A Moving Average Comparison of the Tel-Aviv 25 and S & P 500 Stock Indices

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Abstract

Random Walk and Efficient Market Hypotheses are central ideas in explaining financial market efficiencies. The assumption that market behavior embodies and reflects relevant information has a great impact on securities prices. Any change in the relevant information causes price adjustment. In contrast, technical analysts argue that prices gradually adjust to new information. Thus, historical analysis is useful in diagnosing the repeated pattern behaviors leading to active investment strategies that generate better-than-market returns.

The purpose of this study is to examine the efficacy of using technical trading rules in the emerging market of Israel, through the analysis of the Tel-Aviv 25 Index (TA25) and to compare its weak-form market efficiency to the performance of the S&P 500.

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I.   Introduction

Random Walk and Efficient Market Hypotheses are central ideas in explaining financial market efficiencies. The assumption that market behavior embodies and reflects relevant information has a great impact on securities prices. Any change in the relevant information causes price adjustment. In contrast, technical analysts argue that prices gradually adjust to new information. Thus, historical analysis is useful in diagnosing the repeated pattern behaviors leading to active investment strategies that generate better-than-market returns.

The purpose of this study is to examine the efficacy of using technical trading rules in the emerging market of Israel, through the analysis of the Tel-Aviv 25 Index (TA25) and to compare its weak-form market efficiency [as defined in Fama (1970)] to the performance of the S&P 500.

Meese and Rogoff (1983a) finds that no economic model is available that could outperform random walk models. Raj (1988), employing tick data from the Sydney Futures Exchange, concludes that the application of simple trading rules cannot realize abnormal returns. Hudson, Dempsey, and Keasey (1996) employ 60 years of daily returns from the Financial Times 30 Index on the London International Stock Exchange. They conclude that long-term "buy-and-hold" (BH) strategies in conjunction with "round trip" transaction costs, exclude the possibility of abnormal returns.

Ready (1997), using intra-day data for the US, finds that trading rules do not beat a "buy-and-hold" strategy due to trading costs and the time it takes to execute the actual

trade. Mills (1998), employing the same data set as that of Hudson, Dempsey, and

Keasey (1996), reaches similar conclusions, despite undertaking a more rigorous

econometric analysis. Ojah and Karemera (1999) document evidence which show that

equity prices in major Latin American Emerging equity markets – Argentina, Brazil,

Chile and Mexico- follow a random walk, and that they are, generally, weak-form

efficient.

Coutts and Cheung (2000) investigate the applicability and validity of trading

rules in the Hang Seng Index on the Hong Kong Stock Exchange. They find that in terms

of implementation of a few technical analysis rules, one would fail to provide positive

abnormal returns net of transaction costs, and the associated opportunity costs of

investing. Goodacre and Kohn-Speyer (2001) find that once adjustment for market

movements and risk are incorporated, technical analysis ceases to be profitable even with

an assumption of zero transaction costs.

Technical analysis has its roots in the belief that information contained in past

prices is not correctly incorporated in current prices (Ellinger, 1955, republished in 1971;

Mills, 1992, Lo, Mamaysky and Wang, 2000).

Lo and MacKinlay (1988, 1999) show, for a weekly U.S. stock indexes that past

prices may be used to forecast future returns to some degree, a fact that is the starting

point in any technical analysis. Hodrick (1987) and Frankel and Froot (1987) reject the

Efficient Market Hypothesis (EMH) in the foreign exchange market. Other studies

provide indirect support for technical analysis. These studies include those by Treynor

and Ferguson (1985), Sweeney (1988), Brown and Jennings (1989), Jagadeesh and

Titman (1993), Blume, Easley, and O'hara (1994), Chan, Jegadeesh, and Lakonishok (1996), Lo and MacKinlay (1997), Grundy and Martin (1998), and Rouwenhorst (1998).

