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# Optimization of technical trading strategies and the profitability in security markets

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**Abstract**

The ultimate goal of any testing strategy is to measure profitability. This paper measures the profitability of simple technical trading rules based on nonparametric models which maximize the total returns of an investment strategy. The profitability of an investment strategy is evaluated against a simple buy-and-hold strategy on the security and its distance from the ideal net profit. The predictive performance is evaluated by the market timing tests of Henriksson-Merton and Pesaran-Timmermann to measure whether forecasts have economic value in practice. The results of an illustrative example indicate that nonparametric models with technical strategies provide significant profits when tested against buy-and-hold strategies. In addition, the sign predictions of these models are statistically significant. © 1998 Elsevier Science S.A.

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*JEL classification:* G14; G10

## 1. Introduction

Traders test historical data to establish specific rules for buying and selling securities with the objective of maximizing profit and minimizing risk of loss. Traders base their analysis on the premise that the patterns in market prices are assumed to recur in the future, and thus, these patterns can be used for predictive purposes. The motivation behind the technical analysis is to be able to identify changes in trends at an early stage and to maintain an investment strategy until the weight of the evidence indicates that the trend has reversed.

The earlier literature on stock returns finds evidence that daily, weekly and monthly returns are predictable from past returns. Pesaran and Timmermann (1994) present further recent evidence on the predictability of excess returns on common stocks for the Standard and Poor's 500 and the Dow Jones

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Industrial portfolios at the monthly, quarterly and annual frequencies. Pesaran and Timmermann (1995) examine the robustness of the evidence on the predictability of U.S. stock returns, and address the issue of whether this predictability could have been historically exploited by investors to earn profits in excess of a buy-and-hold strategy.

Evidence of the predictability of stock market returns led the researchers to investigate the sources of this predictability. In Brock, Lakonishok and LeBaron (1992), two of the simplest and most popular trading rules, moving average and the trading range brake rules, are tested through the use of bootstrap techniques. They compare the returns conditional on buy (sell) signals from the actual Dow Jones Industrial Average Index to returns from simulated series generated from four popular null models. These null models are the random walk, the AR(1), the GARCH-M due to Engle, Lilien and Robins (1987), and the EGARCH developed by Nelson (1991). They find that returns obtained from buy (sell) signals are not likely to be generated by these four popular null models. They document that buy signals generate higher returns than sell signals and the returns following buy signals are less volatile than returns on sell signals.

Brock, Lakonishok and LeBaron (1992) do not investigate the profitability of technical rules after realistic commissions, as they focused their attention to a bootstrapped-based view for specification testing. However, the results in Brock, Lakonishok and LeBaron (1992) document two important stylized facts. The first is that buy signals consistently generate higher returns than sell signals. The second is that the second moments of the distribution of the buy and sell signals behave quite differently because the returns following buy signals are less volatile than returns following sell signals. The asymmetric nature of the returns and the volatility of the Dow series over the periods of buy and sell signals suggest the existence of nonlinearities as the data generation mechanism.

Gençay (1997a) investigates the nonlinear predictability of foreign exchange returns from the past buy–sell signals of the simple technical trading rules by using the feedforward network and nearest neighbors regressions. The forecast results of Gençay (1997a) indicate that the buy–sell signals of the moving average rules have market timing ability and provide statistically significant forecast improvements for the current returns over the random walk model of the foreign exchange returns. In Gençay (1997a), the optimal choice of nearest neighbors, optimal number of hidden units in a feedforward network and the optimal size of the training set are determined by the cross validation method which minimizes the mean square error. As the sample moves with the forecast horizon, the cross-validated performance is recalculated to obtain the optimal number of nearest neighbors, number of hidden units and the length of the training set. Therefore, the optimal number of nearest neighbors, number of hidden units and the length of the training data set may be different corresponding to each observation in the prediction sample. The type of the cross-validation method used in Gençay (1997a) allows the optimal number of nearest neighbors, optimal number of hidden units and the length of the training set to be chosen dynamically. This allows nonstationarity to enter into the nonlinear models in an automatic fashion. The results in Gençay (1997b) provide similar conclusions with the Dow Jones Industrial Index series.

The contribution of this paper is to extend the analysis to models where the simple technical trading rules are used to maximize the total returns of an investment strategy. The profitability of an investment strategy is evaluated against a simple buy-and-hold strategy on the security and its distance from the ideal net profit. Sign predictions provide valuable information for market timing. One such test which provides information on market timing is the Henriksson and Merton (H&M) (Henriksson and Merton, 1981) test. In the H&M test, the number of forecasts has a hypergeometric distribution under the null hypothesis of no market timing ability. The second test is by Pesaran and Timmermann (1992) which is based on the direction accuracy of the forecasts and hence may provide important information on the statistical significance of sign predictions. The Pesaran and Timmermann (P&T) (Pesaran and Timmermann, 1992) test is a Hausman-type test and its limiting distribution is $N(0,1)$. These two sign prediction tests are reported in this paper.

