Psychology of Market and Necessity of Embedding Technical Analysis (TA) Knowledge into the Portfolio Models

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Abstract- **Stock markets modeling to maximize stock traders incomes has always been a major concern. However, this field still suggests the need for more accurate and comprehensive models. In this paper subsequent to an introduction to the field of portfolio optimization, the main challenges of the field in development of new models are discussed, and then the potentiality of TA in improving the level of portfolio models is justified. The paper also proposes the general structure in which TA would be helpful.**

Keywords- Psychology Of Market; Portfolio Selection; Emotional Models; Technical Analysis; Investment Decisions

I. INTRODUCTION

Portfolio theory has been organized to overcome the challenge of assigning one's wealth among different assets[1]. Recognizing the best portfolio of assets is one of the major challenges of financial world[2] 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[3,4,5,6]. In spite of continuous contributions of scholars in development of better portfolio models, they are still not completely applicable in real world. Much of the inapplicability is because of the gap between the market realities and simplifying assumptions of such models.

The current portfolio models do have a long way to the ideal point of being applied by the market practitioners directly but there are three challenges that must be encountered first. They are as follows.

1. One of the basic assumptions that scholars have made for their models is the assumption of absolute rational behaviour of investors. That is emotion has no effect on investors decisions. 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[7]. Lo and Repin[8] studied 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, they found different physiological responses during different states of the market. 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 [7]. So it is highly critical for portfolio models to encompass the emotional factors of market but how?

2. The world of finance never waits for anybody or never adapts itself with assumptions of scholar's models. As a matter of fact scholars themselves must obey its imposed circumstances. Any simplifying assumption about the market behaviour however small and partial may reduce the reliability of results considerably. So less restricted a model, more ideal it is.

3. Nowadays flexibility or robustness of models is needed more than any time before. 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[9]. Most or even all the available models cannot do well with this challenge. Because they assume future state of stock markets are in accordance with past state of them[10] but the past data have limited applicability[2]. Efficient and practical portfolio models must be flexible and capable of rapid responses to market changes.

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

II. TECHNICAL ANALYSIS

Developing a model for predicting returns is an important goal for academics and practitioners. TA is a category of such models that has been welcomed by stock traders significantly and there is little dispute that it is very common among practitioners[11].

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[9]. Among them, technical and fundamental analyses in comparison to mathematical approach dominate practice. It is because of the fact that technical and fundamental analyses are much more applicable than mathematical models.

The study of TA has a long history in academia, particularly in the practitioner literature, with mixed results. According to Cesari and Cremonini[12] 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[13] and Rhea[14]. The approach of academic community to TA, particularly according to the results obtained in the 1960s and 1970s, is to some extent unconvinced because of its limited theoretical justification and its contradiction to the conclusions of the efficient market hypothesis.

After many years of being held in almost complete contempt by academics, appearance of some evidences like well-known anomalies and on the other hand promising results of Brock et al.[15], indicated that historical prices can help in predicting future prices. After that TA has enjoyed somewhat of a renaissance in the eyes of both practitioners and financial econometricians[16]. A fairly comprehensive literature related to TA in various financial domains has addressed numerous effective evidences that trading success can be achieved with TA[17].

It is true that not all the scholars confirm TA but there are many reasons in support of this strategy to make model developers courage enough to apply it. Some of such reasons are as follows.

1. TA is the first choice of market practitioners to make investment decisions. For example Brorsen and Irwin[18] report that only 2 of 21 large commodity fund managers surveyed used no objective TA. If TA has not been beneficial to stock traders; because of the semi-negative view of academic community to TA, it should have been disappeared rapidly from practitioner's mind. Not only this has not happened but also the positive academic attitude toward TA has become more and more.

2. For the studies that reject the profitability of TA as a market timing strategy there is possibility of a biased choosing of the technical rule; i.e. the rule was inappropriate for that particular time or place of their experiments and other techniques might produce better results. As a matter of fact professional technical analysts use different rules in different times and markets.