More direct support for technical analysis has been given by De Bondt and Thaler (1985), Pruitt and White (1988), Neftci (1991), Brock, Lakonishok, and LeBaron (1992), Jagadeesh and Titman (1993), Bessembinder and Chan (1995), Neely, Weller and Dittmar (1997), Niederhoffer (1997), Neely and Weller (1998), Chang and Osler (1994), Osler and Chang (1995), Urrutia (1995), Gencay (1996), Gencay and Stengos (1997), and Allen and Karjalainen (1999).

Furthermore, evidence of seasonal ties in stock markets is plentiful. For example, Cadsby and Ratner (1992) find support for seasonal effects in international developed equity markets while Agrawal and Tandom (1994) and Agrawal and Rivoli (1989) identify seasonality in emerging markets.

Some studies have found qualified support for technical analysis. For example, Isakov and Hollistein (1998) report that transaction costs eliminate technical trading profits in the Swiss Stock Market. However, they suggested conditions where large investors may profit from moving average trading rules. Ratner and Leal (1999) examined the potential profit of a few variable length moving average technical trading rules in ten emerging equity markets in Latin America and Asia from 1982 through 1995. They find that only Taiwan, Thailand and Mexico emerged as markets where technical trading strategies may be profitable.

A similarly qualified support is found in Szakmary, Davidson and Schwarz (1999) who apply trading rules to Nasdaq stocks. They find that such trading rules conditioned on a stock's past price history perform poorly, but those based on past movements in the

overall Nasdaq Index tend to earn statistically significant abnormal returns. However, once they incorporated transaction costs, these abnormal returns are generally not economically significant.

It is worthwhile to note that studies concerning profitable trading rules are not restricted only to security prices and currencies. Examples of such studies are, the paper by Blume, Easley and O'hara (1994) mentioned above who studied the role of volume for the U.S., and another study by Antoniou, Ergul, Holmes, and Priestly (1997) for the U.K. and emerging markets.

The main criticism of technical analysis is that it seems to have no plausible explanations as to why these patterns should indeed be expected to repeat. Jegadeesh (2000) provides an up to date summary of such criticism. Given the inconclusive evidence concerning technical analysis in general and the moving average (MA) method in particular it would be interesting to apply this method to the emerging market of Israel, for which no such study of a major stock index of the Tel Aviv Stock Exchange has been reported yet. It would also be interesting to investigate the extent to which the MA method, applied to the TA25 stock index outperforms the simple buy-and-hold (BH) policy, and compare the empirical results of the TA25 to those obtained for the US S&P 500 index, using the same methodology and time period.

Many mutual fund managing firms most of them are affiliated with commercial banks in Israel offer index fund, resembling the TA25 index, and the rest are non-bank mutual fund managing firms. One investment feature related to the transactions costs issue, which is worth emphasizing is that mutual fund managing firms in Israel do not charge an extra fee on revising a mutual fund portfolios as long as the revision involves

mutual fund, index fund and other financial instruments managed by the same managing firm. In such an investment environment, the transaction costs argument in the context of the MA argument is weaker, particularly for institutional investors for whom the transaction costs are much lower than for individual investors.

The organization of this paper is as follows. Section II describes the moving average method; Section III discusses the methodology and the data; Section IV presents the findings, and analyses the empirical results; and the last section contains a brief summary and conclusion.

II.   The Moving Average Method

The moving average (MA) method is one of the most widely used methods of technical analysis.[1] It includes different versions and levels of sophistication. As distinct from a diagrammatic technical analysis, the MA method is easy to quantify and apply in investment decision-making or empirical tests.

Methods of technical analysis that are based on diagrammatic analysis methods are subjective and hence difficult to apply or examine empirically. The MA method in contrast enables the construction of a computerized algorithm for the application of the method, and the indications of buy or sell signals.

A moving average is an average of observations from several consecutive time periods. To compute a moving average sequence, we compute successive averages of a given number of consecutive observations. The objective underlying the MA method is

to smooth out seasonal variation in the data. This technical-analysis method is intended to provide a decision rule concerning the appropriate investment position.

