# Testing the Weak Form Market Efficiency: Empirical Evidence from the Italian Stock Exchange

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**Abstract.** This paper investigates the use of feedforward neural networks for testing the weak form market efficiency. In contrast to approaches that compare out-of-sample predictions of non-linear models to those generated by the random walk model, we directly focus on testing for unpredictability by considering the null hypothesis that a given set of past lags has no effect on current returns. To avoid the data-snooping problem the testing procedure is based on the StepM approach in order to control the familiwise error rate. The procedure is used to test for predictive power in FTSE-MIB index of the italian stock market.

**Keywords:** Random walk, Market efficiency, Multiple testing scheme, Resampling methods.

## 1 Introduction and Background

Efficiency of financial markets is certainly one of the most controversial issue in finance. Volatility, predictability, speculation and anomalies in financial markets are also related to the efficiency issue and are all interdependent. The efficient market hypothesis is a concept of informational efficiency and refers to markets ability to process information into prices. The idea at the bases of the efficient market hypothesis (EMH) emerges already at 1900 but a formal definition of market efficiency is due to Fama who distinguish three forms of efficiency: weak form, semi-strong form and strong form. Weak form of efficiency assumes that actual price of an asset incorporates the past prices information. Thus, it will be not possible for investors, using past prices, to discover undervalued stocks and develop strategies to systematically earn abnormal returns. The semi-strong form hypothesis assumes that all publicly available information is incorporated in the price of the asset and investors cannot take advantage of this information, winning abnormal returns. Finally, strong form of market efficiency hypothesis is more restrictive than the previous two, maintaining that all information, public or private, is incorporated in the current stock prices and investors cannot systematically earn abnormal returns. From that time on, various extensions

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of Fama's definition were proposed to include different levels of information and transaction costs. Anyway, even if there are various critics towards Fama's definition, it is still the most commonly used standard and benchmark for determining market efficiency.

In the following we will focus on the weak form efficiency. Historically, there was a very close link between EMH and the random-walk model and martingale. An *orthogonality* condition where all versions of the random walk and martingales hypotheses are captured is the following ([2]):

$$cov[f(r_t), g(r_{t+k})] = 0 \tag{1}$$

where $f(\cdot)$ and $g(\cdot)$ are two arbitrary functions, $r_t$ and $r_{t+k}$ are asset's returns at $t$ and $t+k$ ($k \neq 0$). For example, if (1) holds when $f(\cdot)$ and $g(\cdot)$ are linear functions, then returns are serially uncorrelated. Alternatively, if $f(\cdot)$ is unrestrected but $g(\cdot)$ is restricted to be linear, the (1) is equivalent to a martingale hypothesis. Finally, if (1) holds for all $f(\cdot)$ and $g(\cdot)$ the returns are mutually independent.

A large body of literature has accumulated in order to test market efficiency using different approaches based on RW and martingale hypotheses (see, for example, [17] or [12] for a nice survey). Further, results are often puzzling since they contradict the conventional wisdom that all developed markets should be more efficient in incorporating information into prices than those markets from the developing economies. For example, Malkiel in [16] justifies return "anomalies" in the major stock markets as chance results that tend to disappear in the long term with a reasonable change in methodology, hence supporting the view that mature capital markets are generally efficient. In contrast, Shiller in [20] has to distance himself from the "presumption" that financial markets always work well and that price changes always reflect genuine information.

Anyway, evidence against the random walk hypothesis (RWH) for stock returns in the capital markets is often shown (see, for example, [3], [14], [15] and references therein). Failure of models based on linear time series techniques to deliver superior forecasts to the simple random walk model has forced researchers to use various non-linear techniques, such as Engle test, Tsay test, Hinich bispectrum test, Lyapunov exponent test. Also in such a literature the market efficiency confirms to be a changelling issue in finance (see, for example, [1]).

The aim of this paper is to test the weak form market efficient hypothesis for the italian stock exchange. According to the evidence of non-linear patterns in stock markets, we propose a neural network approach for characterizing and analyzing the closing price of the FTSE-MIB index, from 1/12/2003 to 23/03/2012.

