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On Development of Technical Analysis Based Portfolio Optimization Models

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ABSTRACT

It has always been a significant concern for scholars to model the complex state of stock markets in the way that traders' satisfaction improves. However, still this field suggested the need for more accurate and comprehensive models. Development of such models is difficult because of the unpredictable economic, social and political variables that surely affect the market manners. However, model developers of the field have escaped the above referred complexities by some simplifying assumptions that have resulted in their less practicability in real world. In this study, subsequent to an introduction to the field of portfolio optimization and a literature review of the investment approach of Technical Analysis (TA), capabilities of TA in improving the present status of investment models and its potentiality to address the main challenges of the field are discussed. The present study also proposes the modular structure in which TA would suppose to be helpful.

Key words: Technical analysis, portfolio optimization, portfolio selection, investment decisions, psychology of market, conceptual models

INTRODUCTION

Portfolio theory has been organized to overcome the challenge of assigning one's wealth among different assets (Deng *et al.*, 2005). Recognizing the best portfolio of assets is one of the major challenges of financial world (Ballestero *et al.*, 2007) and is called portfolio selection. As a matter of fact, portfolio selection is the process of making the portfolio that maximizes the investor's satisfaction (Fernandez and Gomez, 2007; Huang, 2007; Elikyurt and Ozekici, 2007; Huang, 2008). It is impossible to introduce a general strategy for selecting stocks in any market since it is dependent to many factors. For example Kimiagari and Amini (2007) examined the profitability of a broad range of stock selection strategies only in Tehran Stock Exchange over a specific period while it was proved that the most successful strategy in Iran is the multivariate strategy which selects the stocks with high E/P, B/P, C/P, S/P and D/E.

In spite of continuous contributions of scholars in development of better portfolio models, still they are not completely applicable in real world. Much of the inapplicability is because of the gap between realities of market and assumptions of such models. Many of the assumptions are made because the optimization techniques that are used in such models have not been developed exclusively for the field of portfolio theory. And experts of each field have analyzed the portfolio selection problem from their own perspective of expertise. So they have to simplify the complex problem of portfolio optimization to make it possible for modeling and solving. For example there are some unrealistic assumptions in stochastic programming, robust optimization and markov modeling of the portfolio problem; on distribution of parameters, change direction of uncertain parameters and manner of relationship between future and present, respectively. As a result of this approach, the models have not been welcomed by practitioners and there is a gap between products of academic community and what the stock traders apply. So always, the severe need for development of a model that is designed exclusively to optimize a portfolio is felt.

The current portfolio models do have a long way to come to the ideal point of being applied by the market practitioners directly but there are three significant challenges, as follows, that they must encounter first.

One of the basic assumptions that scholars have made for their models is 'absolute rational behavior of investors'. That is emotion has no effect on investors decision making. But both of experiments and experiences have proven the necessity for entrance of psychological effects of markets into portfolio models. That is decisions made by traders struggling in the midst of the financial markets may not be as heartless as they are seemed to be. Lo and Repin (2002) study the importance of emotion in the decision-making process of professional practitioners of stock market by measuring their physiological characteristics like skin conductance, blood volume pulse during live trading sessions while simultaneously capturing real-time prices from which market events can be detected. In their sample that was ten traders, they found different physiological responses during different states of the market and across the ten traders. According to their results even the most hard-boiled trader has heart palpitations during volatility events and less experienced traders can react emotionally to a broader swath of market behavior. So it is highly critical for portfolio models to encompass the emotional factors of market but how?

The world of finance never waits for anybody or never adapts itself with assumptions of scholars' models; rather scholars themselves must obey its circumstances. Any simplifying assumption about the market behavior, however, small and partial may reduce the reliability of results considerably. For example if a model assumes that the stocks returns have chaotic distribution and then develops the model, the stock trader who wants to apply this model should always monitor the stocks returns to determine whether they are chaotic or not. If even the difficulties of testing the supposition are overlooked, a massive amount of work should be done continuously to determine whether the model is applicable or not in that particular market or domain. There are many other examples to demonstrate that how considerably a simple assumption can decrease the practicability of a model. So less restricted a model, more ideal it is.