The method involves a comparison of the most recent market price or index with the long MA of the price or index vector. If the current price is higher by a certain buying filter than the long MA, a long investment position should be adopted, and conversely, if the current price is lower by a certain selling filter than the MA, a short position should be adopted. In another variant of the method, the current price or index can be replaced with a short MA, so that the use of the method involves the comparison of the short MA with the long one.

This description of the MA method is general, and allows a high degree of parameter-value flexibility. This also raises a question concerning the best or most appropriate MA method version. For example, how many days are to be included in the average? How many averages should be used to obtain a signal? What price should be used when calculating the average (close, open, high, low, average)? Which average should be used (linear, weighted, logarithmic); what is the size of the optimal filter?

The MA method is a "led" method; it follows the trends that are developing in the market. The aim of the method is to identify or signal a new trend that is developing in the market, or to signal the end of an old trend. The method attempts to forecast the future behavior of the market in a manner different than that a chart analysis purports to do. The MA is a "smoothing" mechanism, and it facilitates the identification of a trend. At the same time, the MA lags behind what is happening in the market. The shorter the MA, the less it lags, and it follows the market more closely. A long MA, in contrast, is less sensitive to market fluctuations and it lags behind the market more than a short MA

does. It would thus be interesting to compare short and long MAs based on their predictive power.

There are three types of MAs: simple (arithmetic), weighted (linear) and exponential. The simple MA gives equal weight to all the observations of the average. Critics of the simple MA contend that greater weight should be given to more recent observations. The weighted (linear) MA attempts to solve the equal-weight problem of the simple MA. For an MA of n observations, the first observation is multiplied by n, the last observation is multiplied by one, and the total amount is divided by n (n+1)/2, so that the more recent observations are given a greater weight in the average. Both the simple and the weighted MAs share the problem of excluding observations which fall out of the average considered range. This problem is solved by the exponential MA, which considers all the existing observations in the database. In addition, the exponential MA, like the weighted MA, also gives greater weights to more recent observations. It should be emphasized, however, that the differences between the three types of averages noted here do not necessarily imply that one type of MAs is superior upon the other.

When a short MA is used, the average strictly follows the market index, and the market index frequently intersects the average. On one hand, a sensitive (short) MA gives many buying and selling signals and creates a high frequency of position changes, which results in high transactions costs, and relatively many false signals. On the other hand, a sensitive (short) MA gives earlier signals of a new market trend. Both these facts create a dilemma concerning the length of the average to be used. The objective is to find a sufficiently sensitive average which gives signals at the early stage of a new trend, but not so sensitive to be affected by "market noises". A less sensitive (long) MA is more

efficient when the market maintains a direction. Such an average will not be influenced by market noises as long as the trend exists. But the disadvantage of a long average is that it is slow in responding to changes in the direction of the market, and signals to this effect are received comparatively late. This implies that a long MA is more efficient when the direction remains fixed, while the short MA is more efficient in times of direction changes. That is the reason why technicians generally use a number of moving averages at the same time. Several computer programs and Internet sites enable their users to create many types of MAs and examine their behavior under various market trends. As we have pointed out, there is no reason to assume that a specific MA that works best in one type of market will also work for another type of market.

III. Methodology

Two types of moving averages (MA) will be used here – short and long. The short MA consists of one day (the index itself), while the longer MAs will be based on varying ranges of 9, 49, 99 and 149 days. Using no filter, a signal to buy (sell) is received when the short MA crosses the longer MA in an upward (downward) direction.

After receiving a buy or sell signal, a market position is adopted. Two investment strategies are investigated: long–cash and long–short. In the long-cash strategy, when a buying signal is received, a long position in the index is initiated, and when a signal to sell is received, the index is sold, and the proceeds are held in cash. In the long-short strategy, in contrast, when a selling signal is received, the index is sold short. The resulting rate of return on each of the two strategies will be compared to the return on a buy-and-hold (BH) policy. That is, the return on the index when held up to the end of the

test period. A strategy return higher than the return of the BH policy indicates market inefficiency in the weak form.