In particular, we focus on a multiple testing scheme in which the null hypothesis specifies that information contained in past returns cannot be used to predict the current returns. To avoid the data-snooping problem and in order to control the familiwise error rate, the testing procedure uses a multiple testing scheme. Given the probabilistic complexity of the neural network model, a resampling technique is proposed to calibrate the test. The procedure is used to test for predictive power in FTSE-MIB index of the italian stock market.

The paper is organized as follows. In Section 2 we describe the structure of the data generating process and the neural network model employed. In Section

3 we propose a testing scheme for the weak form market efficiency based on a multiple testing scheme. In Section 4 we discuss the application of the proposed procedure to Italian stock market. Some concluding remarks close the paper.

## 2 Neural Network Modelling for Financial Returns

Following a standard practice, we construct return time series as $Y_t = \nabla \log S_t$, where $S_t$ is the stock index at time $t$, in order to avoid potential problems associated with estimation of nonstationary regression functions. The model is defined as:

$$Y_t = g\left(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-d}\right) + \varepsilon_t \tag{2}$$

where $g(\cdot)$ is a non-linear function and $\varepsilon_t$ is zero-mean error term with finite variance. The unknown function $g(\cdot)$ can be estimated by using a feedforward neural network with $d$ input neurons:

$$f\left(\mathbf{y}, \mathbf{w}\right) = w_{00} + \sum_{j=1}^{r} w_{0j} \psi\left(\tilde{\mathbf{y}}^T \mathbf{w}_{1j}\right) \tag{3}$$

where $\mathbf{w} \equiv \left(w_{00}, w_{01}, \ldots w_{0r}, \mathbf{w}_{11}^T, \ldots, \mathbf{w}_{1r}^T\right)^T$ is a $r(d+1)+1$ vector of network weights, $\mathbf{w} \in \mathbf{W}$ with $\mathbf{W}$ being a compact subset of $\mathbb{R}^{r(d+1)+1}$ and $\tilde{\mathbf{y}} \equiv \left(1, \mathbf{y}^T\right)^T$ is the input vector augmented by a bias component 1. The network (3) has $d$ input neurons, $r$ neurons in the hidden layer and the identity function for the output layer. The (fixed) hidden unit activation function $\psi$ is chosen in such a way that $f\left(\mathbf{x}, \cdot\right) : \mathbf{W} \to \mathbf{R}$ is continuous for each $x$ in the support of the explanatory variables and $f\left(\cdot, \mathbf{w}\right) : \mathbf{R}^d \to \mathbf{R}$ is measurable for each $\mathbf{w}$ in $\mathbf{W}$.

Single hidden layer feedforward neural networks have a very flexible non-linear functional form. The activation functions can be chosen quite arbitrarily and it can be shown that they can arbitrarily closely approximate (in the appropriate corresponding metric) to continuous, or to $p$-th power integrable, non-linear functions $g(\cdot)$, so long as the activation function $\psi$ is bounded and satisfies the necessary conditions of not being a polynomial [13].

Given a training set of $n$ observations, estimation of the network weights (learning) is obtained by solving the optimization problem

$$\min_{\mathbf{w} \in \mathbf{W}} \frac{1}{n} \sum_{t=1}^{n} q\left(Y_t, f\left(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-d}; \mathbf{w}\right)\right) \tag{4}$$

where $q(\cdot)$ is a proper chosen loss function, usually a quadratic function. From an operational point of view, estimates of the parameter vector $\mathbf{w}$ can be obtained by using non-recursive or recursive estimation methods such as the back-propagation (BP) algorithm and Newton's algorithm.

Under general regularity conditions, both the methods deliver a consistent weight vector estimator. That is, a weight vector $\hat{\mathbf{w}}_n$ solving equation (4) exists and converges almost surely to $\mathbf{w}_0$, which solves

$$\min_{\mathbf{w} \in \mathbf{W}} \int q\left(y, f\left(\mathbf{x}, \mathbf{w}\right)\right) d\pi\left(\mathbf{z}\right) \tag{5}$$

provided that the integral exists and the optimization problem has a unique solution vector interior to $\mathbf{W}$. Moreover, under general regularity conditions the weight vector estimator is asymptotically normally distributed.

