, Gerlow, & Tinker (1997), Neely (1997), Goldbaum (1999), Marsh (2000). Dewachter (2001), Wong, Manzur & Chew (2003), Tauchen & Zhou (2006), Paul et.al.,(2007), Gutierrez & Kelley (2007).

Table (3)
Summary of the results of empirical modern studies performance

Studies	The number of studies		
	positive	Mixed	Negative
A. Stock markets			
Standard	١	٠	٣
Model-based Bootstrap	٧	٢	٣
Genetic programming	٣	١	٣
Reality Check	٠	١	١
Chart patterns	٧	٠	١
Nonlinear	٣	٠	١
Others	١٠	٢	٠
Sub-total	٣١	٦	١٢
B. Currency markets			
Standard	٧	٣	٣
Model-based bootstrap	٨	٠	١
Genetic programming	٥	٠	١
Reality Check	٦	٣	٠
Chart patterns	٢	٠	٣
Nonlinear	٧	٠	٠
Others	٣	١	١
Sub-total	٣٨	٧	٩
C. Futures markets			
Standard	٥	٠	١
Model-based bootstrap	١	٠	١
Genetic programming	٠	١	٠
Others	١	٠	
Sub-total	٧	١	٣
total	٧٦	١٤	٢٤

أداء التحليل الفني: مسح للدراسات الاقتصادية

ملخص

يتمثل هدف تلك الدراسة في استعراض الدليل (النظري والتطبيقي) على أداء التحليل الفني، ولتحقيق ذلك قامت الدراسة بعرض لأهم مؤشرات التحليل الفني الأكثر تداولا في كل الدراسات التي تناولت أداء التحليل الفني ويطلق على تلك المؤشرات أدوات قواعد واستراتيجيات. كما قامت الدراسة باستعراض أهم أسباب اختلاف أداء التحليل الفني في كل من: الأسواق الناشئة وفي باقي الدراسات التي تمت على كل الدول الأقاليم بشكل كلي، والتي تمثل أهمها في: اختلاف المخاطر وفترة البيانات وتكاليف المعاملات(الضرائب، سعر، الفائدة، العمولات وغيره)، بالإضافة للتدخل الحكومي ولغز فرضية كفاءة السوق.

كما تناولت الدراسة الأهمية النسبية للتحليل الفني مقارنة بالتحليل الأساسي، حيث تعد مدى قدرة التحليل على التنبؤ وبالتالي تحقيق ربحية(أداء التحليل الفني) هو الأساس في قبوله وانتشاره كما أشارت العديد من الدراسات، وقد أشارت تلك الدراسات أن بعض المتعاملين والشركات والمديرين التنفذيين سواء في صناديق الاستثمار البنوك وشركات التأمين وشركات الأوراق المالية قد تصل تلك الأهمية وفقا لبعض الدراسات لحوالي ١٠٠%، بينما تراوحت في الدراسات بين ٢٠-٧٥%.

تناولت الدراسة اختلاف أداء التحليل الفني وفقا لاختلاف الأساس النظري(الخلفية النظري) القائم عليها، حيث تم تناول التحليل الفني من شقين، تمثل الشق الأول في: نظرية التمويل Finance theory والتي تقوم على فريضة كفاءة السوق والذي يشمل نماذج السير العشوائي ونماذج التوقع ذو العائد الصفري Maringale Models أو العائد الأيجابيSemi Martingale . والشق الثاني يتمثل في النظرية السلوكية في الاقتصاد والذي يشتمل على نماذج التوقعات الرشيدة الصاخب، ونماذج المتاجرة الصاخبة والتغذية العكسية وغيره من النماذج السلوكية الأخرى.

وأخيرا قدمت الدراسة استعراض للدراسات التطبيقية التي تقيس أداء التحليل الفني لمختلف الأسواق والدول والمناطق، وقسمت للدراسات التطبيقية المبكرة وذلك في الفترة (١٩٦٠-١٩٨٧) وشملت حوالي ٤٢ دراسة جاءت نتائجها موجبة ومختلطة في معظمها وقليل منها كان الأداء سالبا، ثم الدراسات التطبيقية الحديثة والتي تم تناولها في سبعة أشكال، وشملت حوالي ١١٤ دراسة في أسواق الصرف الأجنبي، والاسهم وأسواق المستقبليات، وقد ثبت وجود علاقة موجبة للأداء في حوالي ٧٦دراسة، بينما جاءت ٢٤ دراسة ذات علاقة سالبة وحوالي ١٤ دراسة جاءت نتائجها مختلطة. وبالتالي تستنتج الدراسة أن عدد الدراسات التي حققت ربحية موجبة تعادل أكثر من ثلاثة أضعاف عدد الدراسات التي لم تحقق ربحية وحوالي أكثر من خمسة أضعاف الدراسات المختلطة.