Technical Analysis and Prediction: A Neural Network Approach to the Italian Stock Market

*Angelo Corelli**

Assistant Professor, Bursa Orhangazi University, Turkey

Abstract

The paper analyses the relationship between common technical analysis indicators and the returns of an index for the period considered. It is expected to find correlation between indicators and index prices, as well as showing clear patterns and potential strategies for investment analysis and portfolio management. As an innovative methodology a mixed analysis is carried out, trying to combine classic signals offered by the indicators with the power of neural networks. The neural network plays an important role in that allows for an accurate regression with efficient error minimization, while giving indications about the concentration of results obtained around some reference values. Through a simple hidden-layer, back-propagation algorithm, regressions give interesting result, in term of the forecasting potential of the analyzed indicators. The final step of the project is to conclude about results and summarize the indication coming from the multivariate stage analysis, commenting on the power of the indicators to reveal potential investment opportunities.

Keywords: Technical Indicator, Neural Network, Normalization, Backpropagation, Steepest Descent.

* Department of Business and Administration
angelo.corelli@bou.edu.tr
+904448268

Introduction

For many decades there has been a net separation between academic finance and industry practice, given the separation existing between technical analysts and their academic critics.

Modern quantitative finance scholars immediately accepted fundamental analysis as a scientific basis for valuation, as oppose as technical analysis which was seen as a non-science and rejected at first.

Just to give the sense of the aversion of academic world to technical analysis, just think that, as from Li and Tsang (1999) it has been renamed “voodoo finance” among some academics, while being compared to fundamental analysis as one would compare astronomy and astrology.

Recent academic studies however suggest that, despite the questionable methodologies applied for the analysis, technical analysis may well be an effective means for extracting useful information from market prices.

Technical analysis is an approach based on the belief that there are regularities in trends of historical price series, trading volumes and other statistics. Moreover, technical analysis is divided into two approaches.

The qualitative approach relies on techniques to interpret the shape of geometric patterns of the price curve. Most popular shapes are double bottoms, head and shoulders, and support-resistance level.

Quantitative techniques on the other side generate indicators which are used to forecast possible future patterns of the price, as well as to generate and interpret trading signals, such as buy or sell.

The toughest criticism to technical analysis comes from the weak form of efficient market hypothesis (EMH), as developed by scholars like Fama (1970) and reviewed by Melkiel (1992). Since historical price information is already reflected in the present price, technical analysis is totally useless for predicting future price movements.

But the EMH has been heavily criticized as well in recent years, and many studies report the evidence of predictability of security returns from historical price patterns. This type of evidence in support of technical analysis can be classified into two categories.

The first category resembles systematic dependencies in security returns, in the form of autocorrelation, as observed by Campbell et al. (1997) among others. Those studies have reported positive or negative series correlation in returns of individual stocks or indices on various time frequencies.

The second category deals with the returns that are generated by technical rules, including momentum rules, moving average rules and others, as described by Jegadeesh and Titman (1993) among others.

In the past, the mainstream in academia believed that technical analysis is not useful for improving returns, as confirmed by most empirical studies, from Jensen and Benington (1970), among others.

In most recent years, and in contrast with the previous believes studies by eminent scientists like by Brock, Lakonishok, and LeBaron (1992), for example, demonstrate that a relatively simple set of technical trading rules possess significant forecast power for changes in the Dow Jones Industrial Average (DJIA) over a long sample period.

In general, modern science tends to address the issue of the evidence of return predictability by asserting that if the technical analysis works, some inefficiency is present in the target markets.

More evidence on technical analysis includes a look at Asian markets by Bessembinder and Chan (1995), who report that the same rules are useful for forecasting index returns for a group of Asian stock markets. Sweeney (1986) works on foreign exchange markets and finds out that the success of similar technical rules for forecasting changes in currency exchange rates.

If technical rules possess significant return forecasting power, traders can use the rules to improve returns relative to a buy-and-hold strategy, when transaction costs or return measurement errors are not present. However, since technical trading strategies require frequent transactions, return predictability may not imply increased returns once transaction costs are considered.

The aim of the paper is to perform technical analysis on the index SPMIB of the Italian Exchange (Borsa Italiana), by using selected technical indicators, through univariate and multivariate regressions to be performed for each indicator.

A first stage aims at identifying and isolating the most relevant indicators driving the index, in order to focus on them and analyze their impact on the index trend over time. This is done by lagging the dataset according to some different lags and two different time frequencies (daily and weekly).

After the first stage is completed and the indicators are selected, a second stage involves the regression of the selected indicators in order to perform a second estimation, with the help of a neural network as a mean for error minimization.

The first section of the paper deals with an introduction to financial application of neural networks. The second section deals with the concept of steepest descent as the way neural networks perform linear regression error minimization.

The third section describes the selected indicators, how they can be calculated, and how the signal they give can be interpreted in a trading sense. Fourth section is about data, and description of the software to be used in the project.

The fifth section deals with the dataset normalization and the first regression, the one leading to the selection of the most relevant indicators. The sixth section is the core chapter of the paper and relates to the neural-network-based regression, and the interpretation of the results.

The seventh section is about the final results, after performing the last regressions, and concentrating the work with neural network on the selected indicators. Conclusions and references follow.

1. Neural Networks for Financial Applications

Neural networks in the last decades have become a very popular tool for financial decision making, and several studies have been performed about its ability to predict financial performance, with mixed results.

Given the nature of the topic, it is not even possible to compare the various studies, because they show a vast research design variety and they are subject to several problems.

One of the main issues is the short time horizon of the experiments, as they have been performed in most studies, which makes the experimental results being tampered by situational effect and economic fluctuations.

Another common inconvenient is the small size of samples, making the experimental result biased and hindering the possibility to generalize to the future. Third, many studies do not investigate the statistical significance of performance differences. And variance is significant when dealing with investments, making it undesirable to ignore it in the forecasting process (Dixit and Pindyck, 1994). Finally, these studies choose predictor attributes based on either fundamental or technical analysis.

Fundamental analysis is based on the belief that the value of an investment instruments derives from the performance of its company. It aims at determining the value of an investment instrument by using quantitative tools, like ratios, or qualitative tools, like management policy (Pring, 1980).

It is a common belief in academia that neural networks are an excellent tool for forecasting financial performance for many reasons. First of all, as a computational, numeric tool, they are suitable for processing financial information, in the form of numeric data.

Another advantage of using neural networks is that no distributional assumption for input data must be made, allowing neural networks be applicable to a wider collection of problems than statistical techniques such as regression or discriminant analysis.

Moreover, neural networks are an incremental mining technique, meaning that the network can be fed with new data so that a trained neural network can easily update the previous training result.

When new data are available from time to time, the application of neural networks to finance allows for new information to be accommodated without reprocessing the old information.

Another advantage of neural networks is to be model-free estimators, meaning that interaction effects among variables can be captured without the user being forced to specify the model formulation.

The network can have as many hidden layers as the more complicated the user wants it to be. More hidden layers mean the chance to model very complicated interaction effect among variables (Hornik et al. 1989).
There are also disadvantages in the use of neural network, which cannot be ignored. For example a common issue for applications involves the determination of the optimal combination of training parameters.
Basic important parameters include the network architecture (number of hidden layers and hidden nodes), the learning rate, the momentum rate, the order of submitting training examples to the network, and the number of training epochs.
The selection process for the correct mixing of the above parameters remains more of an art rather than a science, and the specification of the problem to be solved is an important variable of decision.
Data noise is another common problem affecting neural network application, because data are empirically collected from various sources, and they usually are unpolished and partially corrupted during the preliminary processing.
As a system, a neural network is a collection of interconnected simple processing elements. Every connection of neural network has a weight attached to it. Among the various algorithm structures the network can take, the backpropagation algorithm has emerged as one of the most widely used learning procedures for multi-layer networks.
The typical backpropagation neural network is made of an input layer, one or more hidden layers and an output layer. The units in the network are connected in a feedforward manner, from the input layer to the output layer.
The process involves giving initial values to the weights of connections. After the initial network processing, the error between the predicted output value and the actual value is backpropagated through the network for the updating of the weights.
The whole process is then designed as a supervised learning procedure, attempting for to minimize the error between the desired and the predicted outputs (Tao et al. 1999).
Formally, the output value for a unit k is given by the following sigmoid hyperbolic tangent function:

$$y_k = tanh\left(\sum_{i=1}^{n} w_{i,k} x_i - \mu_k\right)$$

where

n is the number of units in the previous layer
x_i is the output of ith unit in previous layer
$w_{i,k}$ is the weight assigned to the connection from the ith unit
μ_k is the threshold

The Neurosolutions™ software used in the project allows for graphical construction of the network, which should then be structured as in figure 1.