Therefore, given a consistent estimator of the asymptotic variance covariance matrix of the weigths, one could be tempted to test hypotheses about the connection strengths which would be of great help in defining pruning strategies with a strong inferential basis. This approach in any case could be misleading. The parameters (weights) of the neural network model have no clear interpretation and this makes this class of models completely different from classical non-linear parametric models. Moreover, the same output of the network can be obtained with very different configurations of the weights. Finally, as a model selection strategy, variable selection and hidden layer size should follow different schemes: variables have a clear interpretation while hidden layer size has no clear meaning and should be considered a smoothing parameter which is fixed to control the trade-off between bias and variability.

As a consequence, we advocate a model selection strategy where an informative set of input variables is selected by looking at its relevance to the model, in a statistical significance testing framework, while the hidden layer size is selected by looking at the fitting or predictive ability of the network.

In this respect the Predictive Stochastic Complexity (PSC) index proposed by Rissanen and already used by Kuan and Liu ([8]) proved to be an effective tool to select appropriate hidden layer size. However, other tools based on "honest" prediction errors $Y_t - f(Y_{t-1}, \ldots, Y_{t-d}; \hat{\mathbf{w}}_\mathbf{t})$ can be used as well, where $\hat{\mathbf{w}}_\mathbf{t}$ is computed by using information up to time $t-1$. The prediction error is labeled as "honest" in the sense that no information at time $t$ or beyond is used to calculate the estimated parameter vector $\hat{\mathbf{w}}_\mathbf{t}$.

The general idea behind variable relevance analysis is to compute some measures that can be used to quantify the relevance of explanatory variables with respect to a given model. Following White and Racine ([24]) and La Rocca and Perna ([9,10,11]), the hypotheses that the $j$-th lag, let's say $Y_{t-j}$, has no effect on $Y_t$, in model (2), can be formulated as:

$$\frac{\partial g\left(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-d}\right)}{\partial Y_{t-j}} = 0. \tag{6}$$

Of course the function $g$ is unknown but we equivalently investigate the hypotheses

$$f_j\left(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-d}; \mathbf{w}_0\right) = \frac{\partial f\left(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-d}; \mathbf{w}_0\right)}{\partial Y_{t-j}} = 0. \tag{7}$$

since $f$ is known and $\mathbf{w}_0$ can be closely approximated. So, if the $j$-th lag has no effect on $Y$ we have

$$\theta_j = \mathbb{E}\left[f_j^2\left(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-d}, \mathbf{w}_0\right)\right] = 0 \tag{8}$$

where the square function is used to avoid cancellation effects.

This approach appear to be justified since, with reasonable assumptions on the activation function $\psi$, a single hidden layer neural network can arbitrarily closely approximate to $g(\cdot)$ as well its derivatives, up to any given order (provided that they exist), as measured by a proper norm (see [7]). Moreover, a feedforward neural network can achieve an approximation rate that grows linearly in $r$ and thus this class of models is relatively more parsimonious than other non-parametric methods in approximating unknown functions. These two properties make feedforward networks an attractive econometric tool in non-parametric modelling.

## 3 Testing the Weak form Market Efficiency by Using Neural Networks

In this paper, in contrast to approaches that compare out-of-sample predictions of non-linear models to those generated by the random walk model, we employ the approach proposed in La Rocca and Perna ([11]) for exchange rates and focus on directly testing for unpredictability by conducting tests of significance on models inspired by technical trading rules. In this perspective, the hypothesis that a given set of lags has no effect on $Y$ can be formulated in a multiple testing framework as

$$H_j : \theta_j = 0 \quad vs \quad H_j' : \theta_j > 0, \quad j = 1, 2, \ldots, d. \tag{9}$$

and each null $H_j$ in (9) can be tested by using the statistic,

$$\hat{T}_{n,j} = n\hat{\theta}_{n,j} \tag{10}$$

where

$$\hat{\theta}_{n,j} = n^{-1} \sum_{t=1}^{n} f_j^2 \left(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-d}; \hat{\mathbf{w}}_n\right) \tag{11}$$

and the vector $\hat{\mathbf{w}}_n$ is a consistent estimator of the unknown parameter vector $\mathbf{w}_0$. Clearly, large values of the test statistics indicate evidence against the hypothesis $H_j$.