Rates of return are computed for each holding period whose length is determined by the signal received from the MA method. The compound rate of return for the whole test period is then compared to the return on the simple BH policy. The specific date of the final signal varies by a few days between the long-cash strategy and the long-short strategy. For the first strategy, it is the date of the final long signal received, while for the second strategy, it is the date of either a long or short signal. That is why the corresponding return on the alternative BH policy may vary a bit between the two strategies, i.e., long-cash and long-short.

An additional "success" measure of the MA method is the "success signal proportion" which is the ratio of the number of successful signals (both long and short) over the total number of signals.[2] The latter is in fact the total number of transactions, or position changes, suggested by the MA method for a given period of time. In addition, for each of the two types of successful signals – long and short, an average periodic return is computed. For any one of these two successful signals, it is expected that the average periodic return will be positive.

Data

The data consist of daily closing values of two market indices; S&P 500, and TA25 which is an index composed of the 25 leading firms listed on the Tel–Aviv Stock Exchange (TASE).[3]

The time period covered is August 20, 1993 to June 20, 1999, which produces a sample size of 1,500 observations. The source for the S&P 500 is finance.yahoo.com site, and for the TA25 index it is Bank Leumi Le-Israel.

For each index, the daily close value of the index is used. The close rather than another type or value is used, since the close value is the most accessible historical information.

To be consistent with prior research, the simple arithmetic average is applied to the close value of the market index, since the close value is the most accessible historical information, particularly when the time period covered is relatively long and the study is conducted in more than one country.

IV. Results

The tests results of the MA method are reported in Tables 1 and 2 for the TA25 Index, and in Tables 3 and 4 for the S&P 500 Index.

IV.1 The TA25 Index

The first striking result concerning the efficiency of the Tel-Aviv Stock Exchange (TASE) with respect to the TA25 index, demonstrated by Table 1, is that for relatively moderate MAs of 9 and 49 days, the MA method yields a much higher return than for the BH policy. This holds true for both the long-cash strategy, and even stronger for the long-short strategy. For the short-long pair of moving averages of 1-9 (namely, 1 day for the short and 9 days for the long), the long-cash strategy yields a total return of 263% for

the entire test period compared with 200% for the BH policy, while the long-short

strategy yields 332%, versus 209% for the BH policy.[4]

This result is also strengthened by the relatively very high success proportion of

78.5% obtained for the MA method. Of the total number of 109 transactions suggested

by the MA method for the studied sample time period, 85 transactions were found

successful in the sense that a signal (short or long) produced a positive return. In other

words, for a long signal for which the 1-day short MA crosses the long MA of 9-day MA

in an upward direction the subsequent actual market trend was positive, as the signal

indicated for the long position. For a short signal, for which the 1-day short MA crosses

the long 9-day in a downward direction, the subsequent actual market trend was negative,

implying a positive return on the short position suggested by the signal.

Though transaction costs, as pointed out in the previous section, may lower the

net (of cost) return on the MA method, it is important in this context to note that mutual

fund managing firms in Israel do not charge an extra fee on revising a mutual fund

portfolio as long as the revision involves mutual funds and securities managed by the

same managing firm. The transaction costs argument, as noted in the literature, is also

weak for institutional investors for whom transaction costs are much lower than for

individual investors.

(INSERT TABLE 1)

The success rate is found higher for the long than for the short signal. For the long

signal, the number of successful transactions is 46 which yields an average (per

transaction) return of 0.99%, while for the short signal, the number of successful transactions is 38 yielding an average return of 0.27%.

(INSERT TABLE 2)

Results similar in direction though lower in magnitude are obtained for the longer MA of 1-49 days. For the very long MAs of 1-99 and 1-149 days, however, the MA method returns are lower than for the BH policy. The success proportion is also lower and comes to 43.8% and 45.5% for the 1-99 and 1-149 MAs, respectively. The success rate is particularly low for the short signal transaction that, on the average, yields a negative return of -0.23% and -0.24% for the 1-99 and 1-149 MAs, respectively.