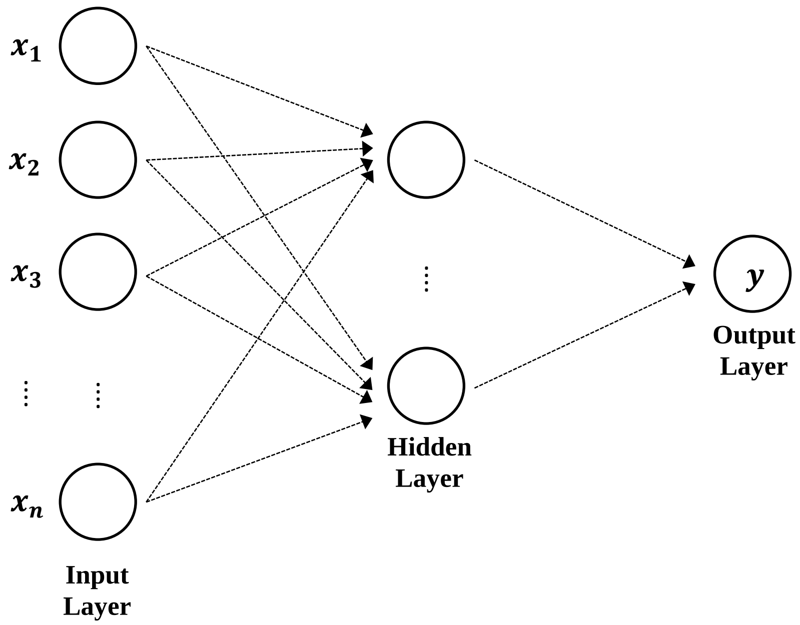

Figure 1: Typical structure of a neural network with one hidden layer.

2. Steepest Descent Regression

System design is highly influenced by the use of neural networks. The first part of the process is specifications. The problem domain must initially be studied and modeled, so that a system can be built to meet the specifications.

A non-adaptive system will have the limitation of meeting current specifications, by always using the designed set of parameters, even if the external conditions change. A design approach based on adaptation is much more flexible.

The two methods that can be used to adapt the system parameters are supervised learning and unsupervised learning. Supervised adaptive system design is based on a linear system with adaptive parameters, a designed target response and an optimality criterion (minimum squared error in our work).

The mean square error (MSE) ϵ^2 can be analyzed as the parameters of the system (α, β) are changed, according to the formula

$$\epsilon^2 = \frac{1}{2N} \sum_{i=1}^{N} (y_i - \alpha - \beta x_i)^2 \tag{1}$$

It is then possible to neutralize the constant, by setting $\alpha = 0$ (or equivalently, that the mean of x and d have been removed), such that ϵ^2 becomes a function of the single variable β.

If the coefficient β is considered as a variable, with other parameters constant, it is straightforward to conclude that ϵ^2 is quadratic on β with always-positive coefficients, and it describes a parabola.

The function ϵ^2 is referred to as the performance surface for the regression, and it is an important tool for visualizing the effects of weights adaptation to the MSE, and it stands in the space of possible β values.
Performance surface allows for a geometric approach for finding the value β^* that minimized the performance criterion. Starting from the surface, the vector gradient corresponding to our problem is composed of just one element, given by

$$\nabla\epsilon^2 = \frac{\partial\epsilon^2}{\partial\beta} \tag{2}$$

There are several methods based on gradient information, with the advantages that the gradient can be computed locally, and it always points in the direction of the maximum change.
Given that the objective is to minimize the error, the search for the right solution must be in the direction opposite to the gradient. It follows that the search can be initialized by choosing an arbitrary initial value β_0.
Then the gradient of the performance surface is computed at β_0 and modify the initial weight proportionally to the negative of the gradient at β_0, in order to shift to another point β_1. Then compute the gradient at the new position, and then apply the same procedure iteratively, according to the formula

$$\beta_{j+1} = \beta_j - \theta\nabla\epsilon_j^2 \tag{3}$$

where θ is a small constant and $\nabla\epsilon_j^2$ denotes the gradient of the performance surface at the *j*th iteration. The constant ensures that the operating point stays close enough to the performance surface, in order to maintain stability in the search. This search procedure is called the steepest descent method.
The gradient is usually unknown and must be estimated, and can be used by the adaptive system to optimize the parameters. In order to get robust estimation through averaging, a good estimate requires small perturbation to the operating point.

An elegant method for estimating the gradient was proposed by Widrow
A good algorithm to estimate the gradient was proposed in the 60s by Widrow, who revolutionized the application of gradient descent procedures. The idea behind the algorithm is to use the instantaneous value as the estimator for the true quantity.
For our case it means to drop the summation in (1) and define the gradient estimate at step *j* as its instantaneous value. This is done by substituting the equation for the MSE, which is given by

$$\epsilon^2 = \frac{1}{2N}\sum_{i=1}^{N}\varepsilon^2 \tag{4}$$

straight into the linear deviation formula, given by

$$y_i = \alpha + \beta x_i + \varepsilon_i$$

After removing the summation, and taking the derivative with respect to β yields

$$\nabla \epsilon_j^2 = \frac{\nabla \epsilon^2}{\nabla \beta_j} = \frac{\nabla}{\nabla \beta_j} \frac{1}{2N} \sum_{i=1}^{N} \varepsilon^2 \approx \frac{1}{2} \frac{\nabla}{\nabla \beta_j} \left(\varepsilon_j^2\right) = -\varepsilon_j x_j \quad (4)$$

Therefore an instantaneous estimate of the gradient at interaction j is the product of current input times current error. It follows that with just one multiplication per weight it is possible to estimate the gradient.
This gradient estimate is at the basis of least means square estimation, and it will be noisy, because of the error being input in the algorithm from single sample instead of summing the error for each point in the data set.
It should be anyway recalled that adaptation process finds the minimum in several steps, so that many iterations are required to find the solution for the minimum of the performance surface. During this process the error is generally filtered out.
The LMS algorithm is then simply obtained by substituting (4) into the error equation

$$\varepsilon_i = y_i - (\alpha + \beta x_i)$$

so to get

$$w_{j-1} = w_j + \theta \varepsilon_j x_j \quad (5)$$

With the LMS rule one does not need to worry about perturbation and averaging to properly estimate the gradient at every iteration, it is the iterative process that is improving the gradient estimator.

3. Description of Selected Indicators

The project data are described in the Data section of the paper. It is important here to describe the technical analysis indicators used in the work. The following 15 indicators, referred to the SPMIB index, calculated on the index prices, have been chosen so to represent all the macro areas of technical indicators, as summarized by table 1.
Indicators are calculations based on the price and the volume of a security that measure such things as money flow, trends, volatility and momentum. They are used as a secondary measure to the actual price movements and add additional information to the analysis of securities.