Thus the problem here is how to decide which hypotheses reject, taking into account the multitude of tests. In such a context, several approaches have been proposed to control the familywise error rate (FWE), defined as the probability of rejecting at least one of the true null hypotheses. The most familiar multiple testing methods for controlling the FWE are the Bonferroni method and the stepwise procedure proposed by Holm ([6]). In any case, both the procedures are conservative since they do not take into account the dependence structure of the individual $p$-values. These drawbacks can be successfully avoided by using a proposal by Romano and Wolf ([18,19]), suitable for joint comparison of multiple (possibly misspecified) models.

The algorithm runs as follows. Relabel the hypothesis from $H_{r_1}$ to $H_{r_d}$ in redescending order with respect to the value of the test statistics $\hat{T}_{n,j}$, that is $\hat{T}_{n,r_1} \geq \hat{T}_{n,r_2} \geq \ldots \geq \hat{T}_{n,r_d}$. In the first stage, the stepdown procedure tests the joint null hypothesis that all hypotheses $H_j$ are true. This hypothesis is rejected if

$\hat{T}_{n,r1}$ (the maximum over all the $d$ test statistics) is large, otherwise all hypotheses are accepted. In other words, in the first step the procedure constructs a rectangular joint confidence region for the vector $(\theta_{r_1}, \ldots, \theta_{r_d})^T$, with nominal joint coverage probability $1-\alpha$, of the form $\left[\hat{T}_{n,r_1} - c_1, \infty\right) \times \cdots \times \left[\hat{T}_{n,r_d} - c_1, \infty\right)$. The common value $c_1$ is chosen to ensure the proper joint (asymptotic) coverage probability. If a particular individual confidence interval $\left[\hat{T}_{n,r_j} - c_1, \infty\right)$ does not contain zero, the corresponding null hypothesis $H_{r_s}$ is rejected. Once a hypothesis is rejected, it is removed and the remaining hypotheses are tested by rejecting for large values of the maximum of the remaining test statistics. If the first $R_1$ re-labelled hypotheses are rejected in the first step, then $d - R_1$ hypotheses remain, corresponding to the labels $r_{R_1+1}, \ldots, r_d$. In the second step, a rectangular joint confidence region for the vector $(\theta_{R_1+1}, \ldots, \theta_{r_d})^T$ is constructed with, again, nominal joint coverage probability $1-\alpha$. The new confidence region is of the form $\left[\hat{T}_{n,r_{R_1+1}} - c_2, \infty\right) \times \cdots \times \left[\hat{T}_{n,r_d} - c_2, \infty\right)$, where the common constant $c_2$ is chosen to ensure the proper joint (asymptotic) coverage probability. Again, if a particular individual confidence interval $\left[\hat{T}_{n,r_j} - c_2, \infty\right)$ does not contain zero, the corresponding null hypothesis $H_{r_j}$ is rejected. The stepwise process is repeated until no further hypotheses are rejected.

Given the probabilistic complexity of the neural network model which makes the use of analytic procedures very difficult, estimation of the quantile of order $1-\alpha$ is obtained by using resampling techniques. Here we will refer to the maximum entropy bootstrap proposed by Vinod [21,22] e used by Guegan and de Peretti [4] and Heracleous et al. [5].

Given the time series $\{Y_1, Y_2, \ldots, Y_n\}$ the resampling algorithm runs as follows (see Vinod and Lopez-de-Lacalle [23]).