The data series includes the first trading day in 1963 of the Dow Jones Industrial Average (DJIA) Index to June 30, 1988. The data set is studied in five subsamples to study the sensitivity of our results to sample variation. The forecast horizon is chosen to be the last 250 observations of each subsample, approximately 1 year of daily observations. The nonparametric model which maximizes the investment strategy is designed by feedforward networks, a class of artificial neural networks. The results indicate that nonparametric models with technical strategies provide significant profits when tested against a simple buy-and-hold strategy. In addition, the sign predictions of these models are statistically significant and the Henriksson and Merton (1981) test rejects the null hypothesis of no market timing ability for all data sets[2].

The model is presented in section two and the empirical results are presented in section three.

## 2. Model

The minimization of the sum of squared residuals may not be the most efficient criteria, given that the investors are ultimately trying to maximize profits rather than error minimization. This paper considers a simple technical trading strategy in which positive returns are executed as long positions and negative returns are executed as short positions. The total return of such a strategy is given by

$$R_{\mathrm{T}} = \sum_{t=1}^{n} y_t r_t \tag{1}$$

where $r_t = \log(p_t/p_{t-1})$ is the return of the stock at time $t$, $y_t$ is a variable interpreted as the recommended position which takes either a value of $-1$ (for a sell signal) or 1 (for a buy signal) and $n$ is the number of observations.

Here, $y_t$ is modelled as a function of the past returns. To compare the performance of this simple technical trading strategy, the return on a simple buy-and-hold strategy ($R_{\mathrm{B}}$)

$$R_{\mathrm{B}} = \log(p_{t+\eta}/p_t) \tag{2}$$

is used as the benchmark where $\eta$ indicates the holding period.

The estimation of $y_t$ is carried out by a feedforward network. As a model selection criteria, a cross-validation method similar to Gençay (1997a) is used to determine the number of hidden units and the length of the training sample. Many authors have investigated the universal approximation

[2]Data-snooping biases refer to the biases in the statistical inference that result from using information from data to guide subsequent research with the same or related data. Lo and MacKinlay (1990) illustrate that the potential magnitude of biases can result from data-snooping. Due to the nonexperimental nature of economics, these biases may be unavoidable. As Campbell, Lo and MacKinlay (1997) point out, data-snooping biases should at least be considered as a potential explanation for model deviations.

properties of neural networks (Gallant and White, 1988, 1992; Cybenko, 1989; Funahashi, 1989; Hecht-Nielsen, 1989; Hornik, Stinchcombe and White, 1989, 1990). Using a wide variety of proof strategies, all have demonstrated that under general regularity conditions, a sufficiently complex single hidden layer feedforward network can approximate any member of a class of functions to any desired degree of accuracy where the complexity of a single hidden layer feedforward network is measured by the number of hidden units in the hidden layer. For an excellent survey of the feedforward and recurrent network models, the reader may refer to Kuan and White (1994).

## 3. Empirical results

The last 250 observations of each subsample are reserved for the out-of-sample forecast comparisons. Out-of-sample forecasts are completely ex ante, using only information actually available. The results are presented in Table 1. The estimated total return is calculated by

$$\hat{R}_{\mathrm{T}} = \sum_{t=n+1}^{n+\eta+1} \hat{y}_t r_t \tag{3}$$

where $\eta$ is the out-of-sample horizon and $\hat{y}_t$ is the estimated recommended position for the $t$th observation. The data used in this paper is daily data so that the model in Eq. (3) generates either a buy or a sell signal for each day. At the end of each day, the positions are closed and a new position is opened the following day. The model allows for short selling.

The sign predictions measure the percentage of times the estimated network output assigns the

Table 1
Out-of-sample tests

| Tests | 1963–66 | 1967–70 | 1971–74 | 1975–78 | 1979–82 | 1983–88 |
|---|---|---|---|---|---|---|
| Total return | 0.22 | 0.37 | 0.50 | 0.40 | 0.44 | 0.31 |
| Net return | 0.07 | 0.22 | 0.35 | 0.25 | 0.29 | 0.16 |
| Sign predictions | 0.60 | 0.61 | 0.58 | 0.57 | 0.57 | 0.57 |
| Ideal profit ratio | 0.15 | 0.21 | 0.18 | 0.23 | 0.21 | 0.10 |
| Sharpe ratio | 0.12 | 0.15 | 0.14 | 0.18 | 0.15 | 0.05 |
| Pesaran and Timmermann | 2.94 | 3.49 | 2.18 | 2.23 | 2.14 | 2.06 |
| Henriksson and Merton | 0.0025 | 0.0004 | 0.0150 | 0.0179 | 0.0224 | 0.0266 |
| Buy and hold return | −0.20 | 0.04 | −0.36 | −0.01 | 0.17 | −0.13 |