Macro Area	Indicators
Momentum Indicators	Accumulation Swing Indicator (ASI) Relative Momentum Indicator (RMI) Chande Momentum Oscillator (CMO)
Trend Indicators	Double Exponential Moving Average (DEMA) Moving Average Convergence/Divergence (MACD) Parabolic Stop and Reverse (PSR)
Volatility Indicators	Average True Range (ATR) Relative Volatility Index (RVI) Commodity Selection Index (CSI)
Support-Resistance Indicators	Envelope Percentage Function (EPF)
Cyclic Indicators	MESA Sine Wave (MSW) MESA Sine Lead (MSL)
Market Strenght Indicators	Projection Oscillator (POS) Projection Lower Band (PLB) Projection Upper Band (PUB)

Table 1: List of the selected indicators, divided by macro areas.

The indicators are all popular and widely used in technical analysis, and can be described one by one, for matter of completeness and clarity to the reader.

Accumulation Swing Index

The Accumulation Swing Index (ASI) was introduced by Wilder in 1978, and represents the cumulative value of the standard Swing indicator, which quantifies the swift in trend, through a numerical value. The indicator is important in that it gives an idea of the real market strength, independent of the noise. Moreover, it offers a clear indication of the short-term trend inversions.

The Swing is calculated according to the formula

$$AS = 50\left[\frac{(c - c_{-1}) + \frac{(c - o)}{2} + \frac{(c_{-1} - o_{-1})}{4}}{r}\right]\frac{k}{t}$$

with

$$k = max(h_t - c_{t-1}, l_t - c_{t-1})$$

$$r = \begin{cases} (h - c_{-1}) + \dfrac{(l - c_{-1})}{2} + \dfrac{(c_{-1} + o_{-1})}{4} & if\ (h - c_{-1}) = max[(h - c_{-1}), (l - c_{-1}), (h - c)] \\ (l - c_{-1}) + \dfrac{(h - c_{-1})}{2} + \dfrac{(c_{-1} + o_{-1})}{4} & if\ (l - c_{-1}) = \max[(h - c_{-1}), (l - c_{-1}), (h - c)] \\ (h - l) + \dfrac{(c_{-1} + o_{-1})}{4} & if\ (h - c) = max[(h - c_{-1}), (l - c_{-1}), (h - c)] \end{cases}$$

where

c is the closing price today
c_{-1} is the closing price yesterday
o is the opening price today
o_{-1} is the opening price yesterday
h is the highest price today
h_{-1} is the highest price yesterday
l is the lowest price today
l_{-1} is the lowest price yesterday
t is the value of a limit move

Relative Momentum Index

The Relative Momentum Index (RMI) was introduced by Altman in 1993, and represents a variation of the popular Relative Strength Index (RSI), which is calculated as

$$RMI = 100\left(\frac{\tilde{u}}{\tilde{u} + \tilde{d}}\right)$$

with

$$\tilde{u} = \left(\frac{\bar{u}(n-1) + u}{n}\right)$$

$$\tilde{d} = \left(\frac{\bar{d}(n-1) + d}{n}\right)$$

and

$$u = \begin{cases} (c - c_{-m}) & if\ c > c_{-m} \\ 0 & if\ c < c_{-m} \end{cases}$$

$$d = \begin{cases} (c_{-m} - c) & if\ c < c_{-m} \\ 0 & if\ c > c_{-m} \end{cases}$$

where

$\bar{u}$ is the average of price in up days in the interval of *n* days
$\bar{d}$ is the average of price in down days in the interval of *n* days
n is the number of days considered in the data interval
m is the number of days considered for momentum

The RMI considers up and down movements of closing prices over a time interval of *n* days, as oppose as RSI which is equivalent over 1-day movements. Therefore the RMI is an indicator of momentum, as oppose as RSI which is an indicator of market strength. The RMI index varies between 0 and 100, with a signal of overbought at about 70 and a signal of oversold at about 30.

Chande Momentum Oscillator

The Chande Momentum Oscillator (CMO) was developed by Chande and is described in the book The New Technical Trader Chande and Kroll (1994). The main difference with RSI in this case is that it goes from -100 to +100, putting at the numerator data about both up days and down days, with direct measure of moment. Moreover, calculation refers to data which are not smoothed, therefore including the information about extreme price movements. The formula of the oscillator is

$$CMO_i = 100\left(\frac{\bar{u}_i - \bar{d}_i}{\bar{u}_i + \bar{d}_i}\right)$$

where

$$u = \begin{cases} (c - c_{-1}) & if\ c > c_{-1} \\ 0 & if\ c < c_{-1} \end{cases}$$

$$d = \begin{cases} (c_{-1} - c) & if\ c < c_{-1} \\ 0 & if\ c > c_{-1} \end{cases}$$

and

$$\bar{u}_i = \sum_{i-n}^{i} u \qquad\qquad \bar{d}_i = \sum_{i-n}^{i} d$$

There are several ways to interpret the CMO. Values over +50 indicate overbought conditions, while values under -50 indicate oversold conditions. High CMO values indicate strong trends. When the CMO crosses above a moving average of the CMO, it is a buy signal, crossing down is a sell signal.

Double Exponential Moving Average

The Double Exponential Moving Average (DEMA) was developed by Patrick Mulloy (1994). It is composed of a single average and a double moving average, in order to eliminate the negative effects of lag increasing, due to increase in length of the moving average. As an indicator it therefore offers a very pronounced smoothing of the data.
The formula of the indicator is

$$DEMA = 2 \times EMA_x - EMA_{EMA_x}$$

where

EMA_x is the exponential moving average of the input data

EMA_{EMA_x} is the second exponential moving average applied to data

Like for all moving averages in general, the signal is to sell when the price line intersects the indicator line from bottom up, and sell in the opposite case.

Moving Average Convergence/Divergence

The Moving Average Convergence/Divergence (MACD) was developed by Gerald Appel (1979) as the difference between two (short and long) Exponential Moving Averages. The Signal line is an Exponential Moving Average of the MACD.

The MACD signals trend changes and indicates the start of new trend direction. High values indicate overbought conditions, low values indicate oversold conditions. When the indicator diverges considerably from the price, the signal is the end to the current trend, especially if the MACD itself is at extreme high or low values.

$$MACD = EMA_+ - EMA_-$$

where

EMA_+ is the short exponential moving average given by

$$EMA_+ = 0.15c + 0.85EMA_{+,-1}$$

and

EMA_- is the long exponential moving average given by

$$EMA_- = 0.075c + 0.925EMA_{-,-1}$$

where

$EMA_{+,-1}$ is the short exponential moving average of yesterday

$EMA_{-,-1}$ is the long exponential moving average of yesterday

The indicator line crossing above the signal line generates a buy signal. On the other side, when the indicator line crosses below the signal line a sell signal is generated. In order to confirm the signal, the MACD should be above zero for a buy, and below zero for a sell.

The time periods for the MACD are often given as 26 and 12. However the function actually uses exponential constants of 0.075 and 0.15, which are closer to 25.6667 and 12.3333 periods. The calculation is given by

Parabolic Stop and Reversal

The Parabolic stop and reversal (PSR) was developed by Wilder (1978). If the investor is long, and calculates a trailing stop. Simply exit when the price crosses the SAR. The SAR assumes that you are always in the market, and calculates the Stop And Reverse point when you would close a long position and open a short position or vice versa.

The condition for stop can be defined as

$$h > x$$

then

$$x = h \qquad\qquad a = a_{-1} + s$$

where

x is the extreme point considered

a is the accelerating factor

s is the step

And, for short position, as

$$l < x$$

then

$$x = l \qquad\qquad a = a_{-1} + s$$

The PSR is then given by

$$PSR = a(x - PSR_{-1}) + PSR_{-1}$$

The indicator assumes that investor is always in the market, and calculates the Stop And Reverse point when the investor would close a long position and open a short position or vice versa. As for the trading strategies associated to the signal, simply exit when the price crosses the PSR.