3. Considerable volume of literature particularly recently support the efficiency of TA.

4. As is going to be discussed in next parts, TA has some characteristics that no other investment strategy can propose. So if models with more real characteristics are wanted, first of all TA should be welcomed in financial models.

III. THE CHALLENGES AND TA

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

A. *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"[19]. 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 m 0000000000000a0terial? It is because of a shared psychology. Everyone believes it will be received, so it is. One time this shared or mass psychology disappea0rs it becomes worthless.

According to the above definition of mass psychology and its intangibility, mathematical approach cannot encompass the factor. 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[19]. But TA is capable of providing a good mechanism to measure the irrational or emotional components that are present in all markets[19]; because securities never sell for what they are worth but for what people think they are worth[20] 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[21].

Since the basis of TA for giving signals including selling, buying or holding is mass psychology analysis of 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 designated intensity of the influence (of TA on the final output) determines the level of sensitivity to the market psychology.

B. *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.

C. *Flexibility*

Flexibility of a model can be analysed from three perspectives of

- how often are the input data updated;
- how much strong is the effect of new input data on the last output;
- in what conditions is the model valid (according to 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.

According to the first perspective there is no difference between different approaches and this factor depends on the data 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 B, TA is the most ideal approach.

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 is that, how a model can learn TA rules or in better words, how the structure of such models would be. The next part is organized to answer such questions.

IV. GENERAL STRUCTURE

The models of this family are modular, in which one module or more are dedicated to TA. The TA module can be parallel or along other modules but the main point here is the effect of TA module on the final output (that can have any intensity). A typical model of such kind is depicted in Fig. 1.

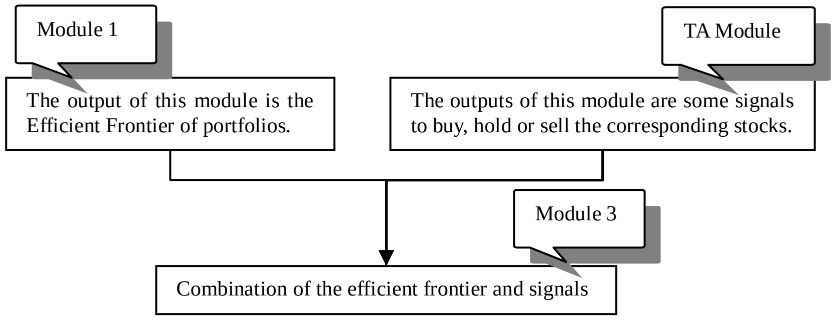

Fig. 1 A typical TA based Portfolio model

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). After feeding the necessary data to these modules, an efficient frontier and some signals (one signal to buy, hold or sell per each stock) 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 let us consider a two module one in which besides the TA module there is only one module that is dedicated 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 the a stocks. For more information in this regard Jasemi et al.[22] and, Jasemi and Kimiagari[23] can be referred.

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 will be the results. 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[24] have discussed some of such rules.

The TA module can be equipped with TA by means of Artificial Intelligence (AI). Performing TA in financial markets by using AI has been surveyed by some researchers with promising results. For knowing more see[9,21,25,26,27,28,29] Actually any shape of AI including neural network, expert system, genetic algorithm and fuzzy theory can be used.

V. CONCLUSION

In this paper all the four constitutive parts are developed in the way that convinces the scholars to combine technical analysis with their models to improve the quality of outputs. The major innovation of this paper is highlighting the fact that Technical Analysis is potential in filling some of the gaps between market practitioners and academic scholars. This work has been done by showing the supportive academic literature, mentioning the exclusive analytic characteristics of TA and discussing why TA is appropriate for the given challenges. Meanwhile development of TA based portfolio models by the mathematical models and then assessing the efficiency of them on the basis of comprehensive numerical experiments is a good research area.

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