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"MARCO FANNO"

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Una visione d'insieme dell'ipotesi di Efficienza di Mercato

INDAGINE SULL'EMH & SUL MERCATO ITALIANO

An Overall View Of The Efficient Market Hypothesis

INVESTIGATION ON THE EMH & ON THE ITALIAN MARKET

Relatore:
Prof. FONTINI FULVIO

Correlatore:
Prof. CAPORIN MASSIMILIANO

Laureando:
FUIANO FRANCESCO

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Firma dello studente

"In God we trust, all others must bring data"

Edwards Deming

Alla mia famiglia che mi ha accompagnato lungo questo percorso

Abstract

Il presente lavoro è stato sviluppato col proposito di esaminare l'ipotesi di efficienza di mercato definita da Eugene Fama. Dopo un'analisi preliminare volta a comprendere le tappe principali che hanno portato alla definizione dell'ipotesi, si è proceduto con un'osservazione relativa alle critiche poste in essere a partire dagli anni '70 contro la tesi di efficienza informativa. Quindi dopo una panoramica più approfondita delle anomalie rilevate negli anni nel mercato, si è proceduto con un'analisi empirica del mercato volta a verificare la presenza di efficienza debole e semi-forte, oltre la presenza di possibili anomalie. Oggetto dell'analisi sono stati i sei indici principali della Borsa Italiana ed un campione di società estratto dal FTSE MIB. Inoltre, dopo una definizione approfondita del loro ruolo nel mercato, si è proceduto ad esaminare l'efficienza nel mercato degli ETF italiani, per verificare se le loro caratteristiche li rendono più funzionali ad un mercato efficiente.

Introduction

The present work has been developed with the aim to explain the complexity over the concept of the Efficient Market Hypothesis (EMH). First, the analysis focuses on the literature relative to the hypothesis since its origin with the Eugene Fama's work. From here onward the attention is on the dualism between the criticism against the concept and the awareness that the hypothesis seems legit. Many detailed works follow one another over the time; that implies an evolution of the concept and its estimation methods. The Technical Analysis, the Fundamental analysis and the Behavioural Finance are the most representatives theoretical argumentations in net contrast with the EMH.

The step forward is to empirically analyse the efficiency for the Italian case, underlying some unsolved aspects such as the anomalies of the market. These second part of our investigation starts with the examination of empirical worldwide evidences during years until the latest ones. Concurrently with this examination, this work presents its own empirical evidence on the Italian case.

These investigations concern the different levels of the EMH, dividing the weak hypothesis from the semi-strong one.

A multitude of methods used over time in the search for efficiency comes up. The analysis ends up with some consideration about the truthfulness of the EMH, showing the results among the various Italian markets, best considering the Exchange-Traded Funds.

1. The Efficient Market Hypothesis.

1.1 The EMH since the beginning

Despite the existence of a certain documentation dated back to the eighteenth century, the first evidence about the concept of Efficient Market Hypothesis was given by Louis Bachelier. In 1900 Bachelier developed the groundwork for the hypothesis considered: first, modelling the mathematics of the Brownian motion, and then, introducing the formulation for a Random walk in security prices. He was the first to provide the law of probability for stock market fluctuations: starting from the total mathematical expectation of a player (sum of the possible gains weighted with their relative probabilities of realization), he found out that the expectation of the speculator was zero. Indeed he stated that past, present, and even future events were reflected by market price, but at the same time, they did not seem to influence price changes. Bachelier developed this analysis assuming that stock returns follow a fair game, that the probability that the future price p_{t+n} is a function of the current one (p_t) and that transactions are uniformly spread across time (finite variance of the distribution of price changes and large transaction number during the given lapse of time). Bachelier's argumentation leads to the Markov-dependence as well as the utilization of the Central Limit theorem to call upon Normality. The consequence is the fact that the conditional and unconditional probability of the future price at the future time is governed by the Gaussian Law and proportional to the square root of time.[1]

Unfortunately, his works passed unnoticed because of the backwardness of his time. Moving forward on the historical evolution of the efficient market concept, we find Wesley Mitchell. He was the first to discover that the distributions of price changes cannot be associated to samples from Gaussian populations. Even John Maynard Keynes, in 1923, stated that investors gained because of the risk bearing and not because they were able to predict better than the market what the future would show them. He confirmed his statement in 1936, comparing the stock market with a beauty contest and claiming that investors' decisions were the results of their animal spirits. It is a duty to mention Holbrook Working too. He equated stock returns to numbers from a lottery.

Early, Cowles concluded that there were no evidences of the possibility to predict the market. However, in 1937, he found evidences of serial correlation in averaged time series indices of stock prices, as long as he reported again that investment professionals do not beat the market in 1944. An important contribute to the Efficient Market Hypothesis was pointed out by Milton Friedman in 1953. Friedman stated that the efficient market held also when trading strategies of investors were correlated; these could happen because of the arbitrage. In the same year, Kendall, examined 22 UK stock and commodity price series discovering they were basically random. Moreover he found out the time dependence of the empirical variance (the non-stationarity). In 1959, after Kendal's contribute, Harry Roberts showed that a random walk and the current stock series resembled themselves.

Lingering on these last two authors, it is possible to summarise the literature point of view of this first studying period of the efficient market. Hence, the random walk formulation was seen as a system that generates the stock price process as follow:

$$p_t = p_{t-1} + r_t, t \in T \tag{1}$$

Random sample model (or chance mechanism)

[1] History of the Efficient Market Hypothesis, Martin Sewell, 2011, UCL Department of Computer Science

Where $r_t \sim IID(0, \sigma^2)$, that is r_t is an Independent and Identically Distributed process with zero mean and constant variance σ^2. Here prices are assumed to be the partial sum of returns, $p_t = \sum_{k=1}^{t} r_k,\ t \in T$.

The issues of this former configuration is both on the absence of explicit distributional assumption and the fact that $\{p_t, t \in T\}$ implies that the first two moments exist (Markov-dependent process[2]). Nevertheless this literature implicitly hid that the distribution of returns was Normal and so the random walk as well. This means that $r_t \sim NIID(0, \sigma^2)$ is a Normal Independent and Identically Distributed process (with *N* stands for Normality).

For this model the process $\{p_t, t \in T\}$ is Markov-dependent with a probabilistic structure given by:

$$\binom{p_t}{p_{t-1}} \sim N\left[\binom{0}{0}, \begin{pmatrix} \sigma^2 t & \sigma^2(t-1) \\ \sigma^2(t-1) & \sigma^2(t-1) \end{pmatrix}\right], \quad t \in T \tag{2}$$

That is discrete-time equivalent to the Brownian motion process proposed by Bachelier.[3]

During the 1950s statisticians focused on the temporal independence of the return process. The independence had non-correlated mean. As a consequence, tests for the independence meant focusing on serial correlations with the aim not to find correlation. Until this period, the evidences of prices dependency were too weak. Another issue was the concept of Identical Distribution. Some observation performed by Kendall led to a new concept: The Heterogeneous Random Walk model: $p_t = p_{t-1} + r_t$, where $r_t \sim NI(0, \sigma^2)$ with $t \in T$. This means that Kendall confirmed the independency but contested the identical distribution (NI stands for non-Identically Distributed). Last concept to be reconsidered concerned the distribution of returns itself. According to Kendall, the bivariate frequency distribution of weekly price changes was nearly perfect symmetry and an appearance of approximate normality. However, the distance from the Normal Distribution, that literature found out until this period, was basically a misunderstanding.

This lead to summarise the main issues of this first development part of the EMH in the search for the truthfulness of the Normal Distribution assumption, the temporal independence, as well the identically distributed one.

At the begging of the 60s Berger and Mandelbrot found out that short-run movement of the price series obeyed the simple random walk hypothesis, but in the long-run they did not. He

[2] A stochastic process has the Markov property if the conditional probability distribution of future states of the process (conditional on both past and present states) depends only upon the present state, not on the sequence of events that preceded it. A process with this property is called a *Markov process*

[3] On Modelling Speculative Prices: The Empirical Literature, Elena Andreou, Nikitas Pittis, Aris Spanos

distanced himself from Bachelier because of the usage of the natural logarithms of prices and the Paretian distribution (a stable non-linear distribution) instead of the Gaussian one. Eugene Fama verified that Mandelbrot's data adjusted to the stable distribution.

In 1964, both Alexander and Steiger separately tested for the non-randomness finding out that stocks did not follow a random walk. At the same time, Sharpe published his work on the Capital Asset Pricing Model.

Here we are: In 1965 Eugene Fama defined the *efficient market* for the first time (*Random Walks in Stock Market Prices, 1965*) and Samuelson the first formal economic argument for efficient markets as well (*Proof that properly anticipated prices fluctuate randomly,1965*). Samuelson stated that observing many future prices sequences constructed with his model until their end-period, they will not show downward or upward movements, regardless the systematic seasonal pattern in X_t and the existence of an inflationary or deflationary period in X_t. He asserted that whether spot prices X_t were subject to the probability law and future prices sequence is subjected to the expected value assumption, hence the least sequence represented a fair game (or a martingale); this means that there exist changes in unbiased prices and finally that $E[\Delta^n Y(T,t)] \equiv 0$ $(n = 1,2,\dots,T)$ and there exist no possibility to get an expected profit by exporting past changes from future prices. Y(T, t) already represented all the available accessible information for future prices in the optic of Samuelson. Easily speaking, Samuelson's hypothesis stated that price changes would be not forecastable whether the market is efficient, or rather, whether prices reflect all the information and expectations of the market. Ensuing that prices fluctuate randomly if news were announced randomly. Mandelbrot was one of the first to show that returns were unpredictable in competitive markets with rational risk-neutral investors.

In 1967, Roberts defined the efficient market hypothesis and distinguished between weak and strong form tests.

The 60s were characterized by the fact that Mandelbrot showed that Bachelier's Brownian motion model was not compatible with recent facts on the speculative prices. He discovered that the distributions of price changes were characterized by peaks distant from the normality. the D'Agostino and Stephen skewness-kurtosis Normality tests, managed by Mandelbrot, showed the impossibility for the Normality assumption to be confirmed. This was a consequence of the excess of kurtosis observed in the index series investigated. Moreover he found out that the non-parametric kernel early esteemed was more peaked with respect to the Normal distribution. Another negative acknowledgment was referred to the infinite variance syndrome of stock returns, the so-called Noah effect. Indeed, during his analysis, Mandelbrot found out that his samples were affected by an erratic fashion for second moments, reflected by the impressive length of the tails of the samples considered. He joined this conclusion thanks to the sample recursive variance[4]. Mandelbrot innovation consisted in the usage of the Stable Paretian family of distribution (Levy, 1925) to best perform symmetry, leptokurticity and infinite variance. The Stable Paretian family appears as follow:

$$\log \emptyset(t) = i\delta t - \gamma |t|^{\alpha} \left[1 + i\beta \left(\frac{t}{|t|}\right) \tan\left(\frac{\pi\alpha}{2}\right)\right] \tag{3}$$

Where:

- α is called Pareto's exponent and it leads to the determination of the peaked degree ($0 < \alpha \leq 2$).
- β helps finding the measure for the skewness ($-1 \leq \beta \leq 1$).

It is important to consider that β=0 makes symmetric the distribution, while a small α returns thicker tails. This capacity allow the Stable Paretian family to be quite flexible, giving the possibility to model the empirical regularities of leptokurticity, symmetry and infinite variance. A crucial point is the ability of this family to be stable. The stability (invariance property) implies that each stable distribution has an index of stability not influenced by the sampling interval. Firstly adopted over IID random variables, quickly adapted to non-ID ones. [5]

Going to the point, Mandelbrot stated the assumption of temporal independence of returns, substituting the Gaussian distribution in favour of the Stable Paretian one. However, he certified that his model did not capture the observed alteration of small and big changes in fluctuations.

So well, during 60s, Madelbrot, Fama and Samuelson confirmed the fact that the efficiency of the market did not depend on IID process.

The concept of efficient market passed through the game of speculation. There existed two options: the game had to be fair, or returns should follow a martingale difference process.

Fair games means that:

$$E\big(p_t | \sigma(r_{t-1}, \ldots, r_1)\big) = 0, \qquad t \in T \tag{4}$$

That means that conditional returns expectation at time t, relatives to past information on returns, should be zero.

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4 $\frac{1}{k}\sum_{i=1}^{k}(r_i - \bar{r})^2$, $k=1,2,3,\ldots,T$

5 On Modelling Speculative Prices: The Empirical Literature, Elena Andreou, Nikitas Pittis, Aris Spanos

The same way for the efficient market case: the best forecast for today's price, is yesterday's prices.

$$E(p_t|\sigma(p_{t-1},\dots,p_1)) = p_{t-1}, \qquad t \in T \tag{5}$$

Martingale formulation

The formulation above constitutes the exact opposite of the Random walk formulation: it considers $\{p_t, t \in T\}$ the main element, in a view from left to right of the previous composition.

$$p_t = E(p_t|\sigma(p_{t-1},\dots,p_1)) + r_t, \qquad t \in T \tag{6}$$

While $\{r_t, t \in T\}$ constitutes:

$$r = p_t - E(p_t|\sigma(p_{t-1},\dots,p_1)) + r_t, \qquad t \in T \tag{7}$$

In 1970, Eugene Fama published the first complete paper of the EMH, *Efficient Capital Markets: A review of theory and empirical work*. Thanks to both Robert and Samuelson's work, he concluded that the efficient market is a market in which prices always *fully* reflect available information. Therefore, available information correspond to unpredictable information; as a consequence, stock prices (which change on the basis of new information) are unpredictable as well. Therefore. the best description that summarised and improved the research on random walk was defined by Fama. He created a model concerning the formation of prices: the Expected Return (or Fair Game) Model. The model appears as follow:

$$E(p_{i,t+1}|\varphi_t) = p_{i,t}[1 + E(r_{i,t+1}|\varphi_t)] \tag{8}$$

Where:

- $E(p_{i,t+1}|\varphi_t)$ is the expected value operator
- $p_{i,t}$ is the price of security *i* at time *t*
- $r_{i,t+1}$ is the rate of returns for security *i* at time *t+1*
- φ_t is the set of information reflected in the price at the initial time period.

The right hand of the equation above explains that the expected price of the security *i* is a function of today's price and the expected return of security *i*. Following the expected return theory, tomorrow's price minus today's price equals to zero:

$$x_{i,t+1} = p_{i,t} - E(p_{i,t+1}|\varphi_t) \tag{9}$$

Hence it is possible to affirm that

$$E(X_{i,t+1}|\varphi_t) = 0 \tag{10}$$

This means that the sequence $\{x_{j,t}\}$ is a fari game with respect to the information $\{\varphi_t\}$. This is equivalent to:

$$z_{i,t+1} = r_{i,t+1} - E(r_{i,t+1}|\varphi_t) \tag{11}$$

And then

$$E(z_{i,t+1}|\varphi_t) = 0 \tag{12}$$

This means that the sequence $\{z_{j,t}\}$ is a fair game as well, with respect to the information $\{\varphi_t\}$. Hence, $x_{i,t+1}$ represents the excess market value of the security *i* at time *t+1*, and as a consequence, $z_{i,t+1}$ is the return at time *t+1* in excess of equilibrium expected return projected at t.