Average True Range

The Average True Range (ATR) indicator was developed by Wilder (1978). It consists in a moving average of the True Range (TR) indicator. The ATR is a measure of volatility being the maximum between the following:

- The difference between maximum price and today's minimum
- The difference between yesterday closing price and maximum price today
- The difference between yesterday closing price and minimum price today

The formula for ATR, which is the moving average of the above intervals, is given by

$$ATR = \frac{(TH_{-1} - TL_{-1})(n-1) + (TH - TL)}{n}$$

where

$$TH = max(h, c_{-1}) \qquad\qquad TL = max(l, c_{-1})$$

and

TH_{-1} and TL_{-1} are the values of yesterday for TH and TL respectively.

n is the number of days considered.

High ATR values indicate high volatility, and low values indicate low volatility, often seen when the price is flat. The ATR is comprised in the family of the Welles Wilder Directional Movement indicators.

Relative Volatility Index

The Relative Volatility Indicator (RVI) was introduced in its original form by Dorsey (1993), and revised by same author in 1995. The RVI indicator as used in this paper is then a revision of the original RVI, which is calculated using the closing price.
The revised version is calculated by taking the average of the original RVI of the high and the original RVI of the low. It is basically a volatility indicator, developed as confirmation of momentum-based indicators.
The Relative Volatility Index (RVI) is based on the Relative Strength Index (RSI), but compared to it, it uses a nine period standard deviation of the price, instead of the average price change.
The RVI indicator as used in this paper is a revision of the original RVI, which is calculated using the closing price. The revised version is calculated by taking the average of the original RVI of the high and the original RVI of the low.
It is basically a volatility indicator, developed as confirmation of momentum-based indicators. Up and down movements in this case are described using standard deviation as from

$$u = \begin{cases} \sigma_{i-9} & if\ c > c_{-1} \\ 0 & otherwise \end{cases} \qquad d = \begin{cases} \sigma_{i-9} & if\ c < c_{-1} \\ 0 & otherwise \end{cases}$$

where

σ_{i-9} is the nine-day standard deviation of prices.

Define the over-time updating average of ups and downs as

$$\bar{u} = \frac{\bar{u}_{-1}(n-1)+u}{n} \qquad \bar{d} = \frac{\bar{d}_{-1}(n-1)+d}{n}$$

The original RVI can then be defined as

$$\widetilde{RVI} = 100\left(\frac{\bar{u}}{\bar{u}+\bar{d}}\right)$$

And the modified RVI as

$$RVI = \frac{\widetilde{RVI}_h + \widetilde{RVI}_l}{2}$$

where

$\widetilde{RVI}_h$ and $\widetilde{RVI}_l$ are the values of the original RVI calculated for the highest prices and lowest prices respectively.

RVI is mostly used to confirm other signals, and the right strategy is to only buy when the RVI is above 50 and only sell when the RVI is below 50. If a signal is ignored, buy when the RVI is above 60 and sell when the RVI is below 40. Exit a long position if the RVI drops below 40 and exit a short position when the RVI rises above. The distinguishing feature of RVI compared to other indicators is then the high diversification of signals that can be grasped from its interpretation.

Commodity Selection Index

The Commodity Selection Index was developed Wilder (1978) as a composite indicator calculated by multiplying two other indicators, the Average Directional Movement Rating (ADXR) and the ATR. The result is then then multiplied by a constant that incorporates the move value, commission and margin.

The reader is invited to read Wilder (1978) for a complete description of the three indicators involved in the analysis, given that the ADXR is derived by the Average Directional Movement Index (ADX), which is itself derived from the Directional Movement Index (DX).

Once the formulations for the ADXR is known, the CSI in its analytic form can be defined as

$$CSI = ADXR \times ATR \times \rho$$

The constant ρ is calculated as

$$\rho = 100 \frac{\left(\frac{V}{\sqrt{M}}\right)}{(150 + C)}$$

where

V is the move value

M is the margin

C is the commission

As a momentum indicator, the CSI can indicate which commodities are good to negotiate in the short term. Commodities with a high value of CSI are suitable for trading, given a high factor of volatility and trend.

Envelope Percent Function

The scope of the Envelope Percentage Function (EPF) is to create plus and minus bands around a series of values on a percentage of the data series. This allows for example to create support support/resistance bands around the close.

The function is composed of two moving averages, both being subject to a vertical and horizontal percentage shift. The upper band EPF_h and the lower band EPF_l therefore include the movements of the reference instrument, by acting as containment bands.

$$EPF_h = x(1 + \delta) \qquad\qquad EPF_l = x(1 - \delta)$$

where

x is the input variable (price)

δ is the percentage shift

When the price reaches the upper band, a sell signal is generated, while a buy signal is generated when the price reaches the lower band. The interpretation is that too active buyers (sellers) push the price high (low) to levels that are not sustainable in the long term, therefore likely to get back to more realistic values.

Maximum Entropy Spectral Analysis Sine Wave

The Maximum Entropy Spectral Analysis (MESA) Sine Wave was developed by Elhers (1996) and comprises two sine plots, MESA Sine Wave (MSW) and MESA Sine Lead (MSL) to indicate if the market is in a cycle mode or in a trend mode.

When the two plots represent a sine wave, the market is in the cycle mode. When the plots start to diverge from sinusoid, the market is said to be in the trend mode. In the trend mode, the Sine Wave and Sine Lead plots typically stand around a zero pattern, running parallel and distant from each other.

The calculation is quite complex and goes through several steps. First of all a real part $r_i$and imaginary part i_i are calculated as

$$r_i = \sum_{j=0}^{n}\left(sin\left(\frac{4\pi j}{n}\right)c_{-1}\right) \qquad\qquad i_i = \sum_{j=0}^{n}\left(cos\left(\frac{4\pi j}{n}\right)c_{-1}\right)$$

Then a condition is set on the imaginary part so that the dominant cycle for the phase (DC) can be calculated as

$$DC = \begin{cases} atan\left(\frac{r_i}{i_i}\right) + \frac{\pi}{2} & if\ i_i > 0.001 \\ \frac{\pi}{2} & otherwise \end{cases}$$

Over time it holds that

$$DC = \begin{cases} DC_{-1} + \pi & if\ i_i < 0 \\ DC_{-1} - 2\pi & if\ DC > \frac{3}{2}\pi \end{cases}$$

And the two curves are calculated as

$$MSW = sin(DC) \qquad\qquad MSL = sin\left(DC + \frac{\pi}{4}\right)$$

Signals are generated only when the market is in a cycle. A buy signal is generated when the Sine crosses up over the Lead Sine, and a sell signal when the Sine crosses down below the Lead Sine.

Projection Bands

Projection Bands were developed by Widner (1995) and consist of a Projection Upper Band (PUB) and a Projection Lower Band (PLB). They are calculated by finding the highest *h* and lowest *l* over the last *n* periods and plotting them parallel to a regression

line of the high vs. low. The Projection Bands are defined as standard support and resistance levels.
The bands are calculated as

$$PUB = max\left(h_{-j} + \beta_h(i-j)\right) \qquad\qquad PLB = max\left(l_{-j} + \beta_l(i-j)\right)$$

where

j is a day in the lookback period
i is the reference day over which the analysis is projected
β_h is the slope of the regression on highs
β_l is the slope of the regression on lows

The signal comes when the price reaches the bands. When the upper band is reached, it signals a price top and probable reversal. Likewise, when the price reaches the bottom band, it signals a bottom. Unlike other support resistance levels like Bollinger bands, the price will never actually break above or below the bands.
When prices are too close to the upper band, the market is characterized by excessive optimism, and prices will soon move down to more realistic levels. The opposite holds when prices are too close to the minimum.