Another interesting issues investigates is whether the average return per transaction in either the long or the short signal transaction has its source in the relatively small number of transactions which inflates the average. To test whether the application or the MA strategy to the present sample produces systematic and uniform returns, Table 2 presents the segmentation of the number of successful transactions (or signal) by the position return on both the long and short signals. Starting with the short-long MA strategy of 1-9, Table 2 indicates that most of the successful transactions suggested by the long signal achieved return levels up to 5% per transaction (on average), while about 1/3 of them achieved a return level higher than 5% per transaction (on average). Similar results are obtained for the successful transactions suggested by the short signal, as indicated by the lower part of Table 2 for the 1-9 MA. For this MA, as noted above, the return was found much higher than for the BH policy. The distribution of the successful

transactions by their return, as demonstrated in Table 2, indicates that the success in beating the BH policy is not necessarily due to very high returns achieved in very few transactions.

For the 1-49 MA, the results are similar to those of the 1-9 MA, except for the lower number of successful transactions, which has been already noted above. Table 2 also indicates that for the very long MAs for 1-99 and 1-149 too, their relative low success rate or failure in beating the BH policy does not stem form the concentration of extreme return values in very few transactions. Rather, the failure is more systematic and is reflected by a relatively low number of successful transactions - 14 and 10 for the 1-99 and 1-149 MAs, respectively, with a roughly 50-50 split between the long and short successful signals.

IV.2   THE S&P 500 INDEX

The empirical results of applying the moving average method to the S&P 500 Index are presented in Tables 3 and 4. The major conclusion implied by the results in Tables 3 and 4 is that, in contrast to the TA25 Index, the MA method yields substantially lower returns than those for the BH policy. This result is obtained for any one of the moving average pairs tested, and for both the long-cash and the long-short strategies.

(INSERT TABLE 3)

Furthermore, in contrast to the TA25 results, the long-short strategy returns are even lower than for the long-cash strategy. For the 1-9 MA, for example, while the BH

policy total return for the sample period tested is 295%, the total return on the long-cash strategy is 159%, and for the long-short strategy it is as low as 85%, implying a lower success rate (or equivalently a higher failure rate) in the short signals mainly. Indeed, while the number of successful long signals (transactions) for the 1-9 MA is 51, the number of successful short signals (transactions) is as low as 21. This brings the total success rate to 50.4% given by the ratio of 51 plus 21 over the 143 total signals (transactions) for the time period studied. In fact, not only is the number of successful long signals low, but also the average per transaction return for the short signals is negative.

Another interesting result which is in contrast to the TA25 result is that for the S&P 500 Index the superiority of the BH policy is higher for relatively short MAs of 1-9 and 1-49, and lower for the very long MAs of 1-99 and 1-149. The return difference between the BH policy and the MA method is 136% for the 1-9 MA pair, and only 57% for the 1-149 pair. For the long-short strategy, this return difference is 211% and 110% for the 1-9 and 1-149 pairs, respectively. This inferiority of the MA method with respect to the BH policy is also reflected in the relatively low success proportion that ranges from 40% to 50% for the four MAs examined.

Another difference between the TA25 and S&P 500 test results is the total number of signals (transactions) received for the time period examined – 1,500 daily observations for both cases. For the relatively moderate MAs of 1-9 and 1-49, the number of transactions is 143 and 52 for the S&P 500, respectively, compared with 107 and 41 for the TA25, respectively. However, for the very long MAs of 1-99 and 1-149, the total number of transactions is higher for the TA25 than for the S&P 500. These

differences may imply that the TA25 Index compared with the S&P 500 Index is more stable in the short run but less so in the long run.