In addition, considering the (8) it is possible to define the sub-martingale model:

$$E(p_{i,t+1}|\varphi_t) \geq p_{it} \quad \text{or} \quad E(r_{i,t+1}|\varphi_t) = 0 \tag{13}$$

This is equal to say that the expected price in t+1 is higher or equal to the current one (considering the current set of information). However if (8) is considered such as an equality, then:

$$E(p_{i,t+1}|\varphi_t) = E_t p_{i,t+1} = p_{i,t} \tag{14}$$

That corresponds to a martingale process which explains that the best expected value of $p_{i,t+i}$ (hence, of all the future value of p_i) is the current value $p_{i,t}$.

The concept of fully reflection of the current price leads to the consequence that two consecutives price variations are independent and identically distributed.

This above is the Random Walk model, written as:

$$f\left(r_{i,t+1}|\varphi_t\right) = f\left(r_{i,t+1}\right) \tag{15}$$

If the expected return is constant over time, hence:

$$E\left(r_{i,t+1}|\varphi_t\right) = E\left(r_{i,t+1}\right) \tag{16}$$

That means that it is just the mean of the distribution $r_{i,t+1}$ to be independent from the information at time *t*, not the whole distribution as stated by the random walk.

During his argumentation, Fama distinguished three different form of market efficiency: weak-form, semi-strong form and strong-form:

1. Weak-form efficiency: this form, following the efficient market hypothesis, assumes that stock prices already reflect all information. This means that none could obtain any excess return managing trading data such as history of past prices, training volume or short interest.
2. Semi-strong-form efficiency: this second efficient form asserts that all the *public available information* regarding the prospects of a firm, are included in the current stock prices. This suggest that none could understand if a stock is underestimated or not. As a consequence, none could earn an extra-return. This form assumes that there are no learning lags in the distribution of public information (balance sheet composition, earning forecasts, accounting practices, etc.).
3. Strong-form efficiency: this form asserts the inclusion in prices of the information inside companies (*private information*) as well as the previous form kind of information. So, the insider informative, following the strong form, is useless as well.

In the following years some authors published papers about the predictability of markets, while in 1973 Samuelson included pay dividends situations in the analysis of the market.

In 1978, Ball showed the generation of excess returns after public announcements of firms' earnings and in the same year, Jensen gave his own definition of the EMH. Two years later Sanford J. Grossman and Joseph E. Stiglitz showed the impossibility for the market to be efficiently informed: information has a cost and, whether the information would be instantaneous available, investors that look for information would not receive compensation.

LeRoy and Porter showed excess volatility and rejected the EMH (*1981*). In 1986 Fischer Black firstly thought about noise traders, investors that trade just on the basis of information, underlying that their existences were a necessity for the liquidity of the market itself.

19 October 1987, called Black Monday, the worldwide stocks market crashed. It causes the largest percentage of loss ever seen on Dow Jones Index.

In 1988 Lo and MacKinlay rejected the random walk hypothesis for weekly stock market returns using the variance-ratio test. A year later Shiller would publish its *Market Volatility*, in which he considered the sources able to challenge the efficient market hypothesis.

In 1991 Matthew Jackson showed there exists an equilibrium with revealing prices and costly information acquisition, basing his evidences on the assumption that agent are not price-takers. In the same year, Fama published the second paper about the EMH, in which the weak-form test was switched with a general area of tests for return predictability.

In 1995 Robert Haugen demonstrated that an overreaction in the short-run can affect the long-run responses (*The New Finance: The Case Against Efficient Markets*). Chan et al. underlying the fact that the market probably responds only gradually to new information, but then, they evidenced the fact that the worldwide markets could be weak-form efficient.

In 1998 Fama ended his work with the third of his three reviews, ensuring that market efficiency survives the challenge from the literature on long-term return anomalies. Then, Zhang showed a theory of marginally efficient markets. Shleifer, in 2000, argued about the assumption of investor rationality and perfect arbitrage in his paper (*Inefficient Markets: An introduction to Behavioral Finance*). These are the assumption whose support the EMH: Investor Rationality, Arbitrage, Collective rationality and Costless information and trades.

In 2003 Malkiel supported the EMH after an investigation on the challenges against the efficiency. Another positive statement was given by William Schwert that showed that anomalies became weaken or disappeared.

In 2007 Wilson and Marashdeh showed the inconsistency of stock prices in the short-run, but, on the other hand, they demonstrated there exists consistency in the long-run. Years later Ball exploited the collapse of the Lehman Brothers to argue that the crisis arose because of the low attention to the EMH lesson. Otherwise in 2010 Lee et al. investigated the stationarity of real stock prices for developed and developing countries ending up with the conclusion that stock markets are not efficient.[6] [7]

[6] The Econometrics of Financial Markets, John Y. Campbell, Andrew W. Lo, A. Craig MacKinlay, Princeton University Press, 1997

1.2 Critics and hints on Behavioural Finance

This paragraph emphasises the criticism about the efficient market hypothesis recalling the most important cases discussed.

It is easy to imagine who are the opponents of the EMH and why they do not believe in it. Each investor, each financial promoter, each trader involved in the search of extra-return could not affirm that they cannot beat the market. There are a series of discrepancies that many authors brought to light over years.

Burton Malkiel wrote that *monkey throwing darts at a newspaper's financial pages could select a portfolio that would do just as well as one carefully selected by experts.* This was congruous with the impossibility to predict prices.

However, this kind of view began to be seen with suspect. The possibility to get excess of return through the forecast of pricing began to be seen as possible. The market itself seemed to suggest it through events such as financial crisis, bubbles, herd phenomenon, etc.

Nevertheless, the fact that these gaps are supposed not to be easily forecasted despite their existence, could provide first aid to the mangled hypothesis.

If efficiency equals not to earn excess returns without excess of risks, then it is possible to affirm that markets are efficient although the existence of anomalies. Moreover evaluation errors would be adjusted in the long run.

Coming back to the inefficiency proofs, Burton G. Melkiel summarized some quotable evidences relative to the EMH:

Short-term Momentum including under-reaction to new information: autocorrelation in short run returns equals to suggest the possibility to forecast future prices. These investment tactics are inconstant over time and tend to vanish after their literature demonstration.

Long-run return reversals: negative autocorrelation showed over time by different authors have been interpreted as an excessive reaction to endogenous news (optimistic or pessimistic views). This leads to the possibility of exploiting the return to the mean of stocks in order to gain extra-returns. However there exist the possibility this will not happen.

Seasonal and Day-of-the-Week Patterns: In certain periods of the year, or months rather than weeks, it has been showed a tendency of stocks belonging to a same weighted stock index to perform high unusual returns. These held, for instance, for the January effect, as well as the Day-of-the-week effect. However there is no dependency from a period to another one. This fact, obviously, entails the non-predictability of the patterns or anomalies.

[7] On Modelling Speculative Prices: The Empirical Literature, Elena Andreou, Nikitas Pittis, Aris Spanos

Predictable patterns based on valuation parameters: the category contains all the attempts to perform extra-returns by giving attention to the initial valuation parameters, through valuation ratios such as P/E (Price/Earning) or D (Dividend Yield).

Predicting future returns from initial dividend yields: this tactic is based on the exploiting of certain elements to perform better results. Generally the dividend-price ratio was interpreted as a good forecaster for future returns; the main strategy based on dividends was the Dogs of Dow, that consisted in the purchasing of the top ten Dow Jones Industrial Average stocks.

Predicting market returns from initial price-earnings multiples: investors have tried to earn wider returns purchasing stocks to assemble their portfolio of investment, on the basis of the low price-earnings multiples.

Other predictable time series patterns: there is a huge literature relative to the usage of financial statistics to analyse the predictability of stock returns. An example could be the use of the short-term interest rates to forecast future stock returns. Since the financial elements documented consist in a larger sample with respect to the non-financial, they will be selected and empirical analysed ahead in this paper.

The Behavioural Finance, that is a theoretical current opposed to the efficient market hypothesis, includes some of the results of the cited tests as a proof to reject the EMH. In the early 90s, academic focus shifted to the human behaviours, meaning that speculators' decisions could be affected by them personal orientation rather than rational thinking.

The fathers of the BF could be identify in Kahneman and Tversky who developed a work concerning the analysis of decision under risk in 1979, but the literature is quite wide. In 2003, Shiller defined the BF as the finance with the widest social perspective, which include psychology and sociology.

The cognitive heuristics on the basis of the BF concerns *representativeness*, *anchoring*, *herding*, and *overconfidence*. From another point of view, the investors resulted affected by a sort of fallacies such as the tendency to be risk averse for losses rather than gains (*loss aversion*), the tendency of people to generate different mental accounts relative to past events (*mental accounting*) or the tendency to avoid to immediately sell fruitless stocks because of the pain the sale would generate to them.

The weight of the behavioural finance born by the fact that this cognitive alternative to the theoretical and empirical previous ones, was really able to challenge them at a new level, making authors questioning whether their path has to be modified.[8] [9] [10]

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[8] The Efficient Market Hypothesis and Its Critics, Burton G. Malkiel, Princeton University, CEPS Working Paper No. 91, 2003

[9] A Random Walk Down Wall Street, Burton G. Malkiel

2. Test on the EMH

2.1. An historical review

During the XX century a series of tests of the EMH have been implemented: *the Dogs of the Dow, the January effect, the Thank God it's Monday afternoon pattern, the hot news response*, and so on. The Dogs of the Dow was a theoretical certainty that suggested how to beat the market by means of the purchasing of the ten highest dividend yield stocks in Dow Jones 30-Stock Industrial Average. This strategy was performed by Michael O'Higgins, while tests on its truthfulness were effectuated by James O'Shaughnessy in 1920s. O'Shaughnessy found out that this strategy really had been able to beat the index by over two percentage points per year with no additional risk. This held as long as the strategy became too popular and the market in turn beat the strategy.

Another reason that push researchers to do test on the efficiency of the market was the unexplainable tendency of stock returns to be very high during the first two week of January.

Object of empirical examination was the week-end effect as well. The *Thank God it's Monday afternoon* pattern suggested that the best moment to purchase stocks was Monday afternoon instead of Friday or Monday morning. This, because of the lower selling price with respect to other moments.

The more intuitive doubt concerning the efficient market hypothesis is intuitively the possibility that prices will immediately adjust for news when those come up. This doubt, for instance, subsequent to the announcement of dividends, rather than earnings surprises, has generated a literary trend called *Event Studies.*

At a later stage theories and tests which wanted to critically analyse the EMH branched out in time series strategies and cross-sectional ones.

Time series strategies consist in the *Dividend Jackpot Approach*, the *Trend is your friend* one, the *Initial P/E predictor*, and the *Back we go again strategy*. On the other hand, *Cross-sectional* strategies include the *Smaller is better effect*.

The *Trend is your friend* is also known as the already cited *Short-term momentum*, while the *Dividend Jackpot Approach* is based on the assumption that if stocks generate above-average dividend yields, hence investors will earn higher future returns. This last approach was tested first by Eugene Fama and Kennet French, and then, by John Campbell and Robert Shiller: they concluded that, through this artifice, investors can reach their scopes. Obviously this

[10] From Efficient Market Hypothesis to Behavioural Finance: Can Behavioural Finance be the new dominant model for investing?, A. Konstantinidis, A. Katarachia, G. Borovas, M. E. Voutsa, Scientific Bulletin – Economic Sciences, Vol. 11/Issue 2

was in contrast with the assumption of the randomness of the market. Tests showed that when initial dividend yields were relatively high, investors would gain higher total rates of return. Nevertheless, this eventuality does not seem to hold with an individual investor that simply purchased a portfolio of individual stocks with the highest dividend yields and, in general, does not seem to persist over time. Object of tests was the *Back we go again* strategy as well. This strategy is better known as the *Long-run return reversals* and consisted in buying stocks that did not perform very well in the latest years, convincing oneself that those stocks would generate an above-average returns over the next few years. This depended on the fact that tests underlined the possibility that, even if there existed positive correlation among stock returns over short horizons, in term of years, they showed negative serial correlation. This would lead to gain extra-returns. In his revisionary work *A Random Walk Down Street*, Malkiel accepted the truthfulness of this latest strategy mentioned, asserting that fads and fashions can play a central role in stock pricing.

Moving on in the historical review of the tests over the EMH and its anomalies, the *Smaller is better* effect comes up. It starts from the fact that small company stocks generate larger returns than large company stocks do.[11]

Fama and French divided stocks into deciles according to their size finding out that small firms outperformed larger ones. On the other hand, this could be not true, because it has to be considered that small firms provide higher risks to investors.

Finally there have to be hinted the *Stocks with low price-earnings multiples outperform those with high multiples* approach, also described as the GARP approach, that was tested by Sanjoy Basu during the 70, besides another pattern relatively recently tested, considering the relation between the ratio of stock’s price to its book value and its later return, the P/BV (Price-to-book-value).

In general, the approach for the EMH consisted in statistical tests in security prices and returns or tests based on trading rules. Obviously, trading rules are not disclosed as much as tests because if someone found out a good strategy, he/she would not explain it to his/her trading competitors. Therefore the focus is put on econometrical tests.

For what concerns the weak-form of the efficient market hypothesis, some examples of tests are:

- Autocorrelation (serial correlation) tests
- Runs tests
- Sings tests
- Unit root tests

[11] A Random Walk Down Wall Street, Burton G. Malkiel

Semi-strong-form of the EMH have been tested in three different ways:

- Through the usage of time series analysis over public information (Dividend yield; Default Spread; Term structure spread; Quarterly earnings reports information)
- Through the examinations raised up by Event Studies (the object of these studies is the stock response time to economic events)
- Through cross-sectional analysis of returns over public information. This trend bases its efforts on the assumption that in an efficient market securities have risk-adjusted returns (P/E ratios; Price-Earnings/Growth ratios; The size effect; Book value-Market value)

Among the **Autocorrelation Tests**, used in order to verify the presence of dependence in data series, so used to verify whether each value of the time series considered is influenced by the previous value and, in the same way, influences the following one, it is possible to find the following ones:

- Durbin-Watson Test: this is the first attempt to test for serial correlation in a linear time series model as:

$$y_t = x_t^T \beta + \varepsilon_t \qquad with\ \varepsilon_t \sim WN(0, \sigma^2) \tag{17}$$

It consists is a statistic (rather than a test) that helps to find out whether residual serial correlation exists or not.

The DW-Statistic is based on the following structure:

$$\begin{cases} H_0: P_1 = 0\ no\ first\ order\ serial\ correlation \\ H_0: P_2 \neq 0\ first\ order\ serial\ correlation \end{cases}$$

Here is the formula:

$$DW = \frac{\sum_{t=2}^{T}(\hat{\varepsilon}_t - \hat{\varepsilon}_{t-1})^2}{\sum_{t=1}^{T}\varepsilon_t^2} \tag{18}$$

With $\hat{\varepsilon}_t$ corresponding to the OLS residual.[12]

- Breusch-Godfrey Test: this is a test that allows statisticians to understand whether exists or not serial dependency in the variation of the dependent variable (in a dynamic linear model).