Projection Oscillator
The Projection Oscillator (POS) was introduced by Widner (1995) and is based on the Projection Bands indicator. The Oscillator calculates where the close lies within the band as a percentage.
Therefore, a value of 50 corresponds to the close being in the middle of the band range, whereas a value of 100 indicates that the close is equal to the top band, and zero means that it is equal to the low band.
The calculation of POS is similar to a Stochastic which uses the raw highest high and lowest low value. The Projection Oscillator adds the regression line component to that calculation, making it more sensitive. The calculation is given by

$$POS = 100\left(\frac{c - PLB}{PUB - PLB}\right)$$

The Projection Oscillator can be interpreted several ways. When diverging with price it indicates a trend reversal, while extreme values, above 80 and below 20 indicate overbought/oversold levels.
A moving average of the oscillator can be used as a trigger line. A buy/sell signal is generated when the Projection Oscillator to cross above/below the trigger line. The signal is stronger if it happens above 70 or below 30.

4. Data

The data involved in the project are the prices of Italian SPMIB index, from Borsa Italiana. Daily data range from 1st September 2004 to 18th November 2005, for a total of 311 observations. Weekly data range from 5th November 1999 to 18th November 2005, for a total of 316 observations.

The dataset includes opening prices, closing prices, max and min prices, for every trading day. As a matter of simplicity, and for computational uniformity, in the project only closing prices are used.

For the technical part, 15 indicators of technical analysis are chosen, referred to the SPMIB index, and calculated on index prices, chosen to represent all the major macro areas of technical indicators.

The regressions are supported by Excel for the first step of the analysis, followed by the popular neural network software Neurosolutions™, from Neurodimension. The software is used for the second stage of regressions, after selecting the most relevant indicators, and for the classification of them. Technical analysis is supported by the software Metastock™, of Equis, which is used to construct the indicators and production of graphs.

Neurosolutions™

It is a neural network software, based on object oriented programming and a friendly graphical interface. It allows building, setting and modifying neural network, from the simplest to the most complex.

The interest of the project on the potential of neural networks is their ability to minimize the error from linear regressions, together with the flexibility characterizing the neural components that allow monitoring the whole process. It is then possible to visualize on a graph or table all results obtained during the optimization process, so to better understand the development of the computation stages.

Metastock™

It is highly sophisticated technical analysis software, working on files that can be continuously updated, from which it imports data related to the historical trend of the prices, for chosen financial instruments.

The screen visualization consists of two overlapping windows, the upper one containing the price trend graph and the bottom one showing trading volumes. The user can choose different types of curve visualization and can work on the graphs by selecting technical indicators, with the help of the tools offered by the software.

A very interesting feature of the software is the possibility to directly export the data about prices, volumes and indicators on a third party spreadsheet.

The lags considered for the dataset are summarized in table 2. Lags are chosen in order to be consistent with the frequency of the dataset of reference, so that daily data are lagged in a range from 1 day to 1 month, and weekly data are lagged in the range of 1 week to 3 months.

	Lags				
Daily Data	1 day	3 days	1 week	2 weeks	1 month
Weekly Data	1 week	2 weeks	1 month	2 months	3 months

Table 2: Lags of dataset considered, for daily and weekly data.

5. Dataset Normalization and First Regressions

The first phase of the analysis involves the normalization of available data, through calculation of the daily variations. This is done for both the SPMIB index and the indicators.

Two different approaches are used for normalization, in order to obtain two different datasets to use for regressions and compare results. The normalization formula for daily variation (percentage variation) approach is

$$V_{t+1} = \frac{P_{t+1}}{P_t} - 1$$

where

P_t is the index or indicator value at time t

P_{t+1} is the index or indicator value at time $t + 1$

The second normalization method consists in simply dividing each data by the mean of the whole dataset (quotient-on-average approach), according to the formula

$$V_{t+1} = \frac{P_{t+1}}{\frac{1}{N}\sum_{t=1}^{N} P_t} - 1$$

where

$N =$ total number of available observations

Once data are normalized it is possible to proceed to regression phase. Recall data are lagged, yielding an intertemporal regression. Linear regressions are then performed, lagging the index series towards the indicators.

Single regressions of index vectors vs. price vectors are then performed, plus multivariate regression of the indicators matrix vs. the price vector. The mixed approach involves using the simplicity of a spreadsheet combined with the power of neural network approach.

First regressions are then followed by the isolation of the most significant indicators,

which are further studied in the second stage of the work. Indicators are further involved in a second analysis and regressions, and the outcome is studied through technical analysis of the available data.
To summarize, for each lag 15 univariate regressions (of the variation vector for each indicator, over the index variation vector) and 1 multivariate regression (of the variation matrix of the indicators, over the vector of index variations) are performed.
The results of the regressions are summarized in tables 3-8.

Percentage Variation Dataset
For daily data, in general, univariate regressions show poorly significant results. The only important coefficient in fact belongs to the EPF indicator, with values between 0.21 and 0.43, negative for lags shorter than 2 weeks and positive for the 1-month lag.
Multivariate regression on daily data confirms the significance of EPF coefficient, with same sign trend over lags. Moreover, also the DEMA indicator shows significant coefficients, with an opposite trend over lags, going from positive to negative for longer lags.
Univariate regressions on weekly data show a consistent noise elimination effect, confirming some of the findings at daily frequency. All coefficients are very low and the only interesting information is the confirmation of EPF as significant, but with an inverted trend over lags (from negative to positive for 1-month lag), compared to daily data.
Multivariate regression on weekly data underlines again the significance of both EPF and DEMA indicators, despite showing a net sign contraposition, with the former showing all positive signs over lags, and the latter showing all negative signs instead.

Lags	**ASI**	**RMI**	**CMO**	**DEMA**	**MACD**	**PSR**	**ATR**	**RVI**
1 day	-0,019219	-0,004067	0,000342	-0,072798	0,000018	0,057106	0,021342	0,006007
3 days	0,006724	0,000439	0,000038	-0,004512	-0,000125	-0,018253	0,000458	-0,003202
1 week	0,026554	0,008095	0,000286	-0,041583	-0,000005	-0,014297	-0,005058	-0,003763
2 weeks	0,003474	-0,002096	-0,000144	-0,218829	0,000082	0,002667	0,011205	0,019711
1 month	-0,023402	-0,004734	-0,000028	-0,011798	0,000372	0,078718	0,003881	-0,006145
	CSI	**EPF**	**MSW**	**MSL**	**POS**	**PUB**	**PLB**	***Det. Coeff.***
1 day	0,009130	-0,240725	-0,000189	-0,000007	0,000000	-0,070994	0,075030	*0,002819*
3 days	-0,008252	-0,279756	0,000163	0,000077	0,000000	-0,068009	-0,045366	***F Stat.***
1 week	0,001801	-0,439931	-0,000007	0,000082	0,000000	0,034253	-0,027450	*0,852083*
2 weeks	0,012166	-0,213363	-0,000039	0,000091	0,000000	-0,031089	-0,034185	***Resid.***
1 month	-0,000858	0,353453	0,000033	0,000248	0,000000	-0,159670	-0,030886	*0,000033*

Table 3: Betas associated to indicators. Single regressions on daily data for percentage variations dataset.

Lags	ASI	RMI	CMO	DEMA	MACD	PSR	ATR	RVI
1 day	-0,033769	-0,002850	0,000367	0,112616	-0,000026	0,038828	0,048808	0,011472
3 days	0,005324	-0,002280	0,000058	0,569287	-0,000120	0,007765	0,020773	-0,005831
1 week	0,032610	0,017084	0,000307	-0,140653	0,000006	0,024523	-0,015961	-0,011535
2 weeks	0,010055	0,006025	-0,000175	-0,852090	0,000098	0,032096	-0,008728	0,030500
1 month	-0,019268	-0,005597	-0,000061	0,316336	0,000338	0,055301	0,004744	0,000247
	CSI	**EPF**	**MSW**	**MSL**	**POS**	**PUB**	**PLB**	***Det. Coeff.***
1 day	-0,004145	-0,446739	-0,000182	0,000015	0,000000	-0,136228	0,232092	*0,052570*
3 days	-0,017016	-0,578539	0,000186	0,000132	0,000000	-0,138768	-0,076142	***F Stat.***
1 week	0,005169	-0,573169	-0,000006	0,000098	0,000000	0,136587	-0,155483	*1,063755*
2 weeks	0,013689	0,342836	-0,000042	0,000083	0,000000	0,101588	-0,011341	***Resid.***
1 month	-0,005749	0,164659	0,000023	0,000274	0,000000	-0,265085	-0,015059	*0,000619*

Table 4: Betas associated to indicators. Multivariate regression on daily data for percentage variations dataset.