Nowadays flexibility or robustness of models is needed more than anytime in the past. Winkler (1989) agrees and justified his belief as follows:

"I prefer, however, to take the view that, in many situations, there is no such thing as a true model for forecasting purposes. The world around us is continually changing, with new uncertainties replacing old ones. As a result, the longer-term search for a true model is doomed to fail in many cases because unanticipated changes prevent us from enjoying the luxury of getting to the longer term in a stable environment. This was suggested that models should be adaptive, but even adaptive models only represent our best state of knowledge at a given time; they do not represent the 'truth' in any sense."

This century is time of rapid and discontinuous changes with new risks. Time pressures and rush of events make us design and apply adaptive, unified and efficient decision support systems

(Leigh *et al.*, 2002a). Most or even all the available models can not do well with this challenge. Because they assume future state of stock markets are in accordance with past state of them (Tanaka and Guo, 1997) but the past data have limited applicability (Ballestero *et al.*, 2007). Efficient and practical portfolio models must be flexible and capable of rapid responses to market changes.

This study is to highlight the leading role that TA can take in portfolio models to encounter the three above mentioned challenges.

TECHNICAL ANALYSIS

Developing a model for predicting returns is an important goal for academics and practitioners while for example famous concept of Capital Asset Pricing Model with its vast literature of works like Rahman *et al.* (2006a, b) or Rhaiem *et al.* (2007) is just a small category.

TA is a category of prediction models that has been welcomed by stock traders significantly and there is little dispute that it is very common among practitioners (Roberts, 2005). The main aim of this analysis is to get a signal from market data to buy or sell the risky assets.

Typically the financial services industry relies on three main approaches to make investment decisions: the fundamental approach that uses fundamental economic principles to form portfolios, the TA approach that uses price and/or volume histories and the mathematical approach that is based on mathematical models (Leigh *et al.*, 2002b). Among them technical and fundamental analyses dominate practice. Blanchet-Scalliet *et al.* (2007) justifies this very well and says if one considers a non-stationary economy it is impossible to specify and calibrate mathematical models that can capture all the sources of parameter instability during a long time interval. In such an environment, one can only attempt to divide any long investment period into sub-periods such that, in each of these sub-periods, the financial assets prices can reasonably be supposed to follow some particular distribution. Due to the investment opportunity set's instability, each sub-period must be short. Therefore, one can only use small amounts of data during each sub-period to calibrate the model and the calibration errors can be substantial.

The definitions of TA that have been presented in literature by different scholars are almost the same. Tian *et al.* (2002) know TA as a search for recurrent and predictable patterns in stock prices. Dourra and Siy (2002) define it as an attempt to predict future stock price movements by analyzing the past sequence of stock prices because of the fact that forces of supply and demand affect those prices. They believe that it dismisses such factors as the fiscal policy of the government, economic environment, industry trends and political events as being irrelevant in attempting to predict future stock prices. Roberts (2005) knows it as a broad collection of methods and strategies which attempt to forecast future prices on the basis of past prices or other observable market statistics, such as volume or open interest. According to Wang and Chan (2007), TA studies records or charts of past stock prices, hoping to identify patterns that can be exploited to achieve excess profits. Blanchet-Scalliet *et al.* (2007) believe that TA defines trading rules using the asset's price or/and volume history. There are also other definitions in literature that imply the same meanings and implications as the mentioned ones.

Background: The study of TA has a long history in academia, particularly in the practitioner literature, with mixed results. According to Cesari and Cremonini (2003) TA is perhaps the oldest device designed to beat the market. It has a secular history given that its origins can be traced to the seminal articles published by Charles H. Dow in the Wall Street Journal between 1900 and

1902, and its basic concepts became popular after contributions by Hamilton (1922) and Rhea (1932). A complete jargon of words and pictures has been developed since then and many traders, nowadays, take their buying and selling decisions on the basis of TA results appearing on their screens.