It differs from the DW-statistic because of the possibility to test different serial correlation orders. The structure of the hypothesis is the following:

[12] Dispensa di Econometria delle Serie Storiche, Giulio Palomba, 2014 (P.10)

$$\begin{cases} H_0: \rho_1 = \rho_2 = \rho_3 = \cdots = \rho_q = 0 \\ there\ exists\ a\ \rho_i \neq 0, with\ i = 1,2,3, \dots, q \end{cases}$$

It is a test based on Lagrange multipliers that is approximated as follow:

$$LM_{BG} = TR^2 \sim x_q^2 \quad (19)$$

Where R^2 is the auxiliary regression and T the largeness of the sample case.[13]

- Ljung-Box Test: this is a test to establish if observations over a given time series are serial correlated. The null hypothesis foresee the absence of serial correlation:

$$\begin{cases} H_0: \rho_1 = \rho_2 = \rho_3 = \cdots = \rho_q = 0 \\ there\ exists\ a\ \rho_i \neq 0, with\ i = 1,2,3, \dots, q \end{cases}$$

So, the LB-statistic is:

$$LB = T(T+2) \sum_{i=1}^{q} \frac{\widehat{\rho_i}}{T-i} \sim X_q^2 \quad (20)$$

The **Runs Tests** could be a mean to understand if a data sample follows a random process. The runs test hypothesis follows the trend below:

$$\begin{cases} H_0: the\ sequence\ is\ random \\ H_1: the\ sequence\ is\ non-random \end{cases}$$

The statistic of the Runs test is the following:

$$Z = \frac{R - \overline{R}}{s_R} \quad (21)$$

Where R is the observed number or runs and $\overline{R}$ is the expected number of runs. s is the standard deviation.

The **Sing Test** is a non-parametric test to verify the central tendency. In other words, a sign test tries to verify the central value for a probability distribution.
The null hypothesis is represented hereinafter:

[13] Dispensa di Econometria delle Serie Storiche, Giulio Palomba, 2014 (P.12)

$$\begin{cases} H_0: \mu = \mu_0 \\ H_1: \mu \neq \mu_0 \end{cases}$$

It uses the median. In order to perform bilateral tests, the sign test verifies the following hypothesis:

$$\begin{cases} H_0: me = me_0 \\ H_1: me \neq me_0 \end{cases}$$

In the case of unilateral test the hypothesis are:

$$\begin{cases} H_0: me \leq me_0 \ vs \ H_1: me > me_0 \\ or \\ H_0: me \geq me_0 \ vs \ H_1: me > me_0 \end{cases}$$

The sign test is the non-parametric equivalent of the t test, but it differs because of the binomial distribution. In the practice, each value of the sample is compared with a defined value in order to transform lower values in negative signs and higher values in positive ones. The null hypothesis is not rejected when positive and negative signs appear approximately equal.[14] [15]

Economic and financial series are characterized by the property of non-stationarity, as a consequence statisticians tends to transform them by means of differentiation, logarithms, or logarithmic differences. It is necessary to verify if the time series under analysis are integrated, hence **Unit Root Tests** come to help testers.

Unit root tests try to verify the presence of a stochastic trend in a series. It consists of two different tests. Tests diverge for the null hypothesis. The first one follows the system below:

$$\begin{cases} H_0: \emptyset = 1 \\ H_1: |\emptyset| < 1 \end{cases}$$

The null hypothesis states that the generator process of x_t is *I(1)*, integrated of order one, while the alternative is represented by an autoregressive stationary process.

While the second test follows this other system:

[14] Introduzione alla statistica non parametrica, Luigi Salmaso

[15] Elementi di Statistica Descrittiva per distribuzioni univariate, Metodi non parametrici per un campione, Maria Pia D'Ambrosio, Franco Anzani, Six Sigma

$$\begin{cases} H_0: |\emptyset| < 1 \\ H_1: \emptyset = 1 \end{cases}$$

Therefore, in the second test, the null hypothesis is given by the absence of the non-stationary process, that is, on the other hand, present in the alternative hypothesis.[16] [17]

Here we have the main tests normally used:

- Augmented Dickey-Fuller Test (ADF): it is an univariate test. It uses an autoregressive parametric model. The ADF test is based on estimating the following regression:

$$y_t = \beta^T D_t + \varphi y_{t-1} + \sum_{j=1}^{p} \psi_j \Delta y_{t-j} + \varepsilon_t \quad (22)$$

Where:

- D_t is a vector of deterministic terms (constant, trend etc.).
- The p-lagged difference terms, Δy_{t-j} are used to approximate the ARMA structure of the errors.
- p is set so that the error ε t is serially uncorrelated. T$\varepsilon_t$homoskedastic.

- Phillips-Perron Test: it is used to test the null hypothesis over unit roots. It is based on the following regression:

$$y_t = \beta^T D_t + \varphi y_{t-1} + u_t \quad (23)$$

Where:

- u_t is an *I(0)* process that can be heteroskedastic. This is the main difference between the ADF and PP test.

On the other hand, talking of semi-strong tests, it is opportune to introduce the concept of Event Study. This discipline has the aim to understand the impact of a specific event over a firm's value by means of financial data. Otherwise, event studies study whether a certain event would change or not the course of stocks. At a later stage the semi-strong test branch would be deeper examined.

[16] Dispensa di Econometria delle Serie Storiche, Giulio Palomba, 2014
[17] Introduzione all'econometria, N.Cappuccio, R.Orsi

2.2. Previous studies: the Italian cases

In Italy there were different authors focusing on the efficient market hypothesis question. Among them, Franco Caparrelli could be intended as the main exponent.

He performed several tests on the Italian market[18] [19] [20] [21], considering the whole market efficiency concept. He tested for weak, semi-strong and strong form. Let's see in the next step how he proceeded in his analysis.

2.2.1 The Weak-form

This first form elaborated under the EMH, states that the knowledge given by the past does not allow investors to have a better performance over stocks.

It is possible to sum up this hypothesis as follow:

$$Z_{t-1} = Z^*_{t-1} \quad E(R_t/Z_{t-1}) = E(R_t/Z^*_{t-1}) \tag{24}$$

Where Z_{t-1} corresponds to the prices, returns and exchanged volumes time series.

This form considers information as free and available for investors with homogeneous expectations in a transaction-costless market. This would lead to two consequences: there exist no mispriced stocks and there exist no possibility that an investor could follow an established path to earn extra-profit.

So, the first study Capparelli performed was about 30 securities during the period from December 1978 to December 1983[22].

In his book, *Il Mercato Azionario, Caparelli synthetized results of the serial correlation test as follow:*

	Daily	Weekly	Fortnightly	Monthly
$\bar{\beta}$	-0.1268	-0.1167	0.0139	0.0403
σ	0.1885	0.1394	0.1529	0.1172
$\sigma/\sigma(\beta)$	2.9921	2.2520	1.7434	0.9002
Terms number $> 2\sigma(\beta)$	15/30	11/30	4/30	1/30

[18] La reazione in eccesso del prezzo dei titoli: la teoria e una verifica empirica sulle azioni italiane, Franco Caparrelli e Anna Maria D'Arcangelis, Bancaria, 51(10), 1995, pp. 8-17

[19] Mercato efficiente ed effetto gennaio, Franco Caparrelli et al., Il Risparmio, (1), 1992, pp. 33

[20] Quando comprare e vendere in Borsa. Una verifica dell'effetto fine settimana, Franco Caparrelli e Alessandra Diotallevi, Bancaria, (5), 1991, pp. 27

[21] La Borsa italiana e l'efficienza semiforte, Il Risparmio, (2), 1989, pp. 209

[22] Il Mercato Azionario, Franco Caparelli

Positive terms number	8/30	7/30	13/30	19/30

Table 2.1 – Summary of results for the correlation test 12/1978-12/1983, F. Caparrelli

Where $\bar{\beta}$ represents the mean value of the coefficient β, σ is the standard deviation, and $> 2\sigma(r)$ represents the number of terms higher than $2\sigma(r)$.

This table shows that the hypothesis holds better if monthly data are considered instead of the weekly ones. Indeed the mean value of β reduces. The number of the securities with a coefficient equals to zero decrease as well. Therefore the more the time interval grows the more the empirical result resembles the theory (meaning that the true value of the coefficient is equal to zero).

2.2.1 The Semi-strong-form

This form states that public information are quite instantaneous transferred into stock prices, as a consequence the knowledge of those information cannot produces the possibility to get an advantage over the market.

These information come from the study of companies through their balance sheets, the announcements of results, as well as programs and perspective of the companies themselves. Caparrelli examined 54 events of free share capital increase (intend aumenti di capitale a titolo gratuito – questa dovrebbe essere una traduzione migliore) from January 1975 to April 1987 relative to securities quoted on the stock exchange of Milan. This study focused the attention on the period before and after the announcement of dividends. The first phase was to define the market model for each stock over 148 months, and so defining alpha and beta coefficients. Then Caparrelli found out the expected returns with the aim to compare them to the effective ones. Finally he calculated the simple average residual and the cumulated one. This analysis underlined that there was an increment of stocks and profits since the moment of the announcement, but this increment had been balanced out in two months.

Another experiment was performed considering the period from October 1990 to August 1993. This test was based on the suggestion given by the column “Quanto valgono – Otto azioni ai raggi X degli esperti” of the magazine “Milano Finanza”. The sample was composed of 231 purchasing suggestions against 67 selling suggestions. This study utilized the technique of the event study through the statistic suggest by Brown and Warner:

$$\sum e_t \,/\, \sum \sigma[e_t(m)] \qquad (25)$$

The mentioned statistic consists in the ratio between the average residual of the day *t* and the estimation of the standard deviation of the average residuals during the period before the beginning of the test.

Hereunder the results of the test with the daily average residuals:

Average Residual				
Days	Purchases	t-Stud	Sales	t-Stud
-10	-0.151	-0.804	0.097	0.272
-9	-0.107	-0.568	-0.174	-0.489
-8	0.040	0.212	-0.248	-0.697
-7	-0.222	-1.181	0.136	0.383
-6	0.127	0.677	-0.066	-0.185
-5	-0.113	-0.601	0.212	0.597
-4	0.193	1.029	-0.574	-1.614
-3	0.379	2.017	-0.405	-1.141
-2	0.035	0.185	-0.436	-1.228
-1	0.168	0.896	0.076	0.215
1	0.542	2.883	-1.021	-2.873
2	0.268	1.425	-0.299	-0.841
3	0.024	0.127	-0.332	-0.933
4	-0.156	-0.828	-0.621	-1.749
5	-0.252	-1.339	0.327	0.921
6	0.164	0.873	-0.257	-0.723
7	0.175	0.931	-0.595	-1.674
8	-0.114	-0.607	0.458	1.290
9	-0.039	-0.209	0.318	0.895
10	0.095	0.506	-0.364	-1.023

Table 2.2 – Summary of results 10/1990-8/1993, F. Caparrelli

Results did not permit to refuse the null hypothesis that residuals are not correlated.

2.2.2 A continuing process

Tests to confirm or refuse the EMH have been carried on for years even now some authors try to perform new ones.

Indeed very recently, another form to test the semi-strong hypothesis has been developed. On February 26, of the current year, Arianna Ziliotto and Massimiliano Serati of the Carlo

Cattaneo LIUC University School of Economics and Management, published *The Semi-Strong Efficiency Debate: in Search of a New Testing Framework*. They built their idea on the basis that focusing just on return distribution and profit opportunities would twist the mean of the tests.

Their model is based on a Testing Tree that consists of three steps:

- Step 1: Market Surprise
- Step 2: Volatility
- Step 3: Spillovers

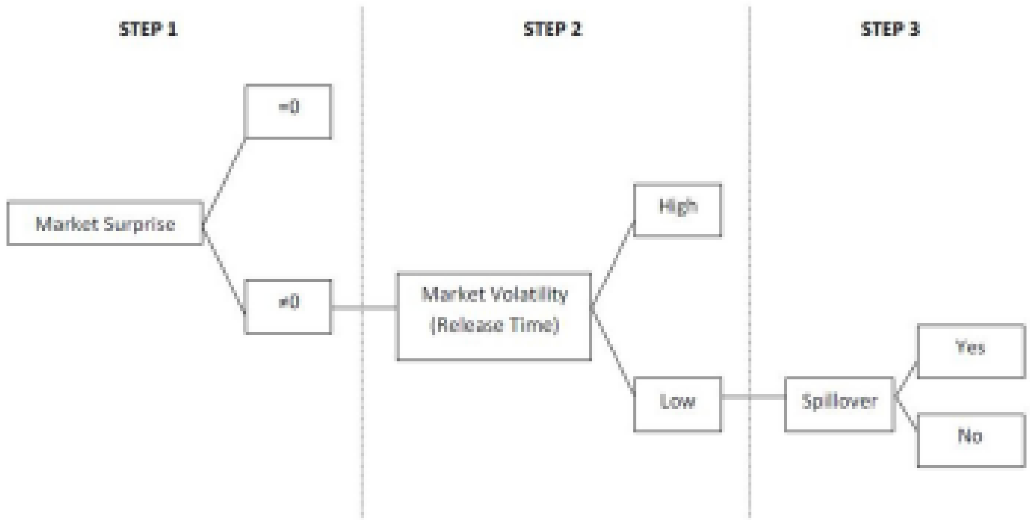


Figure 2.1 Testing Tree, *The Semi-Strong Efficiency Debate: in Search of a New Testing Framework*

In the first step it is possible to understand whether there exist market surprise, and so there is no anticipation of any information, or whether there exist no market surprise, and so there is the need to investigate. The second step lead to another investigation choice with respect to the degree of the volatility, evidencing the need to further investigation patterns in presence of low volatility of the market. Finally the model focuses on spillover effects, exploiting their impact on the market to discriminate on the existence of the efficiency.[23]

[23] The Semi-Strong Efficiency Debate: in Search of a New Testing Framework, Arianna Ziliotto, Massimiliano Serati, Carlo Cattaneo LIUC University School of Economics and Management, February 2015

3. Anomalies on the EMH

As it has been showed hereby, the efficient market hypothesis consists of three forms. However, the most practical and interesting form is the semi-strong efficiency form. During the literature evolution researchers have found interesting way to test this form because of the evidence coming from the market. Dividends announcements, multiple ratios based on price and earnings, calendar events, etc.. are elements came to light by the investigation over the semi-strong form. This branch is known as Anomalies of the Efficient Market Hypothesis. In other words, the anomalies indicate inefficiency into markets, or rather a situation in which stocks deviate from the assumption of the EMH. Often this inefficiency has been proved not to be persistent once discovered, despite this interpretation is not always true. Indeed, after the documentation of an anomaly, there exist three possibility: the anomaly will disappear, reverse or attenuate. This leads to some question regarding the possibility to forecast these anomalies in order to get advantage over the market. On the other hand an anomaly could be the proof of the inadequacy of the model undertaken.

The anomalies branch has developed its literature since 80s as a consequence of the attention previously conferred to the efficient market investigation. Here, the purpose of researchers was to find out some systematic variations of the stock price. This working field is quite interesting because it allows to compare different markets, and so, it allows to understand whether markets follow the same rules. At the end of 80s Samuelson stated that finance was not anymore a perfect model, but it would be possible to accept the presence of anomalies into markets. This was the first step for opening the doctrine doors to events that the current doctrine could not explain.