Lags	ASI	RMI	CMO	DEMA	MACD	PSR	ATR	RVI
1 week	0,032194	-0,008733	-0,000037	-0,054966	-0,000290	-0,053460	0,011842	0,014538
2 weeks	0,017590	-0,009838	-0,000077	-0,170616	0,000060	-0,054330	0,139633	0,004163
1 month	0,021028	-0,019059	-0,000038	0,010094	0,000593	-0,040314	0,064887	-0,024173
2 months	0,033659	0,038559	-0,000023	0,156900	-0,000293	0,127884	-0,019435	-0,009070
3 months	0,052781	0,010369	-0,000033	0,035423	0,000401	-0,037527	-0,059608	0,049538
	CSI	**EPF**	**MSW**	**MSL**	**POS**	**PUB**	**PLB**	***Det. Coeff.***
1 week	0,033351	-0,083176	-0,000663	0,000105	0,000000	0,041888	-0,073786	*0,003542*
2 weeks	0,049349	-0,135484	-0,000302	0,000263	0,000000	0,028933	-0,085084	***F Stat.***
1 month	0,005551	0,076364	0,000262	-0,004125	0,000000	-0,029924	0,020035	*1,103370*
2 months	0,012545	0,200637	0,000198	0,000743	0,000000	0,002297	0,034367	***Resid.***
3 months	-0,015946	0,056206	0,001711	0,002086	0,000000	0,011056	0,094091	*0,000932*

Table 5: Betas associated to indicators. Single regressions on weekly data for percentage variations dataset.

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Lags	**ASI**	**RMI**	**CMO**	**DEMA**	**MACD**	**PSR**	**ATR**	**RVI**
1 week	0,053891	-0,012939	-0,000031	-0,407399	0,000049	-0,047463	-0,056353	-0,011143
2 weeks	0,054766	0,025838	-0,000075	-1,053254	0,000499	-0,064585	0,120820	-0,029777
1 month	0,046343	-0,016154	-0,000038	-0,221080	0,000059	-0,082420	0,186171	-0,040426
2 months	0,049310	0,056994	-0,000018	-0,283737	-0,000273	0,138835	-0,031240	-0,022916
3 months	0,079233	0,047208	-0,000026	-1,318028	0,000674	-0,048304	-0,085136	-0,010634
	CSI	**EPF**	**MSW**	**MSL**	**POS**	**PUB**	**PLB**	***Det. Coeff.***
1 week	0,050265	0,224384	-0,000746	0,000218	0,000000	0,223665	-0,040310	*0,058563*
2 weeks	-0,001734	0,639698	-0,000386	0,000247	0,000000	0,308915	0,130497	***F Stat.***
1 month	-0,039105	0,205593	0,000156	-0,003971	0,000000	-0,043439	0,169968	*1,224361*
2 months	0,036777	0,277887	0,000251	0,000749	0,000000	-0,090347	-0,001774	***Resid.***
3 months	0,038287	0,875518	0,001726	0,002165	0,000000	0,151860	0,303783	*0,015418*

Table 6: Betas associated to indicators. Multivariate regression on weekly data for percentage variations dataset.

Quotient-on-Average Dataset

For a matter of simplicity and synthesis, for the quotient-on-average dataset only the results on daily dataset are reported, especially given the fact that at a weekly frequency that kind of normalization cannot be expected to produce significant results.

The univariate regression on daily data confirms the results obtained before, with DEMA and EPF showing coefficients very close to unity and all positive, over all lags. Moreover, with the new dataset, also other indicators, like ASI, PSR, PUB, PLB show significant coefficients.

Lags	**ASI**	**RMI**	**CMO**	**DEMA**	**MACD**	**PSR**	**ATR**	**RVI**
1 day	0,370977	0,038706	-0,000281	0,930936	0,000089	0,803710	0,017344	0,177591
3 days	0,363540	0,035578	-0,000304	0,905476	0,000084	0,778404	0,022187	0,171532
1 week	0,355727	0,032637	-0,000328	0,879197	0,000022	0,753037	0,024002	0,163582
2 weeks	0,332563	0,022605	-0,000361	0,813835	-0,000001	0,701148	0,029751	0,145549
1 month	0,283013	0,027033	-0,000163	0,693409	0,000133	0,638239	0,043596	0,134105
	CS	**EPF**	**MSW**	**MSL**	**POS**	**PUB**	**PLB**	***Det. Coeff.***
1 day	-0,044094	0,897730	0,000026	0,000004	0,013281	0,954777	0,940777	*0,346359*
3 days	-0,041838	0,876829	0,000027	0,000006	0,014196	0,927520	0,908194	***F Stat.***
1 week	-0,039886	0,855669	0,000020	0,000005	0,014716	0,899899	0,875822	*650,401732*
2 weeks	-0,034807	0,806646	0,000010	0,000005	0,013875	0,829076	0,798139	***Resid.***
1 month	-0,022879	0,716600	0,000028	0,000009	0,004673	0,700776	0,667728	*0,172623*

Table 7: Betas associated to indicators. Single regressions on daily data for quotient-on-average dataset.

According to the multivariate regression on daily data, the DEMA indicator shows positive and increasing values on the whole lag spectrum. The EPF exceptionally shows non-significant coefficients, while PLB seems to get a higher significance.

Lags	ASI	RMI	CMO	DEMA	MACD	PSR	ATR	RVI
1 day	0,039510	-0,001408	-0,000034	0,389841	0,000007	-0,060256	0,025475	0,030111
3 days	0,068726	-0,009626	-0,000064	0,769007	-0,000005	-0,123394	0,020120	0,042080
1 week	0,093539	-0,009287	-0,000091	0,810436	-0,000061	-0,193983	0,015816	0,044093
2 weeks	0,114470	-0,036462	-0,000149	1,777668	-0,000029	-0,226861	0,021618	0,079654
1 month	0,175833	-0,032344	0,000000	2,834621	0,000052	0,022302	0,079148	0,089423
	CSI	**EPF**	**MSW**	**MSL**	**POS**	**PUB**	**PLB**	***Det. Coeff.***
1 day	0,004925	0,095180	0,000001	-0,000001	0,010327	0,099912	0,309682	*0,908475*
3 days	0,008841	0,036063	0,000004	0,000001	0,007046	-0,110222	0,153658	***F Stat.***
1 week	0,010935	0,181238	0,000002	0,000001	0,004520	-0,213783	0,053613	*342,687597*
2 weeks	0,017087	-0,044839	-0,000008	0,000001	-0,002348	-0,935938	-0,088214	***Resid.***
1 month	0,029519	-0,027728	0,000004	0,000002	-0,018039	-2,382413	-0,266420	*0,450826*

Table 8: Betas associated to indicators. Multivariate regression on daily data for quotient-on-average dataset.

As expected some results are very significant, while others are much less. This is why it is important, before proceeding with the analysis, to isolate and select the indicators that better explain the trend of SPMIB prices and their variations.

6. Neural Network Based Regression

Regressions run on the percentage variation dataset show a very low coefficient of determination, due to the fact that this methodology for normalization allows for data relativization on one side.

However it shows important sign divergences (variation can change from negative to positive with very high frequency). Same logic works for the values of the F statistics, which are particularly low, showing then randomness in the relationship identified by the indicators.

The quotient on average dataset allows overcoming the sign problem, showing much more homogeneous signs, and consequently determination coefficients which are very close to unity. Residuals are in any case very low.