The approach of academic community to TA is to some extent unconvinced because of its limited theoretical justification and its contradiction to the conclusions of the efficient market hypothesis. That is, although the vast majority of the professional traders use TA, most academics, until recently, had not recognized the validity of these methods. They prefer the much more theoretical fundamental analysis (Tian *et al.*, 2002). This negative view of TA by academia, perhaps best typified by Malkiel (1985), "Obviously, I am biased against the chartist. This is not only a personal predilection but a professional one as well. TA is anathema to the academic world" (p. 132). But there are also some that are more charitable toward TA, Campbell *et al.* (1997) suggest "perhaps some of the prejudice against TA can be attributed to semantics" (Roberts, 2005) and among the rich literature that exists on whether TA is actually profitable (Roberts, 2005) a fairly comprehensive literature in various financial domains has addressed numerous effective evidences that trading success can be achieved with TA (Wang and Chan, 2007).

Meanwhile it is worthy of mentioning that more recently, there has been a renewal of academic interest in the performance of TA based methods (Blanchet-Scalliet *et al.*, 2007). In other words after many years of being held in almost complete contempt by academics, TA has enjoyed somewhat of a renaissance recently in the eyes of both practitioners and financial econometricians (Mills, 1997). Generally TA remains very popular despite a lack of theoretical foundation and has been used by professional investors for more than a century (Blanchet-Scalliet *et al.*, 2007). Brorsen and Irwin (1987) report that only 2 of 21 large commodity fund managers surveyed used no objective TA.

To be more precise in reviewing the literature of TA, it is to be noted that results obtained in the 1960s and 1970s supported the impracticability of applying TA for prediction of future. For example Alexander (1964) and Fama and Blume (1966) identifying and testing some simple technical strategies found that although they may have some predictive power, they were unable to consistently generate positive profits. Benington and Jensen (1970) conclude that TA is not useful. Over the succeeding decades, many researchers reached similar conclusions, especially when transactions costs were included in the analysis. But TA literature also owns some famous supporting studies during these decades. For example according to what cited by Wang and Chan (2007) and Levy (1967) employed the TA of relative strength.

Appearance of some evidences like well-known anomalies on one hand and promising results of Brock *et al.* (1992) on the other hand indicated that historical prices can help in predicting future prices. Pruitt and White (1988) developed the CRISMA trading system which combined trading rules of on balance volume, relative strength and moving average and confirmed the profitability of technical trading rules. Sweeney (1988), Allen and Taylor (1990) and Taylor and Allen (1992) found that trading rules can outperform statistical models in predicting exchange rates and stock prices. Neftci (1991) unfolded the fact that technical trading rules require some form of nonlinearity in prices to be successful and nonlinearity is being increasingly found in financial time series. Brock *et al.* (1992), followed by Bessembinder and Chan (1995) and Ratner and Leal (1999) demonstrated the profitability of simple trading rules, moving average and trading range break out. Indeed Brock *et al.* (1992) after applying 26 trading rules to the Dow Jones Industrial Average found that they significantly out-perform a benchmark of holding cash. Based on this same universe of 26 trading rules, Bessembinder and Chan (1995) argued that although the technical trading rules do have predictive ability in US data, their use would not allow investors to make excess returns in the presence of costly trading. Sharpe *et al.* (1995) summarized some observations regarding the recent evidence in TA, stating "the apparent success of these strategies offers a challenge to those who contend that the stock market is highly efficient". Sullivan *et al.* (1999) examine close to 8000 technical trading rules and repeat Brock *et al.* (1992) studied while correcting it for data snooping problems. They find that the examined trading rules do not generate superior performance out-of-sample. Hudson *et al.* (1996) showed that moving average trading rules can be utilized for USA and UK markets. Mills (1997) investigated the predictive ability of technical trading rules of moving average oscillator and trading range break-out by analyzing daily data on the London Stock Exchange FT30 index for the period 1935-1994. It is found that the trading rules worked, in the sense of producing a return greater than a buy-and-hold strategy, for most of the sample period, at least up to the early 1980s while Gunasekarage and Power (2001) showed that technical trading rules have predictive ability in South Asian stock markets.

