TECHNICAL ANALYSIS AND TYPICAL COGNITIVE BIASES

Piotr Zielonka
Warsaw University SGGW and Leon Kozminski Academy of Entrepreneurship and Management, Poland

ABSTRACT

The paper describes a study carried out on a group of 24 Polish financial analysts. The analysts responded to a questionnaire with 24 items (signals). They were asked to rate the predictive value of different signals for the movements of stock prices. The signals were of three types:

(a) regular technical analysis signals, representing some common psychological biases (gambler's fallacy, ignoring the principle of regression to mean, anchoring effect and herd behaviour),
(b) technical-like signals created by the author of the research that imitated technical signals and represented the same types of biases as real technical signals,
(c) other technical-like signals that did not represent any biases.

It turned out that the analysts tended to ascribe high predictive value to the questionnaire items associated with psychological biases (either technical or technical-like signals). At the same time, these items were rated very similarly by different analysts. On the other hand, the technical-like signals not related to any biases were given very low predictive values by the analysts. These results suggest that popularity of technical analysis is associated with its relation to the typical cognitive biases of humans.

INTRODUCTION

In spite of a long list of publications showing that market movement is random or at least very difficult to predict, a lot of effort has been made in forecasting future stock prices (Bernstein, 1992).

One of the forecasting tools very popular among practitioners is technical analysis. Technical analysis is the examination of past price movements in order to forecast future price movements. Technical analysis, as previous research shows, is more an art than an objective analytical tool and its efficiency has not been proven (Fama and Blume, 1966), (Jensen and Bennington, 1970). Technical analysis is open to interpretation. Many times two technicians will look at the same chart and paint two different scenarios or see different patterns. Both would be able to come up with logical support to justify their position.

In addition, even if stock prices completely followed a random walk, people would be able to convince themselves that there are patterns having a predictive value. In laboratory experiments, subjects are reported to have been searching for patterns in purely random sequences of stock prices (Warneryd, 2001).

A following, fundamental question arises: if there is no evidence that technical analysis can result in exceptional profits, why is it so popular? Since technical analysis started in the beginning of the twentieth century when the possibilities of testing its efficiency were very limited, it has become more and more popular, as it offered an unlimited set of tools and signals and seemed to be an interesting method of market analysis. But recent studies, after the 1950's have shown that its efficiency is low or none. So why does technical analysis still remain so popular? The first answer can refer to tradition and education. Investors have used it for over a century and new market participants learn it from more advanced market participants. The second answer refers to some common cognitive biases that affect people’s behavior. It has been proven that stock prices most of the time approximately follow a random walk pattern. Psychologists have described a number of ways in which people deal with randomness. Additionally, market participants may be subject to herd behavior. Perhaps these psychological mechanisms are the invisible fundamentals of technical analysis. Below is a list of 4 common psychological inclinations affecting stock market participants.

1. Gambler's fallacy is observed in a casino where after a long run of red, the roulette player is inclined to believe that black will be next. In financial markets the gambler's fallacy manifests itself in predicting a trend reversal. If a trend continuation is predicted then the

behavior is called antiregressive. (Wagenaar, 1988)

2. Misperception of regression to the mean disregards the statistical fact that in a long series of a chance process extreme values are likely to be followed by less extreme values (Tversky, 1974).

3. Anchoring effect shows that most people tend to base their estimations or assessment of information initially on a first source of reference value (anchor) and subsequently to adapt this to the real value. Empirical research shows that the adjustment process is regularly cut short and is incomplete. The original value (anchor) is afforded too much weight (Slovic, 1971; Tversky and Kahneman, 1971; Goldberg and Nitzsch, 2001). For example decision makers (investors) overestimate the importance of a recently quoted or otherwise significant stock price. This price may then serve as an anchor for further probability assessments.

4. Herd behavior reflects the immense power of social pressure on individual judgment. (Asch, 1952) Many people accept the perceived authority of others on stock market valuation and stop trusting their own judgments if the majority of market participants hold a different opinion.

The present research tested if technical analysis signals are associated with some common cognitive biases. A questionnaire was administered to 24 Polish financial analysts. There were three groups of the items within the questionnaire:

* regular technical analysis signals representing four common psychological inclinations,

* technical-like signals created by the author of the questionnaire, representing the same four inclinations,

* technical-like signals created by the author of the questionnaire, not representing any psychological inclinations

Hypothesis 1: *A majority of the financial analysts will highly rate signals belonging to either the first or the second group and will assign no predictive value to the signals from the third group.*

If Hypothesis 1 is supported by this research it can be stated that some technical analysis signals represent common cognitive biases and this may be responsible for the great popularity of technical analysis.

Hypothesis 2. A majority of the financial analysts will agree on the impact of particular items for future stock prices.

If the hypothesis is supported by the results of this research it can be inferred that the analysts are subject to some psychological biases since they agree on the predictive value of unproven measures.