(INSERT TABLE 4)

Similar to the statistical analysis for the TA25, the return distribution of the successful transactions is demonstrated in Table 4. The test results indicate a pattern similar to that found for the TA25. That is, the average (per transaction) return on a successful signal – long in the upper part of Table 4, and short in the lower part – is not necessarily due to the existence of extreme values which can affect the average substantially.

V.   SUMMARY AND CONCLUSIONS

This paper compares the Tel-Aviv Stock Exchange (TASE) 25 to the S&P 500 Index, with respect to the extent that a technical analysis method of moving averages can beat the simple buy-and-hold (BH) policy. Previous research on the S&P 500 is inconclusive, while TA25 was never tested in this respect.

The moving average (MA) method is a type of technical analysis intended to provide a decision rule concerning the appropriate investment position to adopt at a given point in time. For a market index, it involves the comparison of the most recent index level or its short (say, 1 day) MA with the long MA of the index. If the short MA is higher by a certain filter than the long MA, a long investment position should be adopted, and if it is lower, a short position should be adopted. A short 1-day MA and varying long

MAs of 9, 49, 99 and 149 days are used in this study, in conjunction with a zero filter.

For these four pairs of MAs two investment strategies are used: long-cash and long-short,

where the MA's selling signal results in holding cash in the first strategy and selling short

the index in the second strategy. The return on each of these two strategies is then

compared to the return achieved on a buy-and-hold policy for the same period of time. If

the strategy's return is higher, it implies weak-form market inefficiency. Another

"success" measure of the MA method used is the "success signal proportion," which is

the ratio of the number of successful long and short signals over the total number of

signals received for the relevant time period. A success is defined when the actual

market movement of the index is in the direction predicted by the MA signal.

The data consist of daily closing values of two market indices: S&P 500 and the

Tel-Aviv Stock Exchange (TASE) 25 stock index, TA25. The time period concerned is

1993 to 1999, which produces a sample the size of 1,500 observations. Transaction costs

are not incorporated in this study due to one of the features of the mutual fund industry in

Israel, according to which no extra fee is charged on revising a mutual fund portfolio as

long as the revision involves mutual fund, index fund, and financial instrument managed

by the same managing firms. Many of these managing firms offer index fund, which

resemble the TA25 index. In such an investment environment, the transaction cost

argument is weaker, particularly for intuitional investors for whom transaction costs are

much lower than for individual investors.

Starting with the TA25, our findings suggest that for (relatively moderate) moving

averages of 9 and 49 days, the MA method beats the BH policy, and it holds true for both

the long-cash and the long-short strategy. The relatively high success proportion of

78.5% obtained for the MA method further affirms this result. That is, of the 107 signals initiated by the method, 85 were found successful in the sense that the signal produced a positive return. However, for the very long MAs of 99 and 149 days the MA method yields lower returns than those of the BH policy.

In contrast to the TA25, the MA method for the S&P 500 Index yields substantially lower returns than those of the BH policy. This result is obtained for any one of the MAs tested and for both the long-cash and long-short strategies. Furthermore, in contrast to the TA25 results, the long-short strategy returns for the S&P 500 are lower than those produced by the long-short strategy, implying a particularly lower success rate for the long-short strategy. This is also reflected by the negative average returns on the long-short signals. The superiority of the BH policy over the MA method is higher for short MAs of 1 and 9 days than for the long MAs of 99 and 149 days.

Another difference between the S&P 500 and TA25 Indices in the context of the MA method is that the number of signals (transactions) initiated by the MA method for the short MAs is lower for the S&P 500 than for the TA25, while the opposite is true for the long MAs. This difference may imply that the TA25 compared with the S&P 500 is more stable in the short run but less stable in the long run.

A possible reason for the lack of success of the MA method found in this study for the S&P 500 may be related to the fact that technical analysis, including the MA method, is more prevalent in the United States than in Israel so that, as with any widely used method, the benefit of using the method is limited. Despite the legitimate criticism arising due to the arbitrary nature of the MA method, it is difficult to ignore the relative success of technical analysis methods reported in prior research and found in this study,

too, particularly for emerging capital markets characterized by a relatively low degree of market efficiency.