According to *Latif et al.* (2011) it is possible to distribute anomalies into three basic area: Fundamental anomalies, technical anomalies and calendar (or seasonal) anomalies. Most common anomalies concerned rates of change on the basis of variations in specific temporal circumstance.[24]

3.1 Calendar Anomalies

This category consists of those effects, based on the calendar, which are cyclical in returns. Most of the calendar effects have been diminished, disappeared or reversed as affirmed above. Calendar anomalies are observed in presence of each significant change in time: year, month,

[24] Market Efficiency, Market Anomalies, Causes, Evidences, and Some Behavioral Aspects of Market Anomalies, M. Latif, S. Arshad, M. Fatima, S. Farooq, Institute of Management Sciences Bahauddin Zakaria University, Multan, Pakistan, 2011

week or day. They became popular because of their huge typology and their affordable investigation. Calendar anomalies still face controversial opinion over their existence, especially by whom support the idea that transaction price would cancel them. In any case, it is possible to list the most common anomalies:

- Week-end/Monday effect
- January effect
- Holidays effect
- Intraday effect
- Halloween effect
- Turn of the month effect

3.2 The week-end effect

In 1973 F. Cross observed for the period 1953-1970 that the Stock Exchange Index has highly positive changes on Friday with respect to the other days, otherwise there were less increments on Monday. In 1980 Kenneth French disclosed an anomaly that consisted in the production of negative average return over weekends. French studied the Standard and Poor's (S&P) portfolio in the period 1953-1977. This analysis was integrated by Schwert including estimations of the weekend effect from February 1885 to May 2002, and other sample periods not included in French's study. The starting point was the following regression:

$$R_t = \propto_0 + \propto_w Weekend_t + \varepsilon_t \quad (26)$$

Where Weekend = 1 when the return spans Sunday, and zero otherwise. $\propto_w$ represents the difference in average return over the weekend versus other days. [25]

Hereinafter the results of the estimation:

Sample period	α_0	$t(\alpha_0 = 0)$	α_w	$t(\alpha_w = 0)$
1885-2002	0.0005	8052	-0.0017	-10.13
1885-1927	0.0004	4.46	-0.0013	-4.96
1928-1952	0.0007	3.64	-0.0030	-6.45
1953-1977	0.0007	6.80	-0.0023	-8.86
1978-2002	0.0005	4.00	-0.0005	-1.37

Table 3.1 Day-of-the-week effects in the U.S. stock returns, *Anomalies and Market Efficiency*. G. William Schwert

[25] Anomalies and Market Efficiency. G. William Schwert, University of Rochster, and NBER, 2003

The coefficient a_w appears negative when the returns over the weekend are lower than the ones in the other days. From data is evident that results from test have become less negative, underlying that the effect studied have started decreasing (or at least attenuating) since 80s (the discovered of the weekend effect). It leads to understand that the variance per time unit of the differences in price series is slower in the weekend. This means that Monday's price is the result of a random walk process that lasts three days. Following this ideology and starting again from daily data (1975-1989, historic MIB index by Milan Stock Exchange), Barone tried to verify whether the velocity of the stock prices generating process would change when markets are supposed to be closed. Therefore, in 1990, he published his study where standard deviations and averages of the index MIB rates were divided day by day. The rate averages resulted negative on Monday and Tuesday, and positive on Friday. Even the stock generating process velocity (standard deviation) resulted higher on Monday.[26]

Moreover Barone tested the same sample also by means of a regression:

$$R_t = a_1 + b_2 D_2 + b_3 D_3 + b_4 D_4 + b_5 D_5 + u_t \quad (27)$$

Where D_2 is a dummy for Tuesday ($D_2 = 1$ if the observation falls on Tuesday, $D_2 = 0$ otherwise), D_3 is a dummy for Wednesday, and so on as follow:

$$D_2 = \begin{matrix} 1\ if\ the\ return\ belongs\ to\ Tuesday \\ 0\ if\ the\ return\ belongs\ to\ the\ other\ days \end{matrix}$$

$$D_3 = \begin{matrix} 1\ if\ the\ return\ belongs\ to\ Wednesday \\ 0\ if\ the\ return\ belongs\ to\ the\ other\ days \end{matrix}$$

$$D_4 = \begin{matrix} 1\ if\ the\ return\ belongs\ to\ Thursday \\ 0\ if\ the\ return\ belongs\ to\ the\ other\ days \end{matrix}$$

$$D_5 = \begin{matrix} 1\ if\ the\ return\ belongs\ to\ Friday \\ 0\ if\ the\ return\ belongs\ to\ the\ other\ days \end{matrix}$$

a_1 is the average rate of change on Monday, while b_n represents the difference of the average rate of change on the other days.

[26] Aspects of Market Anomalies, M. Latif, S. Arshad, M. Fatima, S. Farooq, Institute of Management Sciences Bahauddin Zakaria University, Multan, Pakistan, 2011

Period	*Degree of freedom*		*Ordinary Least Squares*		*Generalized Least squares*	
			F	Confidence level	F	Confidence level
1975-1989	4	3384	6,69	0,000	6,95	0,000
1975-1979	4	1129	3,02	0,017	2,88	0,022
1980-1984	4	1169	2,37	0,050	2,50	0,041
1985-1989	4	1076	3,16	0,013	3,18	0,013

Table 3.2 *Il Mercato Azionario Italiano: efficienza e anomalie di calendario,* E. Barone, 1990

The zero-hypothesis ($H_0: b_2 = b_3 = b_4 = b_5 = 0$) has been tested in the chart above. Results show that it is possible to reject the hypothesis at a confidence level of 95%. Rates of change on Monday appears reliably different from the others.
It is important to mention that the test used in this context was the F statistic of Snedecor:

$$F = \frac{\left[\frac{R^2}{(k-1)}\right]}{\left[\frac{(1-R^2)}{(n-k)}\right]} \tag{28}$$

With *k* and *n-k* degrees of freedom, where *k* represents the number of independent (forecasting) variables and *n* the number of observations:
It is possible to note that Barone did not report just the OLS data, but the GLS too. He found out that standard deviations results could suffer an heteroskedastic problem and so it would be better to standardize variables in the regression (27). As reported, he included in the analysis the generalized least squares contribution, underlying how results did not change. [27]
So, this test underlined how the rates of change on Monday were reliably different from the ones on the other days of the week.
M. Gibbons and Hess got results quite similar to French using a linear regression model with different dummies. Indeed these dummies represented the expected returns of the various days instead of the difference with respect to Monday.

3.2.1 Other calendar anomalies

As aforementioned, there exist some other anomalies. An interesting anomaly is the holiday effect: Jacobs and Levy noted that the 35 percent of stocks growth in 1963-1982 occurred in the eight non-working days of the year. This leads to understand that this effect often occurs

[27] Il Mercato Azionario Italiano: efficienza e anomalie di calendario, E. Barone, 1990

on the national days, in the new year's day, etc. It is possible to distinguish between pre-holiday effect and post-holiday effect, both representing a change of direction in stock prices flow. Therefore, the holiday effect consists in a better performance on days preceding a holiday, and in a worst performance on next days. In 1990 Ariel verified a significant increment of stocks returns before Christmas and before the May Day with respect to other holidays.

Recently, Tamara Backovic Vulic tested this effect over the 13th July (Montenegrin Statehood day) for the period 2003-2009. Some results could be appreciated in the following graphic:

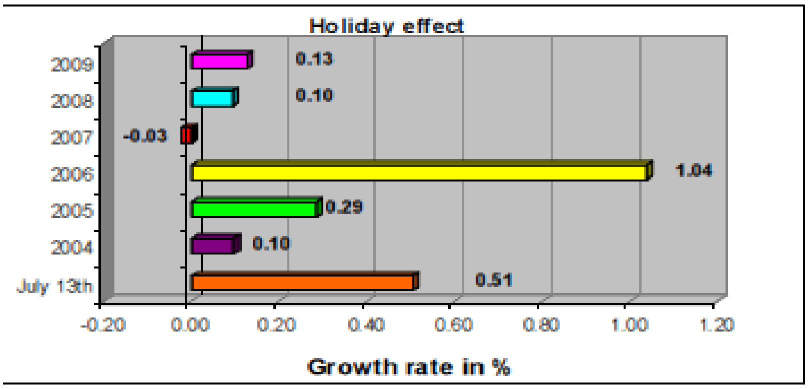


Figure 3.1 *Testing the Efficient Market Hypothesis and its Critics - Application on the Montenegrin Stock Exchange*, Tamara Backovic Vulic,

These results showed that this effect is not really effective in Montenegro, apart from two deducible cases.[28]

The January effect has been the main famous calendar anomaly. It consists in a reliably higher rate of changes for every stocks in the month of January (with respect to the other months). For what concerns the Italian market, Giannasca and Macchiati (1986) discovered a strong seasonality in 1975-1989. Results based on the historic MIB showed rates of change equal on average to 0.33 per cent and significantly different from zero at a confidence level of 0.001 per cent. It is possible to observe these results in the following figure.

[28] Testing the Efficient Market Hypothesis and its Critics – Application on the Montenegrin Stock Exchange, Tamara Backovic Vulic, MSc University of Montenegro, Podgorica Faculty of Economics, professor assistant of Econometrics, Business Statistics, Operations Research, Applied Econometrics and Decision Making Models

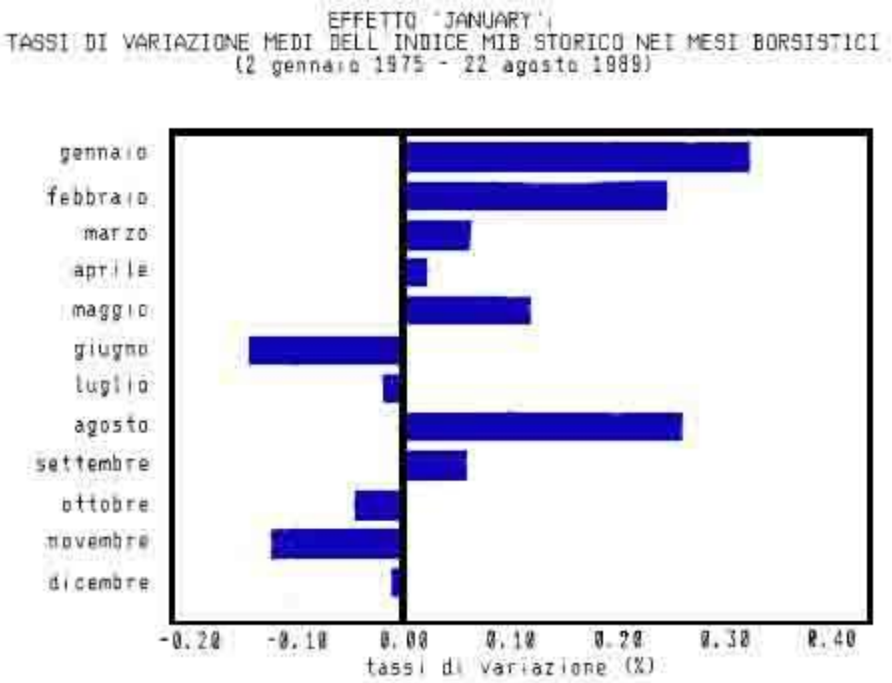


Figure 3.2 *Il Mercato Azionario Italiano: efficienza e anomalie di calendario,* E. Barone, 1990

As stated by Caparelli, there are evidences of the prevalence of the January effect over the weekend effect. In fact the average return on Monday and Tuesday is resulted positive in January although it resulted negative during the other months:

Average Return	*Monday*	*Tuesday*	*Wednesday*	*Thursday*	*Friday*
January	-0.26%	0.23%	0.27%	0.25%	0.40%
Other months	-0.08%	-0.17%	0.14%	0.10%	0.15%

Table 3.3 *Il Mercato Azionario,* F. Caparrelli

Rozeff and Kinney verified the presence of the January effect on a sample of stocks by the New York Stock Exchange in 1904-1974, observing higher returns concentrated in the first fifteen days of the month. The January effect has been justified by psychological belief that investors are affected by the conviction that the new year could start positively, or rather, as affirmed by Jacob and Levy, that investors usually wait the new year to sketch out a new strategy on the basis of the expected scenario proposed by analysts.

It is appropriate to hint the turn-of-the-month effect. The mere turn of the month seemed to be able to lead investors buying securities. This is confirmed by the fact that the rates of change at the beginning and at the last five days of the month appeared to be deeply positive pursuant to Ariel's work (1987). On the other hand, on the basis of Caparelli's work, the Italian market appeared to show stock prices lower in the first part of the month (when the trading cycle ends up) and higher in the second part. However it is evident that these results could be affected by other anomalies such as the afore-mentioned January effect.

Boido et al. (2004) observed the summer-time (or daylight savings time) effect by means of the COMIT index. Results showed the presence of the effect on the basis of the fact that the time after the change of hour underlined a different prices average. In addition, days next to the daylight savings time moment appeared to get an average index value higher than the general mean. [29]

3.3 Fundamental Anomalies

It is possible to gather together some anomalies under the name of fundamental anomalies by underlying the ones that appear to have some value for individual investors on the basis of financial reports. This section includes P/E effect, Book-to-Market ratios, Earnings announcements, Neglected-firm effect, High Dividend effect, and so on.

Going deeper in each meaning it is possible to briefly define these anomalies. The dividend yield anomaly states that high dividend yield stock outperforms the market with respect to the lower ones. Price to earnings ratio anomaly supported the idea that portfolio composed of low P/E stocks often outperform portfolios composed of high P/E stocks. In the same way stocks of companies with high book-to-market ratios outperform stocks with low book-to-market ratios. Moreover this effect seems not to be dependent on systematic risk, but on the fact that companies with low book-to-market ratios are perceived to be companies that grow rapidly. Earnings announcements can have variable effects on stock prices, their effects basically depend on analysts interpretation of the market in pursuit of predictability through earnings expectations published on website or personal relationships with experts. Again, the neglected-firm effect occurs on stocks that has lower trading volume in addition to the approximately absence of analysts support. It is possible to going on listing these anomalies, but a more advisable way is to examine one of them deeper.[30]

3.4 The P/E effect

It has been stated that this effect asserts that the stock with low price to earnings ratio are likely to generate higher returns outperforming the market, while the stocks with high price to

[29] Anomalie di calendario: l'effetto ora legale, Boido, Claudio, Fasano, Antonio, Periodico: AF. Analisi finanziaria, 2004

[30] The neglected firm effect and an application in Istanbul Stock Exchange, Soner Akkoc, Mustafa Mesut Kayali, Metin Ulukoy, Banks and Bank Systems, Volume 4, Issue 3, 2009

earnings ratios tend to underperform with respect to the same market. The P/E ratio is calculated as the following ratio:

$$\frac{P}{E} = \frac{P_0}{EPS} \tag{29}$$

Where P_0 is the price of the security at time zero, and EPS is the earning per share calculated as the ratio between the last reported earnings and the number of stocks.

Among the various hypothesis over the meaning of the P/E effect, there exist some based on the CAPM and others based on risks attitude. Following this concept, low P/E stocks are assumed to be risker than high ones (this means that the β of the low P/E stocks is greater than the β of the high P/E ones), and therefore they would generate higher performance. Nevertheless further studies demonstrated that the leakage between low P/E and high β was not enough to explain the anomaly. Portfolio considered appeared to show greater performances even after the analysis started including risk. In 1977 Basu performed a study on this effect. His analysis followed this outline:

- Calculation of the P/E ratio for each security of the sample
- Composition of five portfolios on the basis of the P/E value
- Calculation of the monthly return for each portfolio
- Re-composition of portfolio (after 12 months)
- β coefficient estimation for each portfolio and indexes estimations

Results showed that the greater performance of low P/E samples was not related to an higher value of the systemic risk.

In 1994 Calcagnini and D'Arcangelis examined a sample of 42 securities for the period 1979-1992. They constructed some portfolios on the basis of the P/E ratio supposing to buy them at the beginning of the year and hold them for the whole year. Then it was constructed the market model to evaluate the performance on the basis of the systemic risk. Results showed unsatisfactory conclusions: in the long run the connection between low P/E and high performance seemed to hold, but there were no possibility to reject the equality hypothesis on the basis of the significance test of portfolio return differences.