1. Sort $\{Y_1, Y_2, \ldots, Y_n\}$ by ascending order and let $\left\{Y_{(1)}, Y_{(2)}, \ldots, Y_{(n)}\right\}$ be the sorted series. Denote $\{i_1, i_2, \ldots, i_n\}$ the index series containing the ordering of the original series.
2. Compute intermediate points $z_t = (Y_{(t)} + Y_{(t+1)})/2, t = 1, 2, \ldots, n-1$.
3. Define intervals $I_1, I_2, \ldots, I_n$ with equiprobability as well as bounds for the first and last intervals. Then compute the trimmed mean of $\Delta Y_t$ and compute the lower bound by removing this mean to $z_1$ and the upper bound by adding this mean to $z_n$.
4. On each interval compute the desired means defined as $m_1 = 0.75Y_{(1)} + 0.25Y_{(2)}$ for $I_1$, $m_n = 0.25Y_{(n-1)} + 0.75Y_{(n)}$ for $I_n$ and $m_j = 0.25Y_{(j-1)} + 0.5Y_{(j)} + 0.25Y_{(j+1)}$ for intermediate values.
5. Draw uniform realizations on $[0, 1]$ and compute the associated quantiles for $\left\{Y_{(1)}, Y_{(2)}, \ldots, Y_{(n)}\right\}$ by linear interpolation.
6. Adjust the quantiles using $z_t$ to preserve the means, and reorder the adjusted quantiles according to $i_t$. This returns a bootstrap realization for $\{Y_1, Y_2, \ldots, Y_n\}$.
7. Repeat steps from 1 to 6, $B$ of times, with $B$ denoting the number of desired runs.

## 4 Empirical Evidence from the Italian Stock Market

To test the weak form of market efficiency for the Italian stock market we considered the closing price of the FTSE-MIB index from 1/12/2003 to 23/03/2012. To avoid spurious effects due to local behaviors we also considered a variety of periods of analysis. We first consider the full data set, and we then move to shorter periods in order to examine periods of analysis which may be more homogeneous than the entire sample. From a visual inspection in figure 1, panel (a), it is clear that up to 15/01/2008 (the first 1070 observations) the data series shows relatively low volatility while, in the remaining sample, volatility appear to be much higher. In all the periods considered, as expected, data show strong kurtosis and the Jarque Bera test clearly rejects the hypothesis of normally distributed returns (see Table 1).

**Table 1.** Descriptive statistics for the FTSE-MIB, daily returns from 1/12/2003 to 23/03/2012. Low volatility period from 1/12/2003 to 15/01/2008, high volatility period from 16/01/2008 to 23/03/2012. P-values are in parenthesis.

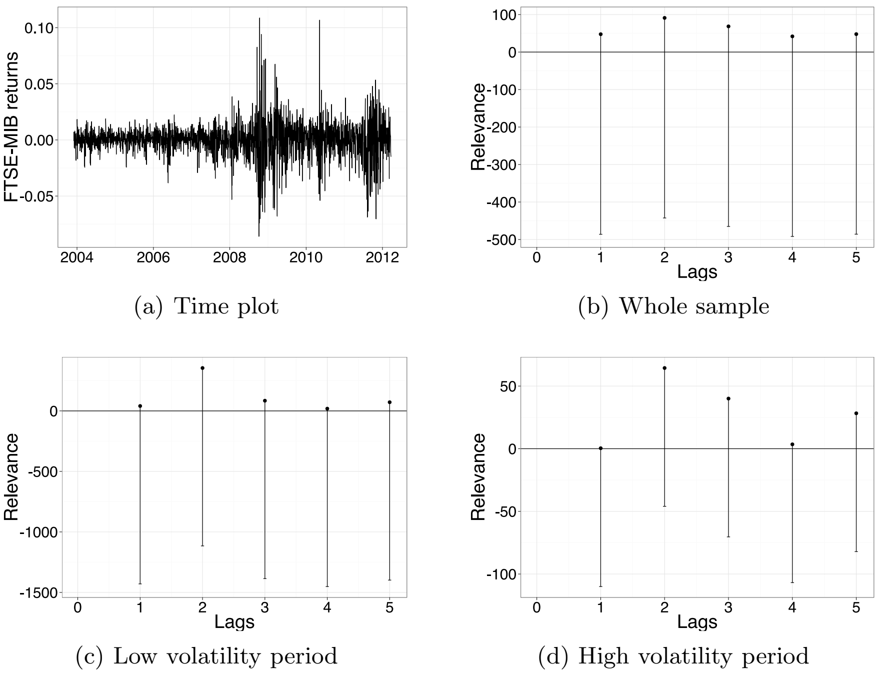
| Statistics | Whole sample | Low volatility | High volatility |
|---|---|---|---|
| Min. | -0.0860 | -0.0384 | -0.0860 |
| 1st Quartile | -0.0063 | -0.0034 | -0.0107 |
| Median | 0.0007 | 0.0008 | 0.0003 |
| Mean | -0.0002 | 0.0003 | -0.0008 |
| 3rd Quartile | 0.0065 | 0.0049 | 0.0111 |
| Max. | 0.1087 | 0.0229 | 0.1087 |
| Skewness | -0.0884 | -0.6619 | 0.0260 |
| Kurtosys | 6.8252 | 1.8478 | 3.4026 |
| Jarque Bera test | 4159.9 | 232.1 | 518.0 |
| | (0.0000) | (0.0000) | (0.0000) |