METHOD

The study was carried out in Warsaw in January-February 2002. The participants were 24 financial analysts or dealers employed by banks and Polish capital market institutions. The sample was not random. Each participant was administered a 24–item questionnaire.

There were three groups of items within the questionnaire. Each group consisted of 8 items.

The first group consisted of regular technical analysis signals representing four common psychological inclinations. Each inclination was represented by two signals. Usually one from a pair of signals was a predictor of a stock fall (-), whereas the other signal was a predictor of a stock rise (+).

· Gambler's fallacy

  - Rising WIG[1] index breaks its main trend line (-),

  - After a big rise, WIG index creates a "head and shoulders" formation (-),

· Anchoring effect

  - Rising WIG index repeatedly bounces from a resistance level (rising WIG fails to surpass some barrier) (-),

  - Rising WIG index breaks strong psychological barriers (+),

· Misperception of the regression to the mean

  - Falling WIG index breaks successive levels of support (-),

  - Rising WIG index confirms its main trend line (+),

· Herd behavior

  - WIG index fall accompanied with a decreasing popularity of stock market (-),

· - Dramatic rise in the value of a buy order (+),

[1] WIG is the main Polish stock exchange index; a total-return index encompassing all shares listed on the main market, calculated since 1991.

The second group consisted of technical-like signals created by the author of the questionnaire, representing the same four psychological inclinations (two items for each inclination).

- Gambler’s fallacy
  - Rising WIG fails to surpass 4/5 of the last peak (-),
  - After the index falls, a big overbalance of demand occurs (+)
- Anchoring effect
  - Falling WIG index breaks October effect peak (-),
  - Rising WIG breaks local peak of January effect (+),
- Misperception of the regression to the mean
  - The fall of WIG index accompanied by a government crisis (-),
  - WIG index’s increase accompanied by a drop of the unemployment rate (-),
- Herd behavior
  - Diminishing rate of a WIG fall accompanied by a vanishing trade turnover (+),
  - Over two months WIG’s rise accompanied by a high trading volume (+),

The third group consisted of technical-like signals, created by the author of the questionnaire, that did not represent any psychological inclinations.

- Drop of chemical companies' prices,
- Horizontal, typically sinusoidal WIG index movement,
- Rising WIG index creates longer and longer horizontal shelves,
- A fan formation support line moves upward,
- Diminishing dynamics of price rise in textile branch,
- An alternate large and small daily trade volume,
- Second MACD derivative goes negative,
- WIG index creates horizontal small amplitude sinusoid curve.

The cover page of the questionnaire stated that the survey was designed to better understand the opinions of experts on implementation of technical analysis. This remark allowed the participants to feel more like experts whose opinion is needed for some further research rather than merely the persons to be examined. Respondents were assured of confidentiality. Demographic information was collected on the participants’ age, educational level, sex, and employment status.

The participants of the questionnaire were asked to assign a score of –3, -2, -1, 0, +1, +2 or +3 to each item, depending on how they estimated the impact of the item for the future (within a few weeks) behavior of stock prices (the WIG index). The analysts were asked what market movement they would expect if certain technical signal occurred, with a higher score indicating a stronger positive impact of the item, resulting in a stock price rise. Thus –3 meant that the item was expected to evoke a strong stock price drop, while +3, a strong rise. Zero meant that the item was regarded by the participant as a neutral measure, having no effect on stock price changes.

All 24 respondents filled out the questionnaires. On average less than 3% of the questionnaire items remained unscored. No regularity was noticed among unscored items. Statistical analysis of the scores was done with the use of the StatSoft computer program Statistica.

RESULTS

In order to examine which of the 24 items received the highest, lowest and median marks, indicating respondents' opinions on its power to affect stock prices, a cluster analysis was carried out (Hartigan, 1975). The cluster analysis was conducted in two stages. A horizontal hierarchical tree plot and a graph of the amalgamation schedule (Ward's method amalgamation rule, Euclidean distances) indicated 3 main clusters. K-means clustering (constant intervals) divided all 24 items into 3 clusters. The clusters are presented in Fig. 1. Cluster 1 consists of 8 signals, which according to respondents have little or no impact on future stock prices. All eight in this cluster were technical-like signals created by the author of the questionnaire, not representing any psychological inclinations

Cluster 2 consists of 8 items, rated as highly important predictors of stock price drop. All the technical and technical-like questionnaire items representing cognitive biases associated with the stock fall are included into this cluster.

Cluster 3 consists of 8 signals, rated by questionnaire participants as highly important predictors of stock price increase. All the technical and technical-like questionnaire items representing cognitive biases associated with the stock rise are included into this cluster.

.

{Fig. 1}

These results strongly confirm the Hypothesis 1. The respondents did not discriminate between real technical signals and technical-like signals and assigned a high predictive value only to those that represented some cognitive bias. On the other hand the financial analysts did not assign any predictive value to technical-like signals that did not represent any cognitive bias. This result shows that some technical analysis signals are associated with psychological biases typical for people who face randomness, and it may be an explanation of the large popularity of technical analysis.