Returns and statistics	*Portfolios*		
	1	*2*	*3*
Average P/E	8.27	17.18	57.71
Average return of the year	48.22	40.12	32.86

Systemic Risk (β)	1.03	0.99	0.92
Return/β	46.77	40.42	35.75

Table 3.4 *Il Mercato Azionario*, F. Caparrelli

3.4.1 Other fundamental anomalies

Akkok *et al.* (2009) studied the neglected-firm effect in 1999-2008 (Istanbul Stock Exchange) using monthly volume data. They found out that the portfolio they have constructed by popular stocks earned the highest abnormal return when compared to the abnormal returns earned by the other two portfolios constructed consisting of neglected and normal stocks. This leads to understand that ISE (Istanbul Stock Exchage) was not affected by the neglected-firm effect, even if previous tests have documented some evidences. Popular stocks showed higher average with respect to the portfolio consisting of neglected stocks in all years but 2008. Furthermore the monthly average abnormal return of neglected portfolio is negative. Moreover t-test showed values for popular portfolio which were statistically significant in each year, t-values for normal portfolio were statistically significant in 7 years out of 10 years and the ones for neglected portfolio were significant in all years but 2008 at the 5% level.

They tried to establish whether their results were a consequence of the January effect as well. However they got same results and concluded their findings were not consistent with the January effect, contradicting the Neglected-firm effect.

Brian T. Brian T. Allman *et al.* gave a contribute to the Small-firm effect research analysing NYSE and AMEX stock prices in 1962-1975. They found out that portfolios of smallest firm on average experienced returns over 20% which were reliably higher than portfolios of largest firms. There were evidences that allow to think that investors could construct portfolios with systematically abnormal returns on the basis of firm size[31].

3.5. Technical Anomalies

For technical anomalies it has been considered the techniques used to forecast future prices of stocks on the basis of past prices and past information which seemed to have some effect on markets. So, the purpose of the technical analysis is to study time series and exchanged volumes without considering the object, this raised some interesting anomalies. Among the anomalies identified in the technical field we found the Moving Averages and the Trading Range beak.

3.5.1 Hints on technical anomalies

[31] The Size Effect, Brian T. Brian T. Allman et al, 2009

Hons and Tonks examined trading strategies in the US Stock Market founding signs of momentum strategies during the period 1977-1996. They discovered the possibility to gain advantages by past positives securities. Hence, the momentum anomaly states that securities that reliably went up in the past would probably continue to go up in the near future. This means that stocks which outperform on the short run period tend to perform well also in the future. The momentum strategy is based on the assumption that price of securities are more likely to keep moving in the same direction, than to change it. Momentum effect has been proved to be effective in the US Small and Large Cap universe[32]. Resistance and support level are the basis of the Trading Range Break strategy. Support level represents the level of price corresponding a break in the negative trend of a stock, while resistance level represents an abstract level in which prices stops to grow. Support level occurs when a big amount of purchasing affect those stocks which have performed negative trends, while resistance occurs when many stock sales take place at the same time. A trading range break tries to forecast and exploit these circumstances. A price penetrating the resistance level would generate a buy signal while a price penetrating the support level would generate a sell signal. The belief is that investors sell at the resistance level and buy at the support level. In 1992 Brock *et al.*, analysed the above-mentioned effect on the Dow Jones Industrial Index from 1897 to 1985.
They found out that this technical analysis would be effective against the market unless costs should be not carefully took into account since the beginning. Obviously there are contrasting examination on technical anomalies, but they are not be examined here.

3.6. Do famous anomalies persist nowadays?

This is a conflicting issue. The persistence of the anomalies appeared over the time do not persuade everyone. In 2002 Schwert observed that all the well-known anomalies in the finance literature do not hold up in different sample periods. Examples could be represented by the size and the value effects, which seem to have disappeared after the papers their existence have been brought to light.

In certain market happen that even the weekend and the dividend yield effect decreased their predictive power.

The small-firm turn-of-the-year effect became weaker in the years after it was first documented in the academic literature, although there is some evidence that it still exists.

[32]Does Momentum Investing Work?, Alex Bryan, 2013 (http://ibd.morningstar.com/article/article.asp?id=591675&CN=brf295,http://ibd.morningstar.com/archive/archive.asp?inputs=days=14;frmtId=12,%20brf295)

The reason might be the popularity these anomalies achieve. In other words, investors that have been able to experience these anomalies, have tried to exploit them to beat the market as well. Moreover once anomalies have been discovered, prices could be corrected by operators on the basis of new information received.

Hence, Schwert suggested that anomalies could be more apparent than real. They could be the consequences of an hysteric research by many authors. It could be easy to share Schwert's opinion, but it is true that anomalies, in general, have been documented in different markets and different period corresponding similar, or even equal, results. Anomalies existed and will exist, especially considering that the first to give way were the calendar anomalies, the easier to be identified. Nevertheless this is an opinion that have to be replaced by facts, hence it will find an answer at the end of the path this paper is covering.

3.7. How many ways to test the EMH?

It is sure that the efficient market hypothesis has been over-tested over time. Researchers thought up many ways in order to satisfy or reject this theory. Beyond the latest effort produced by Zilotto and Serati, other authors invented strategies curiously different from the econometric and technical studies. Tests go from the data mining concept to the fractal estimation. The ways to test the EMH could be divided depending on calculation methods (as the latter two procedures cited) or on the kind of data collected. Concerning this second way, It is useful mention the field of the Event Studies. Event Studies consist in an empirical methodology based on a relevant specific event such as the stocks split, the announcement of financial reports, issues of new securities and so on. In other words, the ES are a mean to verify the impact of a specific event on a firm's value. Typically the process consists of many phases. First, a selection of one or more interest events have to be collected on the basis of revealed and expected returns. Then, the existence of these abnormal returns has to be proved, so the next step consists of statistic tests. Obviously the whole analysis depends on the availability of data. This means that the mere usage of statistical and mathematical tools has been surpassed. This continuing process probably will not end as long as authors will challenge themselves. However, nowadays, the wider solutions to test in different way the hypothesis Fama refined, consist of Fundamental and Technical analysis.

3.7.1 Hints on different ways to test the EMH and the anomalies affecting it: Fundamental and Technical analysis.

Basically the fundamental and technical studies are fields born to refuse the efficient market hypothesis. The Fundamental analysis studies the security in order to esteem the intrinsic value to compare with the stock price. It is called “fundamental” because its methods focus on company fundamentals, or rather everything comes from financial documentation. Stocks current value is a function of the asset, economic and financial trend of a company. So, Fundamental analysis could consist in the study of financial data, management, business concept and competition in order to derive a forecast and profit from future price movements, but it could affect the industry level focusing on supply and demand forces for the products offered. Moreover, it bases its work on the comparison between the intrinsic value and the share of the security. On the contrary the technical analysis studies time series and volumes. Technical analysis raised at the beginning of the Twentieth Century thanks to Charles Dow’s work. It started developing after the financial crisis in USA to arrive in 50s in Europe. The aim is to characterize instruments and techniques able to underline buying or selling signals in order to beat the market. Murphy defined technical analysis as the study of the market action by means of graphics for determining future price trends. The technical analysis tries to forecast a change on trends and maintain it as far as evidences will confirm it.

The explanations over the effectiveness of the technical analysis could be found on the repetitiveness of human behaviours or in their irregular rationality. However these elements are pointless/of no interest in the analysis I am doing here.

4. Is the Italian market efficient?

Everyone investing in the Exchange Market would know the answer to this question. The definition of the efficiency of a market is strictly related to the quantity and quality of the available information. Indeed markets are supposed to be efficient whether prices are correctly determined on the basis of the whole available information. In an efficient market securities issued present valuation relatives to the potential profit that their companies could reach. Financial markets have many functions: they finance investments through the transfer of sources from surplus to deficit sectors; they allow to negotiate investment; they control for the efficiency of the companies through the determination of prices of securities. This makes clear that efficient market is a necessary condition to have a stable and well operating market. This is the reason of the huge literature explained before. As it has been show in the previous chapters, there exists some literature relative to the Italian case, but in order to observe recent conditions, from here onward, it is shown an independent analysis over the Italian Stock Exchange.

4.1 Testing the EMH on the Italian Market

Index Analysis

Purpose of the analysis on Index: stock market indexes represent the measure of the value of a section of the stock market. They are computed from the prices of selected stocks and represent a description of the market. An indexes combines several stocks or other investment vehicles together at aggregate level. The aim is to track the market's changes over time. Therefore indexes represent the perfect way to understand whether a market follow one of the three form of efficiency described in the financial literature.

4.1.1 Data

The first step in order to examine the Italian Market, in order to prove or reject the efficient market hypothesis, is defining data.

I collected indexes and companies data from Yahoo Finance Database[33]. The former on indexes analysis, the latter on companies one (collected also from Datastream). For this study daily (Monday to Friday), weekly and monthly price index data has been used. The observation period fluctuates from January 1, 2009 to December 31, 2014.

The empirical analysis of this study uses data of adjusted close prices for six indexes of the Italian Stock Exchange: FTSE MIB; FTSE IT MICRO CAP; FTSE IT SMALL CAP; FTSE ITALIA ALL-SHS; FTSE ITALIA MID CAP; FTSE ITALIA STAR.

The period chosen for examinations start the year next the occidental financial crisis to the end of the last year in order to avoid to consider the effect of that crisis.

Index	Notations	Sample Period	Observations		
			Daily	Weekly	Monthly
FTSE MIB	FTSEMIB.MI	1/1/2009-31/12/2014	1548	311	72
FTSE IT MICRO CAP	ITMI.MI	1/1/2009-31/12/2014	1519	311	72
FTSE IT SMALL CAP	ITSC.MI	1/1/2009-31/12/2014	1520	311	72
FTSE ITALIA ALL-SHS	ITLMS.MI	1/1/2009-31/12/2014	1520	311	72
FTSE ITALIA MID	ITMC.MI	1/1/2009-	1520	311	72

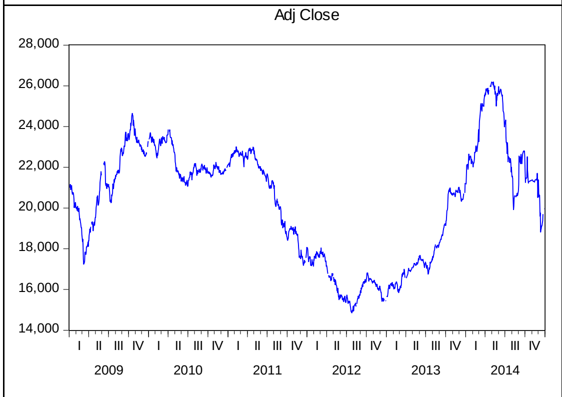
[33] https://it.finance.yahoo.com/indices?e=milano

CAP		31/12/2014			
FTSE ITALIA STAR	ITSTAR.MI	1/1/2009-31/12/2014	1548	313	72

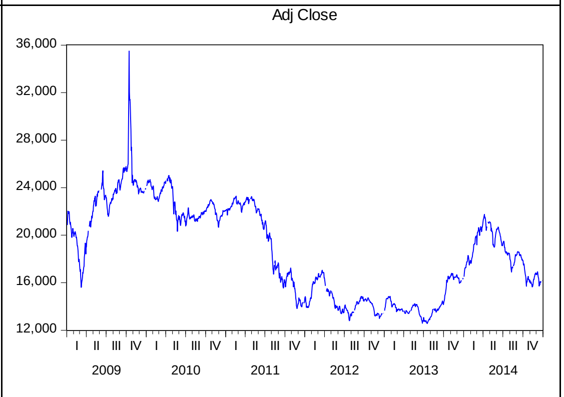
Table 4.1 Description of Data Samples

Hereinafter I drawn indexes graphs divided on the basis of days, weeks and months during the six years above defined.

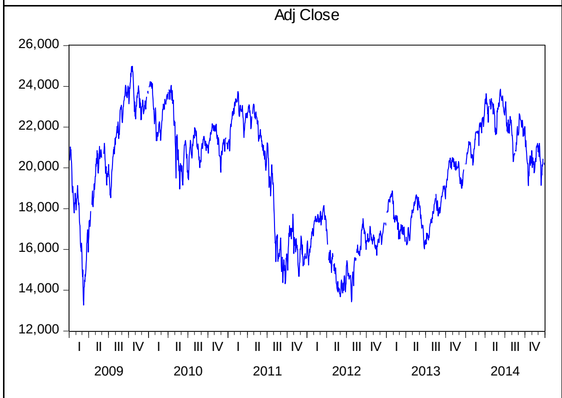
FTSE IT MICRO CAP (ITMI.MI)



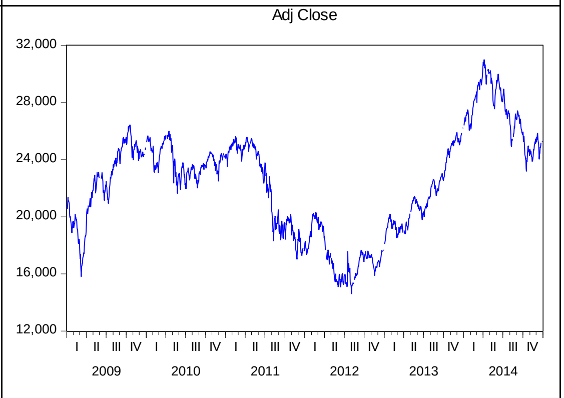
FTSE IT SMALL CAP (ITSC.MI)



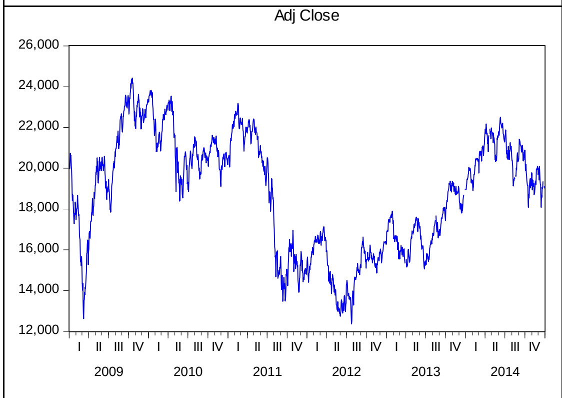
FTSE ITALIA ALL-SHS (ITLMS.MI)



FTSE ITALIA MID CAP (ITMC.MI)



FTSE ITALIA STAR (ITSTAR.MI)



FTSE MIB (FTSEMIB.MI)

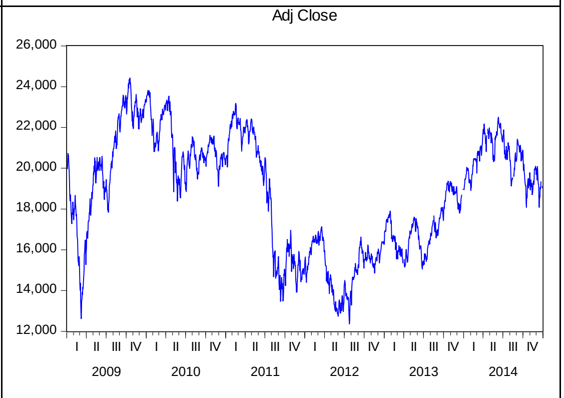
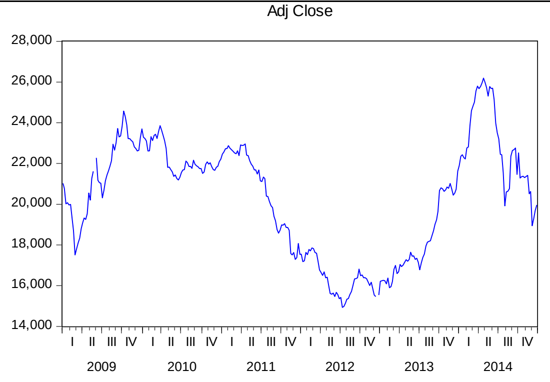
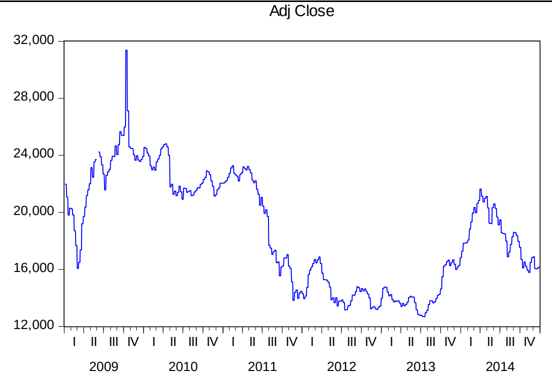