In order to test market efficiency hypothesis in its weak form, as described in the previous section, we directly focus on testing for unpredictability by testing the null hypothesis that a given set of past lags has no effect on current returns. More precisely, we consider the following model for the involved stock price at time $t$, $P_t$:

$$P_t = g(P_{t-1}, \ldots, P_{t-5}) + \epsilon_t \tag{12}$$

and we estimate the unknown function $g$ by using a neural network depending on the considered period (whole: from 1/12/2003 to 23/03/2012, characterized by low volatility: from 1/12/2003 to 15/01/2008, characterized by high volatility: from 16/01/2008 to 23/03/2012). So the problem becomes to test for the significance of $P_{t-i}$ $(i = 1, \ldots, 5)$ in the model (12).

To avoid the data-snooping problem the testing procedure has been based on the StepM approach in order to take under control the familiwise error rate. The results of the test procedure are reported in figure 1. For the low volatility period we estimated a neural network with $d = 5$ input neurons and 3 neurons




(a) Time plot

(b) Whole sample

(c) Low volatility period

(d) High volatility period

**Fig. 1.** Tests for weak form market efficiency for FTSE-MIB returns on the whole sample and on low and high volatility periods. All tests have been based on feedforward neural networks with $d = 5$ input neurons and calibrated by resampling with 4999 runs. Hidden layer size is equal to 2 for the whole period and, respectively, equal to 3 and 1 for the low and high volatility period.

in the hidden layer. Clearly all the first five lags appear to be not significant at nominal level $\alpha = 0.05$ and we cannot reject the hypothesis for unpredictability (see panel (c)). Same conclusions can be drawn if we consider the high volatility period (see panel (d)). In this latter case the StepM test has been conducted on the base of neural networks with $d = 5$ input neurons and 1 neuron in the hidden layer. Finally, for the whole period we estimated a neural network with $d = 5$ input neurons and 2 neurons in the hidden layer. Again, at the nominal level of $\alpha = 0.05$ we cannot reject the hypothesis of unpredictability (see panel (b)). In all cases hidden layer size has been fixed by using the Rissanen PSC.

Eventually, we can conclude that when we apply our method to test for predictive power in FTSE-MIB index of the italian stock market we find that it does not appear to contain information that is exploitable for enhanced point prediction.

## 5 Concluding Remarks

In this paper we have investigated the use of feedforward neural networks for testing market efficiency in its weak form. In contrast to approaches that compare out-of-sample predictions of non-linear models to those generated by the random walk model, we have focused on checking for unpredictability by testing the null hypothesis that a given set of past lags has no effect on current returns. To avoid the data-snooping problem the testing procedure has been based on the StepM approach in order to take under control the familywise error rate. We have applied our method to test for predictive power in FTSE-MIB index of the italian stock market finding that it does not appear to contain information that is exploitable for enhanced point prediction. Our results suggest that bootstrap-based inference and multiple testing can be a valuable addition to modeling non-linear phenomena with feedforward neural networks.

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