The analysis carried on so far shows the major role of EPF and DEMA as leading indicators for explaining the SPMIB price variations. The rest of the work is then focused on the two indicators, and their relationship with the index.

A very first technical analysis is possible through plotting on graphs the trend of the indicators, together with the trend of the index in background. The results are shown in figure 1 to 4.

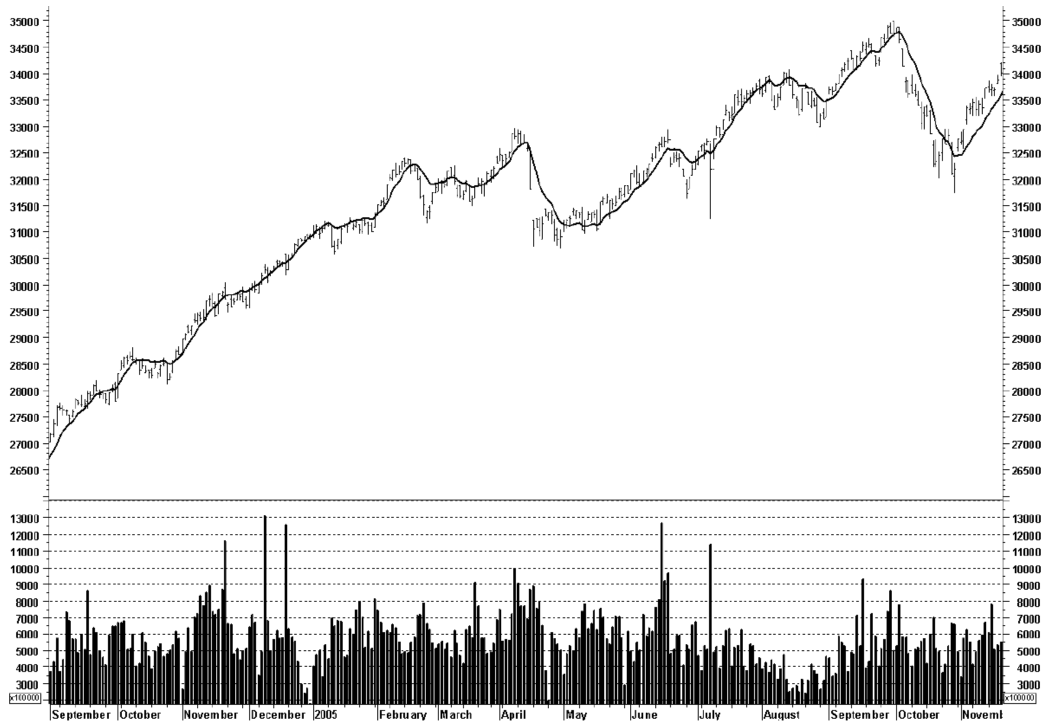

Figure 1: Trend of DEMA over S&PMIB. Daily data.

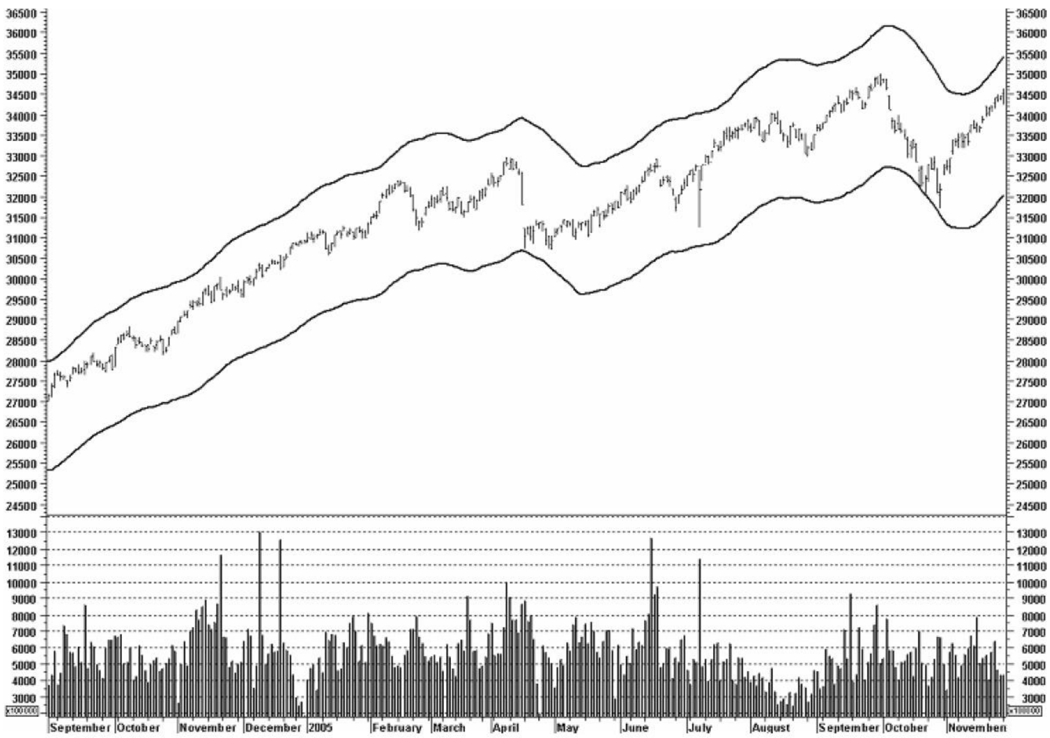

Figure 2: Trend of Envelope over S&PMIB. Daily data.

Figure 3: Trend of DEMA over S&PMIB. Weekly data.

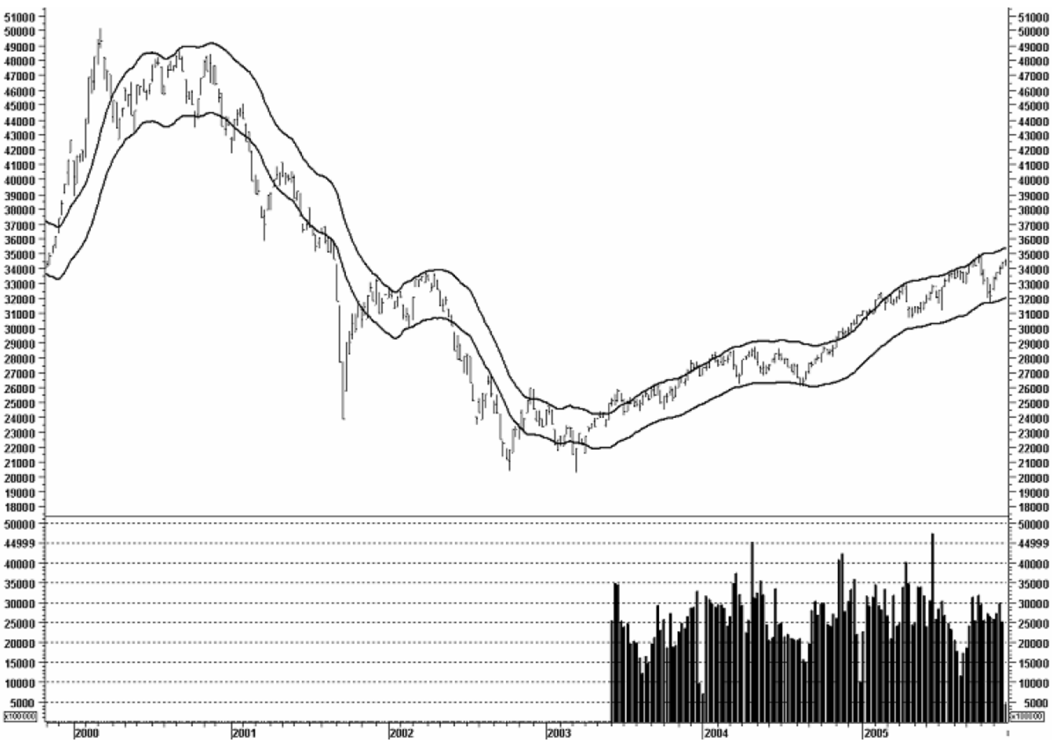

Figure 4: Trend of Envelope over S&PMIB. Weekly data.