Academic study of TA has mainly adopted quantitative indicators as prediction variables, for example relative strength index, moving average and so on. Meanwhile, charting pattern, for example head-and-shoulder, flag, etc. are comparatively rare. Nevertheless, complying with the development of computer technology and cross-domain research, academic study has gradually paid increasing attention to pattern analysis for investment decision, including Lo *et al.* (2000) testing price charting patterns using kernel regression for the identification of ten patterns. Based on specific technical indicators such as head-and-shoulder or double-bottoms this study found that over the 31-year sample period, several technical indicators provide incremental information and may be useful. However, as pointed out by Jegadeesh (2000) in its comment of the Lo *et al.* (2000) paper, none of the TA indicators examined by the authors is able to identify profitable investment opportunities. Leigh *et al.* (2002a) implemented a variation of the bull flag charting pattern using a template matching technique from pattern recognition. The results of this study support the effectiveness of the TA approach through use of the "bull flag" price and volume pattern heuristic. Leigh *et al.* (2002b) and (2004) extended the method of Leigh *et al.* (2002a) to test a bull flag volume pattern for trading the NYSE Composite Index for the period of the Great Bull Market of the 1980s and 1990s.

Tian *et al.* (2002) concentrate on markets with different efficiency level and they find that the trading rules are quite successful in predicting stock price movements in Chinese markets and allowing traders make possible excess profits in 1990s while the results in US. during the same period is disappointing. Ausloos and Ivanova (2002) present a generalization of the classical TA concepts taking into account the volume of transactions. Dourra and Siy (2002) propose a new method to map TA indicators into new inputs that can be fed into a fuzzy logic system. This method relies on fuzzy logic to formulate a decision making when certain price movements or certain price formations occur. The new stock evaluation method is proven to exceed market performance and it can be an excellent tool in the TA field. Cesari and Cremonini (2003) make an extensive simulation comparison of 9 popular dynamic strategies of asset allocation, including 2 of benchmarking type, 5 of portfolio insurance and 2 of TA. Both the historical and the Monte Carlo simulations show that no strategy is dominant in all market situations. Roberts (2005) develops some trading rules by genetic programming. The results of this study do not preclude the existence of profitable technical trading strategies. Wang and Chan (2007) examine the potential profit of bull flag technical trading rules for the Nasdaq Composite Index (NASDAQ) and Taiwan Weighted

Index (TWI). The empirical results indicated that all of the TA rules correctly predict the direction of changes in the NASDAQ and TWI. Blanchet-Scalliet *et al.* (2007) examine chartist and mathematical models based trading strategies by providing a conceptual framework where their performance can be compared. According to Monte Carlo numerical experiments, the results show that under parameter mis-specification, the TA technique out-performs the optimal allocation strategy.

There are also many other studies in field of TA that can not be referred completely here. But the already mentioned works are supposed to be enough in showing the general attitude toward TA from the beginning until now.

Reliability: Based on the literature, it is not possible to state firmly about validity or good organization of TA. That is, still soundness of TA has not been proved explicitly and there are many people who suspect its outputs. However, usage of TA in financial models can be justified logically according to the following reasons:

- As was referred to in part 2.1, TA is the first choice of market practitioners to make investment decisions. If TA has not been beneficial to stock traders; because of the semi-negative view of academic community to it, TA should have been disappeared rapidly from practitioners' mind. Not only this has not happened but also the positive academic attitude toward TA has become more and more
- For the studies that deny the profitability of TA as a market timing strategy, there is a possibility of biased choice of the technical rule; i.e., the rule was inappropriate for that particular time or market (in their experiments) while other techniques might produce better results. As a matter of fact professional technical analysts use different rules in different times and markets
- Considerable amount of literature particularly recently support the efficiency of TA
- As is going to be discussed in next parts, TA has some characteristics that no other investment strategy can propose

THE CHALLENGES AND TA

The ability of TA based models in addressing the three challenges mentioned in part 1 is discussed in the three following sub-parts.