INTER-JUDGE AGREEMENT

Standard deviation of the scores assigned to each questionnaire item was between 0.5 and 1.3 which can be considered as a relatively small value. The small standard deviation values confirm that the analysts were in general agreement about the predictive value of different signals of unproven efficiency. Why? Because they are subject to some psychological biases typical for all humans. The results of this research confirm the Hypothesis 2. The demographic features of the participants did not correlate in any way with their responses.

DISCUSSION

The popularity of technical analysis appears mysterious to the academic world. In spite of much evidence of its low or zero efficiency for stock market forecasting, technical analysis remains one of the most popular analytical tools among practitioners. Its popularity derives in part from tradition as an attractive way of analysis in comparison, for instance, to fundamental analysis. The present research shows that many technical analysis signals represent common psychological biases such as the gambler's fallacy, anchoring effect or herd behavior.

All real technical analysis signals were assigned a high predictive value by the financial analysts who responded to the questionnaire. The "technical" signals created by the author of the research either represented psychological biases or not. If they did, they received high scores from respondents as good predictors the of stock market behavior. If they did not, the respondents estimated them as bad predictors. In addition, the respondents were in general agreement about their judgments. These results confirm both hypotheses of this research: technical analysis signals represent some common psychological biases and financial analysts are subject to these biases.

REFERENCES

1. Asch, S., (1952), Social Psychology, Englewood Cliffs, N.J. Prentice Hall.
2. Bernstein, P., (1992), Capital Ideas. The Improbable Origins of Modern Wall Street, John Wiley & Sons, Inc.
3. Fama, E., Blume, M., (1966), Filter Rules and Stock Market Trading,, Journal of Business, 39, 226-241
4. Goldberg, J., Nitzsch, R (2001) Behavioral Finance, John Wiley & Sons.
5. Hartigan, J.A. (1975), Clustering algorithms, New York, Wiley
6. Jensen, M., Bennington, G., (1970), Random Walks and Technical Theories: Some Additional Evidence, Journal of Finance, XXV, No. 2, 469-482.
7. Slovic, P., Lichtenstein, S. (1971), Comparison of Bayesian and Regression Approaches to the Study of Information Processing in Judgement, Organizational Behaviour & Human Performance, Nov. 1971, 6(6), pp. 649-744.
8. Tversky, A., Kahneman, D., (1971), Belief in the Law of Small Numbers, Psychology Bulletin, Aug. 76(2), 105-10.
9. Tversky, A., (1974), Judgment Under Uncertainty: Heuristics and Biases, Science, Sept. 1974, 185 (4157), 1124-31.
10. Warneryd, K-E., (2001), Stock-Market Psychology, Edward Elgar Publishing

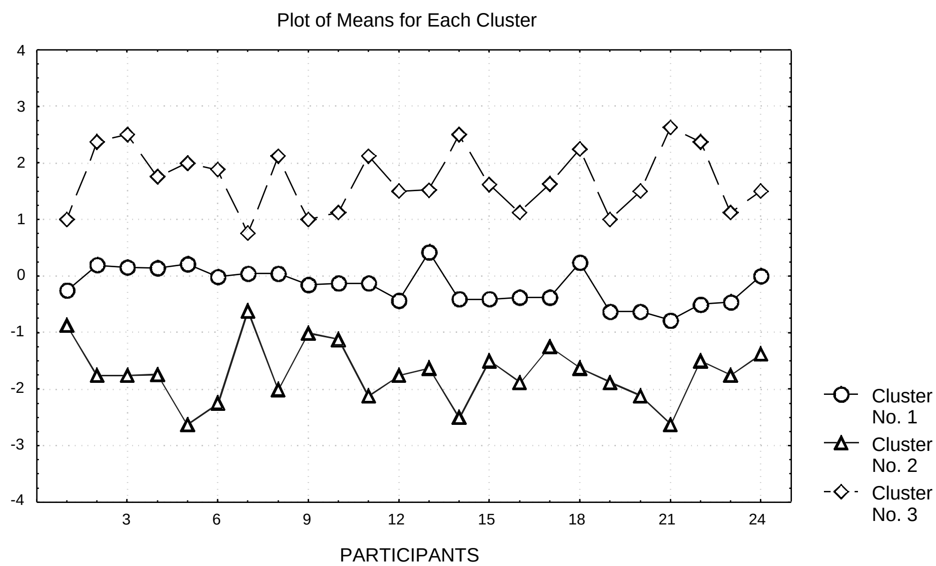

Fig. 1 The plot of the means for each of 3 clusters.

All eight technical-like signals created by the author of the questionnaire, and not representing any psychological inclinations, belong to Cluster 1.

All the technical and technical-like questionnaire items representing cognitive biases associated with a stock fall are included into Cluster 2.

All the technical and technical-like questionnaire items representing cognitive biases associated with a stock rise are included into Cluster.3.