In order to improve the valuation at a predictive level, it is very useful to analyze the parts of graphs related to the last dates in the dataset. These zooming are shown in figure 5 and 6.

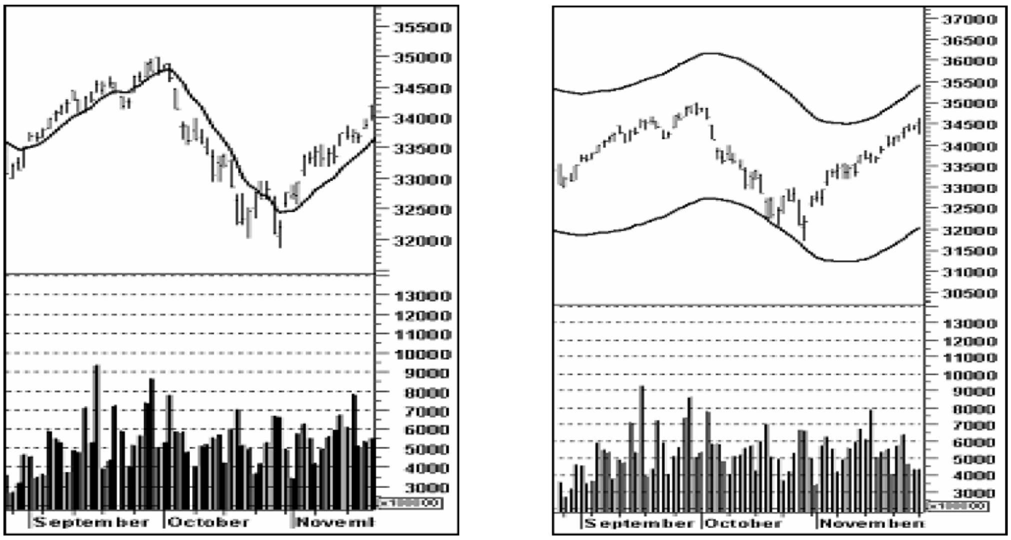

Figure 5: Zoom on DEMA and Envelope. Daily data.

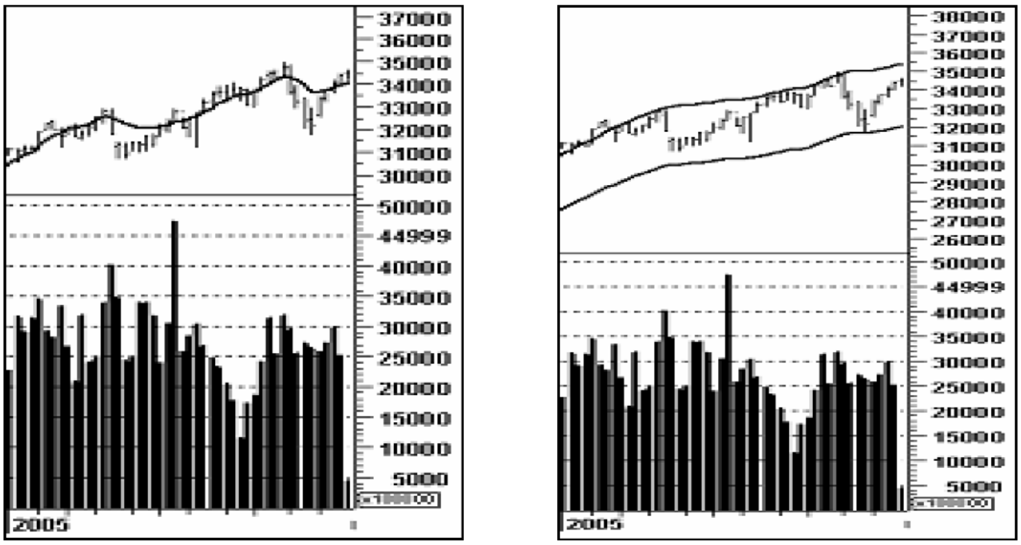

Figure 6: Zoom on DEMA and Envelope. Weekly data.

It is clear from observing the zoomed graphs for daily data that there is a consolidated bullish trend. The DEMA is very tight around the index price (in background). It is therefore crucial to pay attention to the single crossing of lines, in order to optimally interpret the signal from the indicator.

As oppose as DEMA, the EPF is presented with a wide shift around the index. The trend seems to be bullish as well, at least in the short term, given that the upper band of EPS has not been reached yet.

7. Final Results

As mentioned before, the DEMA gives a signal by crossing it with the price curve, while EPF offers the buy-sell signal as the index price curve gets close to its upper or lower band.

Final regression allows generating a coherence check for the activity of the two indicators over the whole dataset, so to determine whether the parallelism on the predictive power of the two indicators should be taken into consideration.

Recall that only the upper band of EPF is available to this study, therefore the analysis focuses on the sell signal only. DEMA instead is about crossing of two curves, with the indicator falling below the SPMIB.

This particular setting facilitates things, in that the coherence between indicators can be checked by just considering for both the difference between the SPMIB and the indicator value, calculated for any time tick. The difference is then normalized through Gaussian approximation using the mean and standard deviation of the dataset.

With the application of a backpropagation neural network, the regression gives two new vectors of value-difference, both containing elements tending to zero. This can be explained by the fact that the signal comes to life when the lines cross (DEMA) or get close (EPF).

Next step is to regress one of the two new value-difference indicators on the other. Together with classification, this step allows to identify the consistency and periodicity of the signals offered by the two indicators.

This allows confirming the hypothesis of a potential combined use of the two indicators when trying to formulate investment strategies. There are a total of four regressions, each referred to a particular dataset, with the results summarized in table 9 and 10.

Daily Data		Weekly Data	
Coefficient	0,75858	Coefficient	0,74029
Intercept	0,00000	Intercept	0,00371
Det. Coeff.	0,57545	Det. Coeff.	0,54608
Residuals	420,18449	Residuals	377,75550

Table 9: Regression results for percentage variation, for daily and weekly data.

Daily Data		Weekly Data	
Coefficient	0,75859	Coefficient	0,73914
Intercept	0,00000	Intercept	0,00000
Det. Coeff.	0,57546	Det. Coeff.	0,54633
Residuals	420,18451	Residuals	373,31242

Table 10: Regression results for quotient-on-average, for daily and weekly data.

Results show some kind of dependence between the two series when calculated as difference. Signals are clearly concentrated on specific periods, with a very interesting regression coefficient of about 0.75, for all datasets analyzed.

Conclusions

Technical analysis is widely used as an investment approach among practitioners, given its relative simplicity, but it is not accepted yet by academics, which rely on more scientific approaches, like fundamental analysis.

The aim of the paper is not to defend technical analysis, nor to sponsor it as a major tool for financial analysis or investment planning, although some of the results show that there is some predictability in the SPMIB index.

This paper aims at combining traditional least square with neural network approach to estimation in order to minimize the estimation error and achieve more accurate results. In doing so, major technical indicators are chosen, so to represent all macro areas.

Although human judgment still has to be considered superior to most computational algorithms in the area of visual pattern recognition, technical analysis may represent an important further step in the application of computational methods.

The paper suggests that even a relatively simple neural network structure, as the single hidden layer, backpropagation network, can provide interesting results, while introducing significance in coefficients apparently non-significant when dealt with in standard linear regression.

The evidence suggests how two indicators in particular, the DEMA and the EPF, are strongly correlated to the SPMIB index, with the consequence of opening the way to important and useful considerations.

Signals of the two indicators can be taken in account as reliable predictors and, if combined, as a primary source of information for investment planning and portfolio management.

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