Psychology: Markets are influenced at times by emotionalism of stock traders. As John Manyard Keynes stated, "there is nothing as disastrous as a rational investment policy in an irrational world" (Nison, 1991). Generally the intention from market psychology is mass psychology. For example mass psychology is a support to money applicability in market. Why is money, with no inherent worth, exchanged for something real like material? It is because of a shared psychology. Everyone believes it will be received, so it is. One time this shared or mass psychology disappears it becomes worthless.

According to the above definition of mass psychology and intangibility of it mathematical approach can not encompass the factor and a review on literature of Robust Optimization, Markov chain, Multi Objective Decision Making (MODM), Possibility and Fuzzy theory or Minimax modeling of portfolio optimization, proves this. Fundamental analysis also only provides a gauge of price/earnings ratios, economic statistics and so forth and there is no psychological component involved in such analysis (Nison, 1991). But TA is capable of providing a good mechanism to measure the irrational or emotional components that are present in all markets (Nison, 1991), because securities never sell for what they are worth but for what people think they are worth (Dourra and Siy, 2002) and TA is the only mechanism that without paying attention to real worth of securities, merely considers price and volume of past transactions. TA shows that how much the market practitioners are going to value a particular stock because of the equilibrium that TA maintains among human, politic and economic events simultaneously (Chavarnakul and Enke, 2008).

Since the basis of TA for giving signals is mass psychology of the market, if the result of a portfolio model is affected by outcomes of a TA processor, naturally the model would be an emotional one and the designated intensity of the influence (of TA on the final outputs) determines how much emotional it is.

Simplifying assumptions: TA as an investment strategy is free of any limiting constraints that are common in present portfolio models especially mathematical ones. For example TA is independent of the distribution that the input data have.

Flexibility: Flexibility of a model can be analyzed from three perspectives of

- How often are the input data updated?
- How much strong is the effect of new input data on the new output?
- In what conditions is the model valid according to the pre-determined assumptions?

That is, a flexible model is the one that on one hand its input data are updated rapidly and also the new input data affect the output significantly and on the other hand the model is independent of outer conditions. For example consider two models of A and B that are similar in the first two perspectives but according to the third one Model B is looser than A in the way that Model A only accepts data with normal distribution. Apparently Model B is more flexible because of its robustness in front of data distribution.

According to the first perspective there is no difference between different approaches and this factor depends more on the established information support system. About the second perspective since the input data of TA techniques are usually from short time intervals the sensitivity of them to new data are much more than the portfolio selection models that their input data are from time intervals of several months. At last about the third perspective as was discussed in sub-part 3.2, TA is the most ideal one.

It can be seen that the current state of TA without any extra contribution is a completely appropriate option to fill the mentioned shortcomings of the literature. But the questions that may arise are those, what would be the structure of TA based portfolio optimization (TAbPO) models? Or how can a model learn one or several TA rules? And so forth. The next part of the paper answers such questions.