This study's results for the TA25 Index in Israel imply that further empirical tests are required in order to determine more accurately the efficiency degree of emerging capital markets such as that of Israel studied here.

FOOTNOTES

1. See, for example, the following studies: de Jong and Penzer (1998), Gencay and Sangos (1997), Lui and Mole (1998), Gencay (1998), Neely and Weller (1999), Ojah and Karemera (1999), Ratner and Leal (1999), Szakmary, Davodson and Schwarz (1999), Coutts and Cheung (2000), and Goodacre and Kohn-Speyer (2001)].

2. The term "short" signal is used for the base where the MA method predicts falling prices for both the long-cash and the long-short strategies.

3. See Appendix A for a brief description of the S&P 500 and TA25 Indices.

4. As noted in the previous section, since the specific date of the final signal during the test period varies by a few days between the long-cash and the long-short strategies, the time length of the buy-and-hold policy, and the associated return will vary mildly correspondingly for the two strategies examined here.

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TABLE 1

Moving Average Returns and Success Proportion for the Tel Aviv 25 Index*

Moving Average	1-9	1-49	1-99	1-149
Return on Buy and Hold Strategy (%)[1]	200 209	202 206	156 157	158 161
Return on Long Plus Cash Strategy (%)[2]	263	218	142	150
Return on Long Plus Short Strategy (%)	332	232	127	140
Return on Long Signals (%)[3]	0.99	2.29	1.53	2.22
Return on Short Signals (%)	0.27	0.25	-0.23	-0.24
Number of Successful Long Signals[4]	46	13	7	6
Number of Successful Short Signals	38	11	7	4
Total Number of Successful Long and Short Signals	84	24	14	10
Total Number of Transactions	107	41	32	22
Success Proportion (%)[5]	78.5	58.5	43.8	45.5

TABLE 1 – Continued

*   A 1-n moving average (MA), where n = 9, 49, 99, and 149, indicates a 1-day (short) MA crossing a n-day (long) MA upward or downward.

1.   Since the specific date of the final signal during the test period varies by a few days between the long-cash strategy and the long-short strategy, the corresponding return on buy and hold policy differs a bit accordingly, and is given above by the first row for the long-cash strategy, and the second row for the long-short strategy.

2.   The return on the long-cash strategy is the total return for the test period achieved from maintaining a long position when the MA signal is upward, and selling for cash when the MA signal is downward. For the long-short strategy, the "sell for cash" transaction is replaced with a short position.

3.   The return on long signals is the (per transaction) average return achieved for all long signal transactions during the test period, while the return on short signals is the (per transaction) average return achieved for all short signal transactions.

4.   A successful long (short) signal is a signal, which successfully predicts an upward (downward) market trend of the index.

5.   The success proportion is the ratio of the total successful long and short signals over the total number of signals (or transactions) during the test period.

TABLE 2

Segmentation of the Number of Successful Transactions (Signals) by the Position

Return on Both Long and Short Signals for the Tel Aviv 25 Index*

Return on Successful Long Signals (%)	1-9 Average	1-49 Average	1-99 Average	1-149 Average
0 – 2.5	19	4	1	1
2.5 – 5.0	10	2	2	0
5 – 7.5	9	1	0	2
7.5 – 10	2	0	0	1
> 10	6	6	4	2
> 0	46	13	7	6
Total Transactions	107	41	32	22
Return on Successful Short Signals (%)	**1-9 Average**	**1-49 Average**	**1-99 Average**	**1-149 Average**
0 – 2.5	18	6	3	1
2.5 – 5.0	9	0	1	1
5 – 7.5	4	0	2	0
7.5 – 10	5	2	0	1
> 10	2	3	1	1
> 0	38	11	7	4
Total Transactions	107	41	32	22
Total Successful Transactions	84	24	14	10

*   See Table 1 for the definitions of long and short signals, and successful long and

short signals (transactions).