Table 4.2 Time Series Plots of Daily Prices of Italian Stock Exchange indices

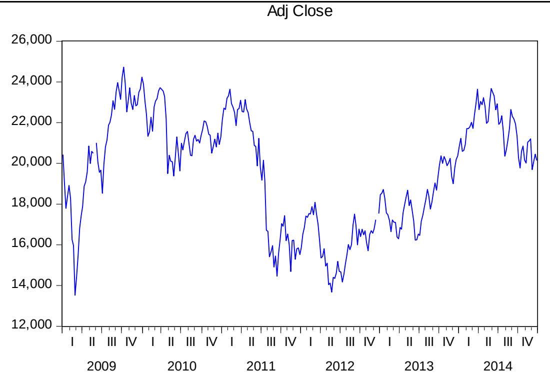
FTSE IT MICRO CAP (ITMI.MI)



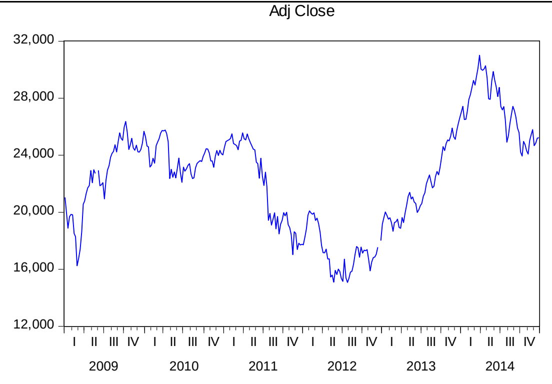
FTSE IT SMALL CAP (ITSC.MI)



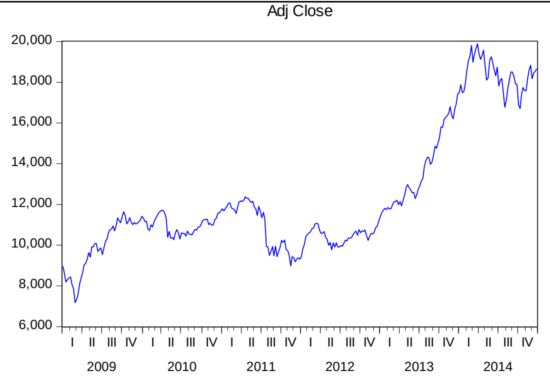
FTSE ITALIA ALL-SHS (ITLMS.MI)



FTSE ITALIA MID CAP (ITMC.MI)



FTSE ITALIA STAR (ITSTAR.MI)



FTSE MIB (FTSEMIB.MI)

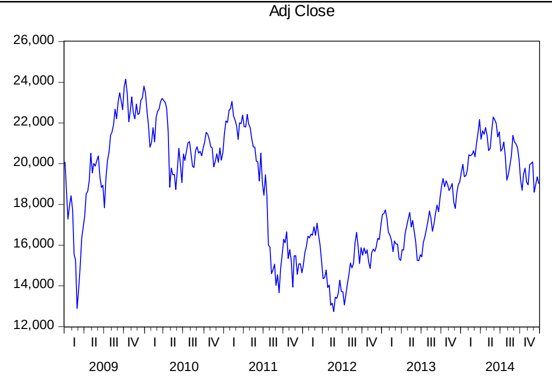
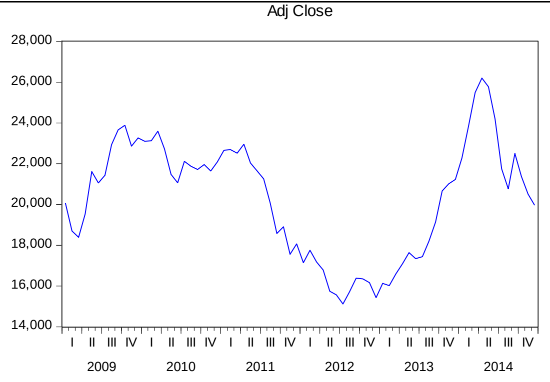
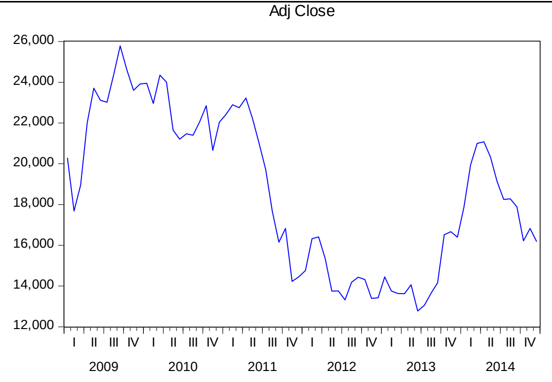


Table 4.3 Time Series Plots of Weekly Prices of Italian Stock Exchange indices

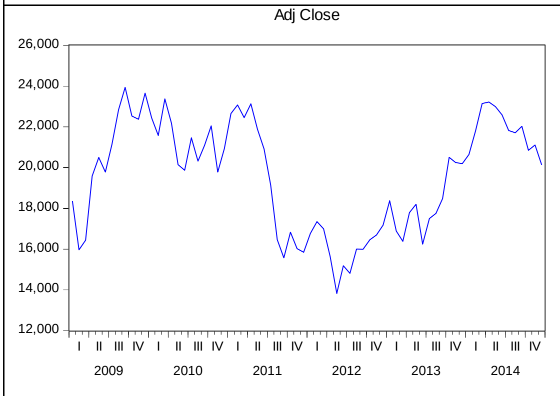
FTSE IT MICRO CAP (ITMI.MI)



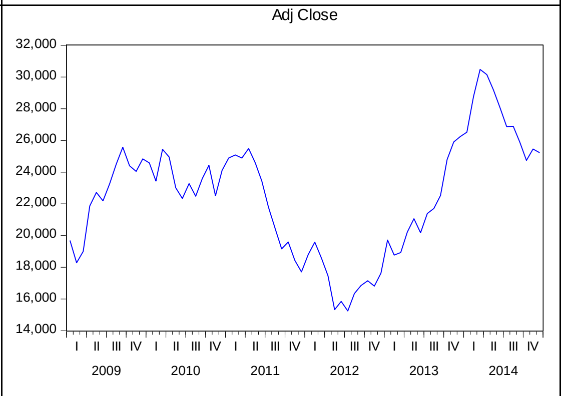
FTSE IT SMALL CAP (ITSC.MI)



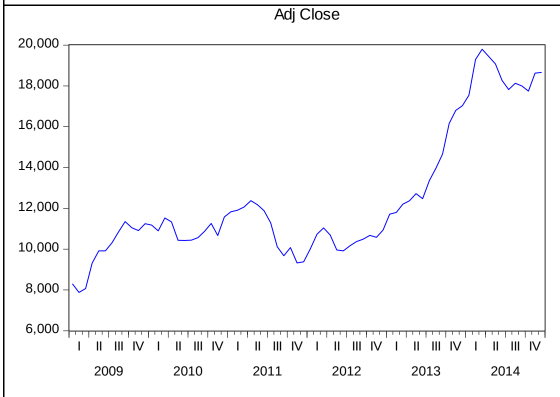
FTSE ITALIA ALL-SHS (ITLMS.MI)



FTSE ITALIA MID CAP (ITMC.MI)



FTSE ITALIA STAR (ITSTAR.MI)



FTSE MIB (FTSEMIB.MI)

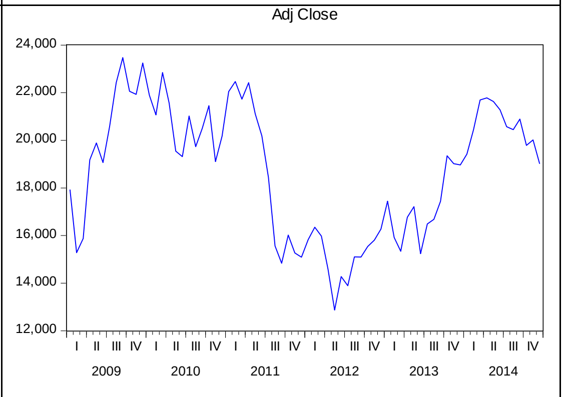


Table 4.4 Time Series Plots of Monthly Prices of Italian Stock Exchange indices

Although there are some differences, it is possible to say that for what concerns daily prices, indexes seem to perform similar trends. On the contrary, in weekly and monthly comparison, FTSE ITALIA STAR index seems to be affected by increasing trends contrastingly with other indexes which appear to be affected by casual trends.

The study of the efficiency concerns return series. Returns have been calculated using the log-difference (continuously compounded formula) of each index price:

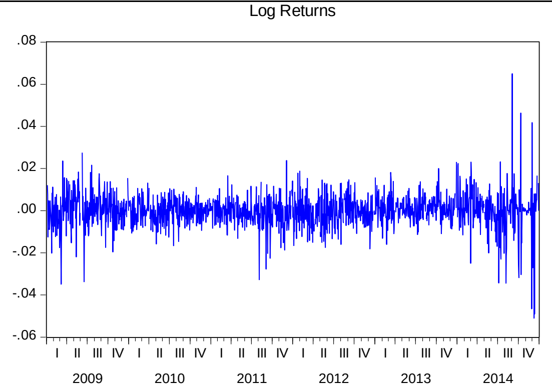
$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \qquad (30)$$

Log return

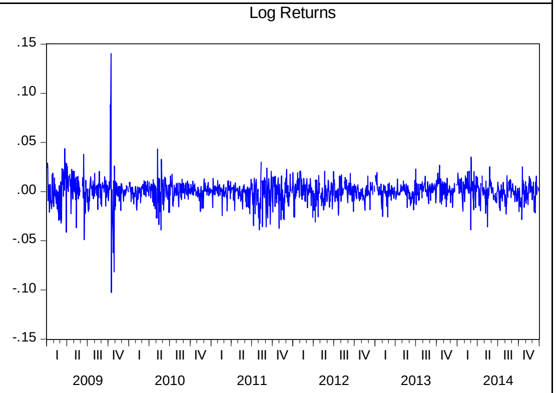
Where p_t and p_{t-1} represent the adjusted closing prices of an index at time t and *t-1*, respectively. In depth, logarithmic returns are differences of log prices sampled at the same unit time interval. The use of log returns born from the necessity to have a constant process with log-normal percentages, because percentage returns are not made up such a normal distribution. Indeed price series do not typically fluctuate around a constant level. So the logarithmic transformation becomes necessary because of the significant asymmetry of the distribution of prices, in order to obtain a log-normal distribution.

Once established the data composition, it is possible to define the hypothesis of the study. The intention is to examine if the Italian Stock Market is weak and/or semi-strong efficient, as well as there exist anomalies over it.

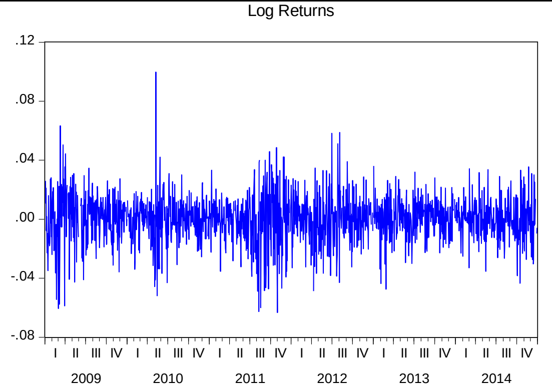
FTSE IT MICRO CAP (ITMI.MI)



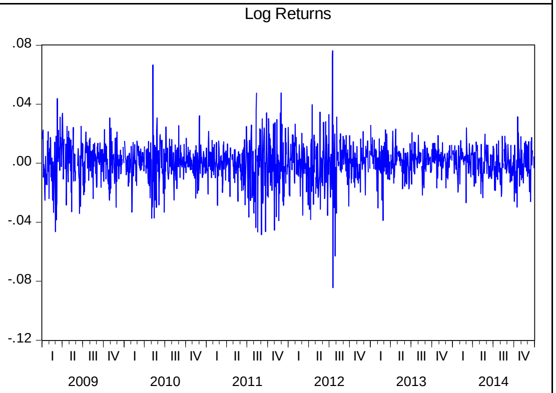
FTSE IT SMALL CAP (ITSC.MI)



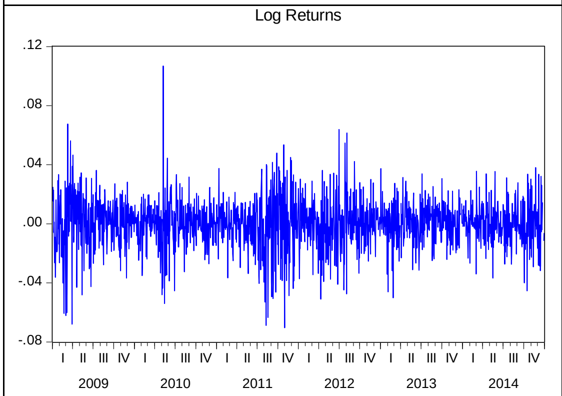
FTSE ITALIA ALL-SHS (ITLMS.MI)



FTSE ITALIA MID CAP (ITMC.MI)



FTSE ITALIA STAR (ITSTAR.MI)



FTSE MIB (FTSEMIB.MI)

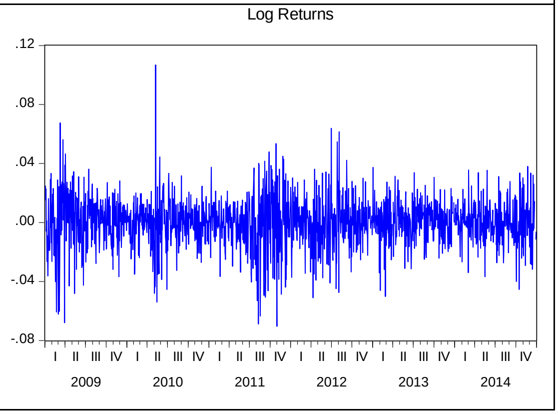
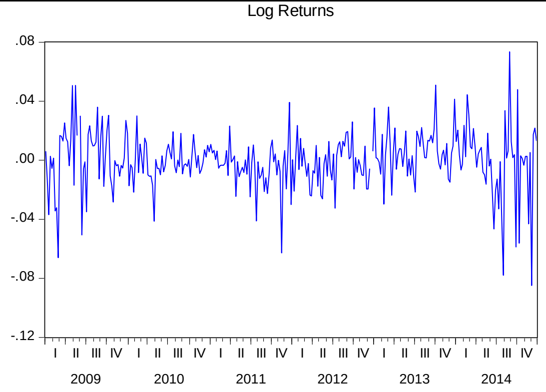
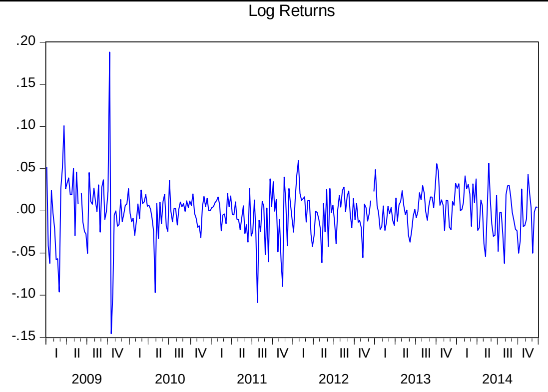