Notes: The *Total Return* refers to the returns generated by the optimization based technical trading strategy over the 250 days of forecast sample before transaction fees are taken into account. The *Net Return* refers to the returns generated by the optimization based technical trading strategy over the 250 days of forecast sample after transaction fees are taken into account. The *Buy and Hold Return* is calculated by $log(p_{t+\eta}/p_t)$ where $\eta=250$ is the holding period, $p_t$ and $p_{t+\eta}$ are prices of the security at time $t$ and $t+\eta$, respectively. In the Henriksson and Merton (1981) (H&M) test, the number of forecasts has a hypergeometric distribution under the null hypothesis of no market timing ability. In the table above, the $p$-values of the H&M test are reported and are statistically significant if less than 5%. The Pesaran and Timmermann (1992) (P&T) test, which is a Hausman-type test, is designed to assess the performance of sign predictions. As the limiting distribution of this test is $N(0,1)$, its one-sided critical values at the 1%, 5%, 10% levels are 2.33, 1.645 and 1.282, respectively.

correct buy or sell decision in accord with the sign of the corresponding return of a given period. The Sharpe Ratio is simply the mean return of the trading strategy divided by its standard deviation

$$\frac{\mu_{\hat{R}_T}}{\sigma_{\hat{R}_T}} . \tag{4}$$

The higher the Sharpe ratio, the higher the return and the lower the volatility. We also use another measure called ideal profit. The ideal profit measures the returns of the trading system against a perfect predictor and is calculated by

$$R_I = \frac{\sum_{t=n+1}^{n+\eta+1} \hat{y}_t r_t}{\sum_{t=n+1}^{n+\eta+1} |r_t|} . \tag{5}$$

According to Eq. (5), $R_I = 1$ if the indicator variable $\hat{y}_t$ takes the correct trading position for all observations in the sample. If all trading positions are wrong, then the value of this measure is $R_I = -1$. An $R_I = 0$ value is considered as a benchmark to evaluate the performance of an investment strategy.

Table 1 presents the return calculations from the technical trading strategy. The forecast sample of each subperiod consists of the last 250 days which is approximately one year of daily data. Therefore, the last year of each subsample is used for forecast calculations. The *Total Return* and the *Net Return* refer to the returns generated by the optimization based technical trading strategy before and after brokarage fees are taken into account, respectively. Discount brokerage houses charge as low as \$30 for up to 1000 shares irregardless of the shares prices. Assuming that each share is worth \$100 and 10 000 shares per trade, the value of a typical transaction is assumed to be \$1 000 000. In this paper, we base the net return calculations on \$30 per 1000 shares. The total transaction cost is calculated as \$600 per trade[3]. This includes the transaction costs for opening and closing of the daily position. In the model, the positions are closed every day and a new trade takes place the following day. Therefore, the total transaction costs for 250 days is \$150 000.

The *Buy and Hold Return* is calculated by $\log(p_{t+\eta}/p_t)$, where $\eta = 250$ is the holding period, $p_t$ and $p_{t+\eta}$ are prices of the security at time $t$ and $t+\eta$, respectively. The buy-and-hold returns are presented in the second panel. The buy-and-hold returns vary substantially across the six subperiods. The largest negative buy-and-hold return occurs at the 1971–74 period whereas the largest positive return occurs at the 1979–82 period. For the 1971–74 period, the technical trading strategy generates a net return of 35% whereas the buy-and-hold return for this period is −36%. In the 1983–88 period, the buy-and-hold return and the trading strategy returns are −13% and 16%, respectively. In the 1963–66 period the technical strategy generates 7% net return whereas the buy-and-hold return remains at −20%. The other subperiods exhibit similar results such that the technical trading returns dominate the buy-and-hold returns.

For all subperiods, the sign predictions for the recommended positions range 57–61%. The Pesaran-Timmermann and Henriksson-Merton tests indicate that the sign predictions of the technical model have market timing value across all subsamples. For all of the subsamples, the Sharpe ratios are

[3]For simplicity the total transaction cost is assumed to be 10 times of \$30 for 10 000 shares.

in similar order indicating that risk/return ratios are consistent across these data sets. The ideal profit measure is consistently greater than zero and remains between 0.10–0.21 across the subsamples.

Overall, the results of this illustrative simple model indicate that nonparametric models with technical rules provide significant excess returns when compared to a simple buy-and-hold strategy after the transaction costs are taken into account. In addition, the sign predictions of these models are statistically significant and the calculated sign predictions reject the null hypothesis of no market timing ability.

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