TABLE 3

Moving Average Returns and Success Proportion for the S&P 500 Index*

Moving Average	1-9	1-49	1-99	1-149
Return on Buy and Hold	295	295	290	285
Strategy (%)[1]	296	295	290	291
Return on Long Plus Cash Strategy (%)[2]	159	202	221	228
Return on Long Plus Short Strategy (%)	85	135	168	181
Return on Long Signals (%)[3]	0.35	1.5	3.76	4.61
Return on Short Signals (%)	-0.43	-0.73	-1.17	-1.17
Number of Successful Long Signals[4]	51	18	9	8
Number of Successful Short Signals	21	3	3	1
Total Number of Successful Long and Short Signals	72	21	12	9
Total Number of Transactions	143	52	24	20
Success Proportion (%)[5]	50.4	40.4	50.0	45.0

TABLE 3 – Continued

   *   A 1-n moving average (MA), where n = 9, 49, 99, and 149, indicates a 1-day (short) MA crossing a n-day (long) MA upward or downward.

1.   Since the specific date of the final signal during the test period varies by a few days between the long-cash strategy and the long-short strategy, the corresponding return on buy-and-hold policy differs a bit accordingly, and is given above by the first row for the long-cash strategy, and the second row for the long-short strategy.

2.   The return on the long-cash strategy is the total return for the test period achieved from maintaining a long position when the MA signal is upward, and selling for cash when the MA signal is downward. For the long-short strategy, the "sell for cash" transaction is replaced with a short position.

3.   The return on long signals is the (per transaction) average return achieved for all long signal transactions during the test period, while the return on short signals is the (per transaction) average return achieved for all short signal transactions.

4.   A successful long (short) signal is a signal, which successfully predicts an upward (downward) market trend of the index.

5.   The success proportion is the ratio of the total successful long and short signals over the total number of signals (or transactions) during the test period.

TABLE 4

Segmentation of the Number of Successful Transactions (Signals) by the Position

Return on Both Long and Short Signals for the S&P 500 Index*

Return on Successful Long Signals (%)	1-9 Average	1-49 Average	1-99 Average	1-149 Average
0 – 2.5	31	10	4	3
2.5 – 5.0	13	1	0	0
5 – 7.5	5	1	0	0
7.5 – 10	1	4	0	0
> 10	1	2	5	5
> 0	51	18	9	8
Total Transactions	143	52	24	20
Return on Successful Short Signals (%)	**1-9 Average**	**1-49 Average**	**1-99 Average**	**1-149 Average**
0 – 2.5	17	1	3	1
2.5 – 5.0	2	1	0	0
5 – 7.5	1	1	0	0
7.5 – 10	1	0	0	0
> 10	0	0	0	0
> 0	21	3	3	1
Total Transactions	143	52	24	20
Total Successful Transactions	72	21	12	9

*　See Table 1 for the definitions of long and short signals, and successful long and

short signals (transactions).

APPENDIX

The TA25 and the S&P 500 Indices

The TA25 Index

The TA25 Index is a weighted average of 25 Israeli shares having the highest market value in the Tel-Aviv Stock Exchange (TASE). The weight of each share in the formulation of the index is determined according to its market value, or 9.5 percent whichever is the lower. The weight of each share is updated daily according to market value changes. The Board of Directors of the TASE revises the composition of the TA25 "basket" twice a year in January and July.

The S&P 500 Index

The Standard and Poors Corporation publishes the S&P 500 Index daily. The index is based on the market value of the shares that compose it. The index includes 400 shares from industrial companies, 40 shares from public services companies, 20 shares from transport corporations and 40 shares of financial corporations. As some of these companies are not traded on the NYSE, it was decided to include in the index, shares that are traded on the OTC as well.

FIGURE 1

TA 25 Index with Moving Averages, 1993-1999

FIGURE 2

S&P 500 INDEX WITH MOVING AVERAGE 1993-1999