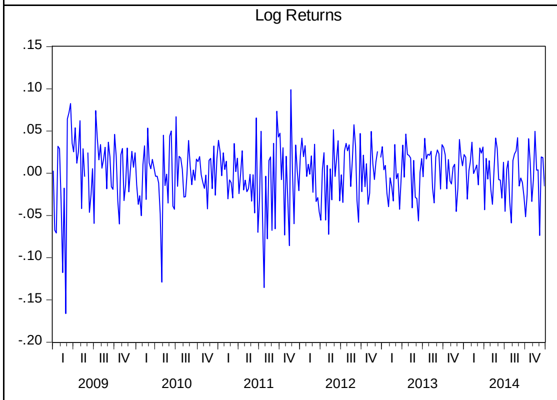
Table 4.5 Time Series Plots of Daily Log Returns of Italian Stock Exchange indices

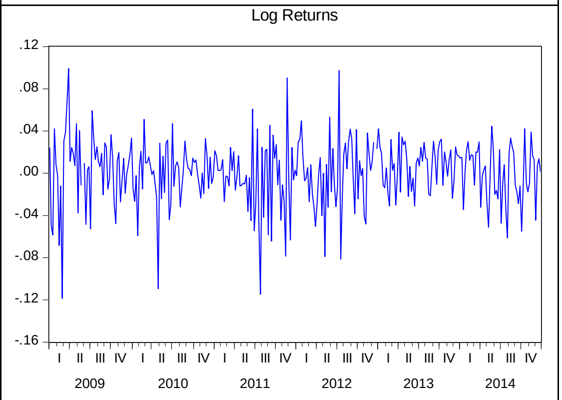
FTSE IT MICRO CAP (ITMI.MI)	FTSE IT SMALL CAP (ITSC.MI)



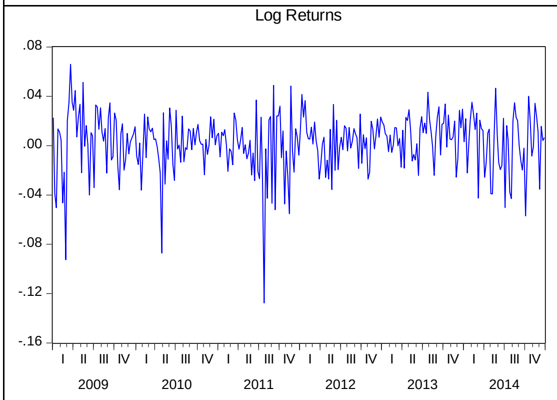


FTSE ITALIA ALL-SHS (ITLMS.MI)	FTSE ITALIA MID CAP (ITMC.MI)





FTSE ITALIA STAR (ITSTAR.MI)	FTSE MIB (FTSEMIB.MI)



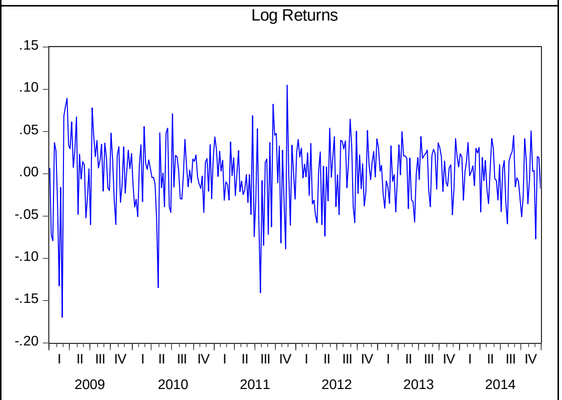
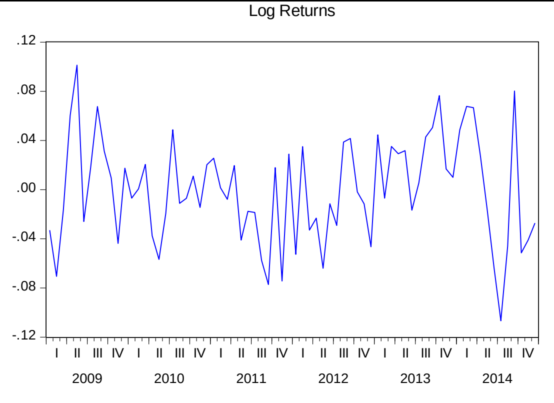
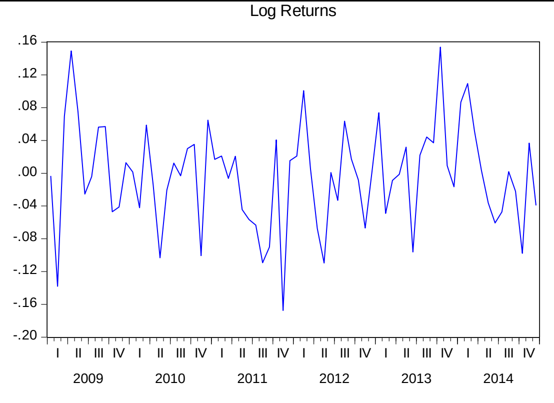


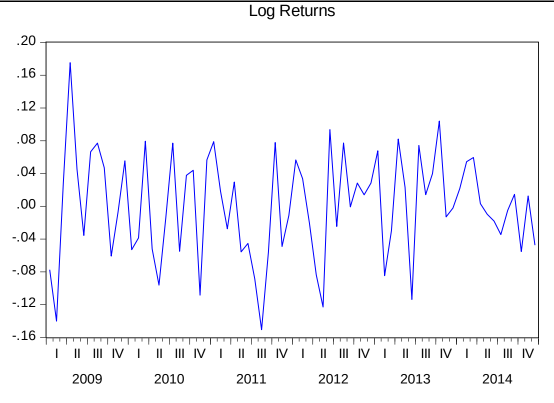
Table 4.6 Time Series Plots of Weekly Log Returns of Italian Stock Exchange indices

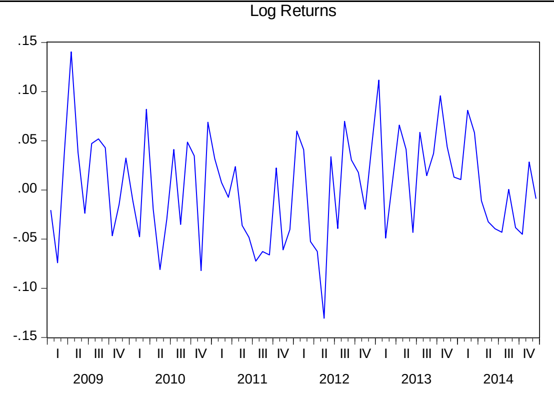
FTSE IT MICRO CAP (ITMI.MI)	FTSE IT SMALL CAP (ITSC.MI)



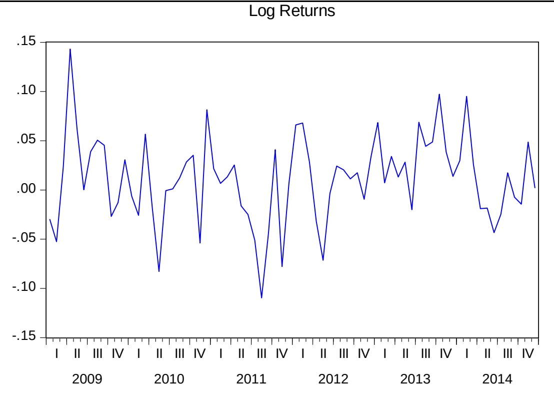


FTSE ITALIA ALL-SHS (ITLMS.MI)	FTSE ITALIA MID CAP (ITMC.MI)





FTSE ITALIA STAR (ITSTAR.MI)	FTSE MIB (FTSEMIB.MI)



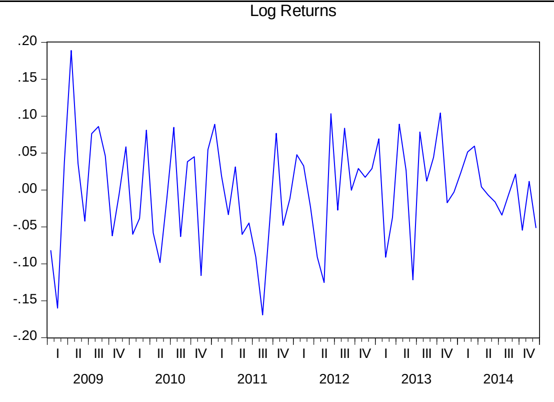


Table 4.7 Time Series Plots of Monthly Log Returns of Italian Stock Exchange indices

Time series plots of daily returns (Table 4.2) suggest that those series do not have a deterministic trend, that means they do not increase or decrease in the long run, also the variability does not blow up or significantly decrease in the long run. Positive values tend to be followed by positive values for brief observations, the same happens for negative values. Moreover, it is clear that all daily markets indexes fluctuate around zero. Differently, weekly and monthly data (Table 4.3 and 4.4) apparently show casual trends that seem to affect the successive one. In general these different indexes seem to follow similar trends for each timeline considered, a part for Micro and Small Cap indexes, but differences appear negligible. However all indexes seem not to show blowing mutations in the last two years.

4.1.2 Weak Hypothesis

$$\begin{cases} H_0: The\ Italian\ Stock\ Market\ is\ weak-form\ efficient \\ H_1: The\ Italian\ Stock\ Market\ does\ not\ follow\ a\ random\ walk \end{cases}$$

4.1.3 Methodology and Results

In order to verify the hypothesis above, it has been used some statistical methods: descriptive analysis; the serial correlation test; the runs test; the sign test; the Augmented Dickey-Fuller and the Phillips-Perron unit root tests. In the following part it is possible to appreciate results of the analysis:

Daily analysis

Descriptive Analysis

FTSE IT MICRO CAP (ITMI.MI)		FTSE IT SMALL CAP (ITSC.MI)	
Mean	-2.53E-05	Mean	-0.000151
Median	0.000207	Median	0.000580
Maximum	0.064990	Maximum	0.140501
Minimum	-0.050985	Minimum	-0.102612
Std. Dev.	0.007917	Std. Dev.	0.011987
Skewness	-0.211812	Skewness	0.500588
Kurtosis	11.05956	Kurtosis	24.22985
Jarque-Bera	4122.567	Jarque-Bera	28608.22
Probability	0.000000	Probability	0.000000
FTSE ITALIA ALL-SHS (ITLMS.MI)		**FTSE ITALIA MID CAP (ITMC.MI)**	
Mean	9.64E-06	Mean	0.000149
Median	0.000544	Median	0.000881
Maximum	0.099795	Maximum	0.076267
Minimum	-0.063289	Minimum	-0.084373
Std. Dev.	0.016156	Std. Dev.	0.013058
Skewness	-0.141469	Skewness	-0.230025
Kurtosis	5.104263	Kurtosis	6.847751

Jarque-Bera 285.5051 Probability 0.000000	Jarque-Bera 951.0660 Probability 0.000000
FTSE ITALIA STAR (ITSTAR.MI)	FTSE MIB (FTSEMIB.MI)
Mean -1.50E-05 Median 0.000215 Maximum 0.106839 Minimum -0.070442 Std. Dev. 0.017078 Skewness -0.139126 Kurtosis 5.255730 Jarque-Bera 333.1904 Probability 0.000000	Mean 0.003577 Median 0.000232 Maximum 9.320000 Minimum -6.430000 Std. Dev. 0.313571 Skewness 13.14048 Kurtosis 646.4820 Jarque-Bera 26752002 Probability 0.000000

Table 4.8 Descriptive Analysis of Daily indexes returns

The descriptive analysis of the index, on the basis of the daily returns, underlines that half indexes have negative mean and half present a positive one. FTSE MIB index, that has the highest value, counteracts FTSE IT MICRO CAP index, that has the lowest value. Results from standard deviations underlines that FTSE MIB index presents the highest volatility compared with other Italian Stock Exchange indexes, that proves more dispersion of data with respect to other indexes. Again, FTSE IT MICRO CAP index presents the lowest standard deviation value, so the lowest volatility among Italian indexes. Moreover, all indexes present negative asymmetry (skewness indicates negative value) a part for FTSE IT SMALL CAP and FTSE MIB indexes which present positive asymmetry. Kurtosis values explain that the distributions of FTSE MIB, FTSE IT MICRO CAP and FTSE IT SMALL CAP are strongly centred with lights tails. Jarque-Bera test suggest that all indexes (more or less at the same level) have been extracted by a sample not distributed such as a normal random variable. P-values are equal to zero for all indexes. Results show none of the indexes can be represented by a normal distribution.

Runs test

A runs test is a non-parametric test that tries to analyse whether there exist a series of returns changes all moving in the same direction. In other words whether price changes are independent or not. Results could be positive in case of returns increments, zero in case of no changes and negative in case of returns decrements.

The null hypothesis states that the series is a random series. Stating the test, this could be demonstrated if the observed number of runs in the series appears to be closer possible to the expected number of runs.
Let’s consider the FTSE IT MICRO CAP index:

(8 vars, 1519 obs)

```
. runtest logreturns
 N(logreturns <= .0002067019959213) = 759
 N(logreturns >  .0002067019959213) = 760
              obs = 1519
           N(runs) = 780
                z  = 1
          Prob>|z| = .32
```

The p-value attests that data are consistent with a random process at the 5% significance level, also the result of the test indicates that z=1 is less than the critical value, hence the returns series appears to follow a random process.

Now, take a look at the gathering outcomes:

ITMI.MI		ITSC.MI		ITLMS.MI		ITMC.MI		ITSTAR.MI		FTSEMIB.MI	
Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value
1	.32	-6	0	.77	.44	-3.23	0	-2.92	0	1.47	.14

Table 4.9 Runs Test for Daily returns on Italian Stock Exchange indexes

The FTSE IT SMALL CAP index definitely shows absence of randomness, as well as the FTSE IT MID CAP and the FTSE ITALIA STAR ones. This means that the RW hypothesis has been rejected for all these three indexes. On the other hand, the FTSE IT ALL-SHS, the FTSE MIB and the FTSE IT MICRO CAP indexes appear all random at significance level. This means that – on the basis of the Runs test – half of the six Italian indexes result efficient looking at day by day opportunities.

Unit Root test

The EMH demands for randomness (so, non-stationarity) in returns series. Established that, it is easy understand what could be the role performed by a unit root test. A unit root test is performed to understand if a series is stationary or less. The test statistic would results higher than the critical value in order not to reject the null hypothesis, and so, in order to verify the existence of the market efficiency.

In this case the null hypothesis states that the variable considered has to be integrated of order one, against the hypothesis of stationarity. The analysis is based on the examination of log prices.