GENERAL STRUCTURE OF TAbPO MODELS

The models of this family are modular ones in which one module or more are allocated to TA. The TA module/s can be parallel or along other modules but the main point here is the effect of TA

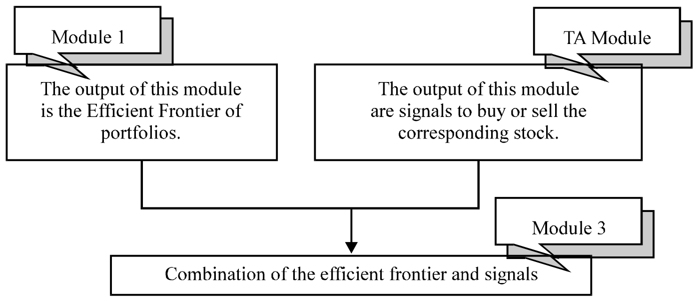

Fig. 1: A typical TAbPO model

module on the final output that can have any intensity. A typical TAbPO model (that is discussed in detail in Jasemi *et al*. (2011a) and Jasemi and Kimiagari (2011)) is depicted in Fig. 1.

In the model of Fig. 1 beside TA module, module 1 also contributes to the final proposed portfolio. Module 1 is a mechanism to yield some portfolios that are on the Efficient Frontier (EF). There is a large amount of works in literature about this module, for example Jasemi *et al*. (2010) discussed a better selection of risk measures for more reliable results. After feeding the necessary data to module 1 and TA module, an efficient frontier and some signals are achieved. These two groups of output are combined in module 3 to give the final proposed portfolio. It is to be noted that the model depicted in Fig. 1 is just an example for this family of models and thousands of other kinds can be innovated. As another example a typical TAbPO model can be a two module one. That is besides the TA module there is only one module that is allocated to mathematical modeling of stock market like Markowitz model. Here, a logical scenario would be that; TA module produces n signals from which a signals are buy ones. The a stocks that correspond to the a buying signals will compose the final portfolio and the role of mathematical module is determination of investment percentage in each of them.

For development of the TA module, there is no limit on technique or indicator that is considered and the main point is its output signals to buy, sell or hold the corresponding stock. Naturally the better this system is designed, more reliable the results will be. The TA module can also be a combination of several techniques that their results are interpreted to one of the three mentioned signals according to a pre-specified rule. For instance Chenoweth *et al*. (1996) have discussed some of such rules.

Artificial Intelligence (AI) is a familiar tool to achieve financial goals, for example Khan *et al*. (2007) and Senol and Ozturan (2008) are aimed to illustrate that neural network can be used for predicting the stock price behavior in terms of its direction. The “TA module” can be equipped with TA by means of AI. Performing TA in financial markets by using AI has been surveyed by some researchers with promising results. Lee and Jo (1999) develop an expert system of candlestick charting analysis to forecast the best timing of stock market. Fernandez-Rodriguez *et al*. (2000) study the applicability of a simple technical rule on the basis of neural networks. Yao and Tan (2000) present some documents for applicability of neural network models for prediction of exchange rate of currency. In this study, time series data and technical analyses like moving average to achieve movement principles of exchange rate of currency, are fed to a neural network. Leigh *et al*. (2002b) show the prospect for application of modern approach of hybrid methods for assessment of buying opportunities in stock market by TA and neural network. Lam (2004) studies the applicability of neural networks especially back propagation algorithm for integration of fundamental and TA for forecasting of financial performance. Chavarnakul and Enke (2008) used a neural network for performing equivolume charting technique. As a new work, Jasemi *et al.* (2011b) presents a model to do stock market timing on the basis of the TA of Japanese Candlestick and concept of Neural Networks with astonishing results.

Actually any shape of AI including neural network, expert system, genetic algorithm and fuzzy theory can be used.

CONCLUSION

In this study after a preface about portfolio optimization problem, three significant challenges of the field have been discussed. Since the paper believes that the investment approach of TA is a superior option for responding to the challenges the remainder of the paper pays particular attention to this strategy of trading. This particular attention shows itself in a literature review, a justification of TA efficiency and lastly discussing how TA is capable of addressing the challenges. Finally the general structure of TAbPO models is discussed. All the four parts of the paper are developed in the way that convinces the scholars to combine TA with their models to improve the quality of outputs.

The literature of portfolio management is full of models that have been developed by mathematical approach; so a good research area would be development of TA based mathematical portfolio models and analyzing the results in a wide range of conditions.

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