Augmented Dickey-Fuller Test

LEVEL						
	ITMI.MI	ITSC.MI	ITLMS.MI	ITMC.MI	ITSTAR.MI	FTSEMIB.MI
t-Statistic	-1.103242	-1.512297	-2.140894	-1.438197	-0.394105	-2.154447
Prob.*	0.7166	0.5273	0.2287	0.5648	0.9078	0.2235
TEST CRITICAL VALUE						
1% level	-3.434451	-3.434454	-3.434448	-3.434448	-3.434376	-3.434371
5% level	-2.863238	-2.863240	-2.863237	-2.863237	-2.863205	-2.863203
10% level	-2.567722	-2.567723	-2.567722	-2.567722	-2.567705	-2.567703

*MacKinnon (1996) one-sided p-values.

Table 4.1.0 ADF Test for Daily indexes log price (level)

Results of the ADF test show values from -0.394105 to -2.154447. This implies that all the companies appear to have a unit root at daily level. In particular, prices of the FTSE ITALIA STAR index appears strongly not correlated, while FTSE ALL-SHS and FTSEMIB indexes appear not correlated with less evidence. The null hypothesis cannot be reject because all the t-statistic appear smaller than relatives critical values, as well as the results given by p-values. ADF test over daily prices of the Italian Stock Exchange supports the weak form hypothesis.

Philip-Perron Test

The ADF test looks at the issue on the basis of the serial correlation of errors in a parametric way. On the contrary, Philip and Perron proposed a nonparametric method of controlling for serial correlation when testing for a unit root. The PP method estimates the non-augmented

DF test equation modifying the t-ratio of the α coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. So, the main difference between ADF and PP test is that the former suffers the possibility of specification errors, while the latter eliminates the consequences of serial correlation directly esteeming long run effects.

LEVEL						
	ITMI.MI	ITSC.MI	ITLMS.MI	ITMC.MI	ITSTAR.MI	FTSEMIB.MI
t-Statistic	-1.373050	-1.442860	-2.127576	-1.508153	-0.410855	-2.135924
Prob.*	0.5969	0.5624	0.2339	0.5294	0.9049	0.2306
TEST CRITICAL VALUE						
1% level	-3.434451	-3.434448	-3.434448	-3.434448	-3.434374	-3.434371
5% level	-2.863238	-2.863237	-2.863237	-2.863237	-2.863204	-2.863203
10% level	-2.567722	-2.567722	-2.567722	-2.567722	-2.567704	-2.567703

*MacKinnon (1996) one-sided p-values.

Table 4.1.1 PP Test for Daily indexes log prices (level)

The PP test gives back same results of the ADF test, underlying another time the strongly evidence for the FTSE ITALIA STAR case.

Serial Correlation Test

The autocorrelation test is probably the most used test to examine a random walk. This test allows to examine whether stock prices are independent from each other. In this case, log returns have been used instead of simple prices. The hypothesis are the following:

$$\begin{cases} H_0: Data\ are\ independently\ distributed\ (the\ correlations\ are\ equal\ to\ zero, so\ any \\ observed\ correlations\ resilt\ from\ randomness) \\ H_1: The\ data\ are\ not\ independently\ distributed\ (serial\ correlation) \end{cases}$$

The last two columns reported in the correlogram are the Ljung-Box Q-statistics and their *p*-values. The Q-Statistic is a test for the null hypothesis (no autocorrelation up to order *k*). If there is no serial correlation in the residuals, the autocorrelations and partial autocorrelations at all lags should be nearly zero, and all Q-statistics should be insignificant with large p-values.

FTSE IT MICRO CAP (ITMI.MI)	FTSE IT SMALL CAP (ITSC.MI)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.010	0.010	0.1441	0.704
		2	0.047	0.047	3.5530	0.169
		3	0.038	0.038	5.7963	0.122
		4	0.098	0.095	20.439	0.000
		5	0.004	-0.000	20.469	0.001
		6	0.020	0.010	21.092	0.002
		7	0.055	0.049	25.790	0.001
		8	-0.014	-0.025	26.081	0.001
		9	0.057	0.052	30.991	0.000
		10	-0.019	-0.025	31.558	0.000
		11	0.044	0.032	34.565	0.000
		12	0.047	0.049	37.962	0.000
		13	0.026	0.012	39.002	0.000
		14	0.028	0.025	40.196	0.000
		15	0.022	0.010	40.912	0.000
		16	0.079	0.064	50.612	0.000
		17	0.028	0.025	51.808	0.000
		18	-0.027	-0.049	52.958	0.000
		19	-0.026	-0.037	54.017	0.000
		20	-0.034	-0.053	55.816	0.000
		21	-0.031	-0.036	57.297	0.000
		22	0.022	0.032	58.052	0.000
		23	0.021	0.020	58.737	0.000
		24	-0.035	-0.030	60.649	0.000
		25	0.034	0.033	62.387	0.000
		26	0.000	-0.004	62.388	0.000
		27	0.028	0.027	63.627	0.000
		28	0.004	0.000	63.651	0.000
		29	0.002	-0.012	63.659	0.000
		30	0.004	0.005	63.681	0.000
		31	-0.003	-0.007	63.700	0.000
		32	0.018	0.016	64.186	0.001
		33	-0.001	0.006	64.189	0.001
		34	0.001	-0.003	64.192	0.001
		35	-0.031	-0.018	65.665	0.001
		36	0.034	0.036	67.447	0.001

FTSE ITALIA ALL-SHS (ITLMS.MI)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.188	0.188	53.734	0.000
		2	0.103	0.071	70.023	0.000
		3	0.060	0.030	75.519	0.000
		4	0.057	0.036	80.494	0.000
		5	0.028	0.006	81.700	0.000
		6	0.040	0.027	84.174	0.000
		7	-0.072	-0.094	92.206	0.000
		8	0.002	0.023	92.212	0.000
		9	0.042	0.049	94.903	0.000
		10	-0.060	-0.078	100.37	0.000
		11	-0.011	0.011	100.56	0.000
		12	-0.002	0.006	100.57	0.000
		13	0.010	0.017	100.71	0.000
		14	-0.047	-0.059	104.14	0.000
		15	0.018	0.036	104.63	0.000
		16	0.041	0.057	107.18	0.000
		17	0.026	-0.007	108.20	0.000
		18	0.019	0.008	108.74	0.000
		19	0.010	0.008	108.91	0.000
		20	0.026	0.020	109.98	0.000
		21	-0.016	-0.045	110.38	0.000
		22	-0.006	-0.001	110.43	0.000
		23	0.019	0.042	111.01	0.000
		24	-0.000	-0.022	111.01	0.000
		25	0.023	0.023	111.80	0.000
		26	-0.020	-0.024	112.44	0.000
		27	-0.019	-0.008	113.02	0.000
		28	-0.001	-0.003	113.02	0.000
		29	-0.012	-0.015	113.24	0.000
		30	-0.026	-0.001	114.28	0.000
		31	-0.030	-0.033	115.70	0.000
		32	-0.015	-0.000	116.06	0.000
		33	-0.003	0.007	116.08	0.000
		34	0.002	0.003	116.09	0.000
		35	-0.002	0.001	116.10	0.000
		36	-0.015	-0.021	116.44	0.000

FTSE ITALIA MID CAP (ITMC.MI)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.010	0.010	0.1545	0.694
		2	-0.003	-0.003	0.1704	0.918
		3	-0.020	-0.020	0.7757	0.855
		4	-0.013	-0.013	1.0523	0.902
		5	-0.044	-0.044	4.0725	0.539
		6	0.047	0.047	7.4151	0.284
		7	0.005	0.003	7.4531	0.383
		8	-0.006	-0.007	7.5005	0.484
		9	0.020	0.021	8.1201	0.522
		10	-0.025	-0.026	9.0461	0.528
		11	0.024	0.029	9.9254	0.537
		12	-0.011	-0.013	10.112	0.606
		13	0.030	0.029	11.509	0.568
		14	-0.029	-0.028	12.835	0.540
		15	-0.006	-0.009	12.897	0.610
		16	0.036	0.042	14.938	0.529
		17	0.054	0.050	19.490	0.301
		18	-0.027	-0.026	20.585	0.301
		19	-0.030	-0.032	21.933	0.288
		20	-0.007	-0.004	22.011	0.340
		21	-0.023	-0.016	22.812	0.354
		22	0.022	0.019	23.540	0.372
		23	-0.015	-0.021	23.867	0.411
		24	0.001	-0.003	23.869	0.469
		25	0.016	0.020	24.263	0.504
		26	-0.006	-0.009	24.319	0.558
		27	-0.004	0.003	24.339	0.611
		28	0.025	0.020	25.332	0.610
		29	0.012	0.011	25.563	0.649
		30	-0.016	-0.015	25.976	0.676
		31	0.005	0.007	26.011	0.721
		32	-0.005	-0.001	26.048	0.761
		33	-0.020	-0.027	26.689	0.773
		34	-0.039	-0.041	29.087	0.707
		35	0.009	0.011	29.214	0.743
		36	-0.028	-0.024	30.435	0.730

FTSE ITALIA STAR (ITSTAR.MI)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.070	0.070	7.5149	0.006
		2	-0.011	-0.016	7.7158	0.021
		3	-0.005	-0.003	7.7555	0.051
		4	0.005	0.006	7.8016	0.099
		5	-0.039	-0.040	10.160	0.071
		6	-0.006	-0.000	10.216	0.116
		7	0.010	0.010	10.378	0.168
		8	-0.017	-0.019	10.819	0.212
		9	0.005	0.009	10.861	0.285
		10	-0.011	-0.014	11.040	0.354
		11	0.023	0.024	11.823	0.377
		12	-0.009	-0.011	11.935	0.451
		13	0.026	0.027	12.998	0.448
		14	0.015	0.012	13.348	0.499
		15	-0.019	-0.022	13.916	0.532
		16	0.007	0.012	13.988	0.600
		17	0.058	0.056	19.181	0.318
		18	-0.012	-0.020	19.412	0.367
		19	-0.020	-0.014	20.048	0.392
		20	-0.014	-0.014	20.339	0.437
		21	-0.034	-0.032	22.109	0.393
		22	0.035	0.044	24.010	0.347
		23	0.008	0.000	24.102	0.398
		24	-0.037	-0.040	26.209	0.343
		25	0.044	0.052	29.139	0.258
		26	-0.014	-0.027	29.456	0.291
		27	-0.000	0.006	29.456	0.339
		28	-0.000	-0.000	29.456	0.390
		29	0.032	0.027	31.005	0.365
		30	-0.038	-0.041	33.228	0.313
		31	0.002	0.007	33.237	0.359
		32	-0.039	-0.038	35.591	0.303
		33	-0.007	-0.002	35.662	0.344
		34	0.006	0.005	35.714	0.388
		35	-0.001	-0.001	35.716	0.435
		36	-0.016	-0.021	36.139	0.462

FTSE MIB (FTSEMIB.MI)

Lag	AC	PAC	Q-Stat	Prob
1	0.004	0.004	0.0280	0.867
2	-0.010	-0.010	0.1974	0.906
3	-0.019	-0.019	0.7609	0.859
4	-0.013	-0.013	1.0150	0.908
5	-0.044	-0.045	4.0874	0.537
6	0.048	0.047	7.6121	0.268
7	0.006	0.004	7.6606	0.363
8	-0.001	-0.002	7.6625	0.467
9	0.021	0.022	8.3489	0.499
10	-0.023	-0.024	9.1449	0.518
11	0.025	0.030	10.115	0.520
12	-0.012	-0.014	10.341	0.586
13	0.028	0.028	11.565	0.564
14	-0.029	-0.028	12.914	0.533
15	-0.013	-0.016	13.188	0.588
16	0.042	0.047	15.938	0.457
17	0.058	0.054	21.232	0.216
18	-0.026	-0.024	22.259	0.221
19	-0.031	-0.033	23.809	0.204
20	-0.003	-0.001	23.825	0.250
21	-0.019	-0.012	24.415	0.273
22	0.021	0.018	25.123	0.291
23	-0.016	-0.022	25.502	0.325
24	0.000	-0.003	25.502	0.379
25	0.009	0.012	25.622	0.428
26	-0.004	-0.006	25.646	0.483
27	-0.004	0.002	25.673	0.537
28	0.025	0.020	26.673	0.536
29	0.011	0.010	26.863	0.579
30	-0.020	-0.018	27.491	0.597
31	0.009	0.013	27.625	0.640
32	-0.001	0.003	27.626	0.688
33	-0.023	-0.031	28.478	0.692
34	-0.045	-0.048	31.752	0.578
35	0.011	0.013	31.960	0.616
36	-0.031	-0.027	33.518	0.587

Lag	AC	PAC	Q-Stat	Prob
1	0.004	0.004	0.0280	0.867
2	-0.010	-0.010	0.1974	0.906
3	-0.019	-0.019	0.7609	0.859
4	-0.013	-0.013	1.0150	0.908
5	-0.044	-0.045	4.0874	0.537
6	0.048	0.047	7.6121	0.268
7	0.006	0.004	7.6606	0.363
8	-0.001	-0.002	7.6625	0.467
9	0.021	0.022	8.3489	0.499
10	-0.023	-0.024	9.1449	0.518
11	0.025	0.030	10.115	0.520
12	-0.012	-0.014	10.341	0.586
13	0.028	0.028	11.565	0.564
14	-0.029	-0.028	12.914	0.533
15	-0.013	-0.016	13.188	0.588
16	0.042	0.047	15.938	0.457
17	0.058	0.054	21.232	0.216
18	-0.026	-0.024	22.259	0.221
19	-0.031	-0.033	23.809	0.204
20	-0.003	-0.001	23.825	0.250
21	-0.019	-0.012	24.415	0.273
22	0.021	0.018	25.123	0.291
23	-0.016	-0.022	25.502	0.325
24	0.000	-0.003	25.502	0.379
25	0.009	0.012	25.622	0.428
26	-0.004	-0.006	25.646	0.483
27	-0.004	0.002	25.673	0.537
28	0.025	0.020	26.673	0.536
29	0.011	0.010	26.863	0.579
30	-0.020	-0.018	27.491	0.597
31	0.009	0.013	27.625	0.640
32	-0.001	0.003	27.626	0.688
33	-0.023	-0.031	28.478	0.692
34	-0.045	-0.048	31.752	0.578
35	0.011	0.013	31.960	0.616
36	-0.031	-0.027	33.518	0.587

Table 4.1.2 Serial Correlation of Daily Indexes Returns

Correlograms above give some fundamental results. FTSE IT MICRO CAP and FTSE IT SMALL CAP indexes show p-values equal to zero, and so, despite AC and PAC values fluctuating around zero, both these indexes show evidences of serial correlation. This means there exist dependency on returns, hence they cannot be considered efficient under the weak form. FTSE IT MID CAP and FTSE ALL-SHS show lags which tend to zero, with p-values increasing as the number of lags increase. Even FTSE MIB and FTSE ITALIA STAR present AC and PAC values close to zero during all the lags, and big p-values to sustain them.
This results show values different from zero, this implies the possibility of weak efficiency for all the index considered a part the first aforementioned two.

Weekly analysis

Descriptive Analysis

FTSE IT MICRO CAP (ITMI.MI)		FTSE IT SMALL CAP (ITSC.MI)	
Mean	-0.000166	Mean	-0.000820
Median	0.000693	Median	0.003088

Maximum 0.073477	Maximum 0.188200
Minimum -0.084839	Minimum -0.145638
Std. Dev. 0.019353	Std. Dev. 0.030450
Skewness -0.567725	Skewness -0.048941
Kurtosis 6.094205	Kurtosis 9.653034
Jarque-Bera 140.7709	Jarque-Bera 2874.019
Probability 0.000000	Probability 0.000000
FTSE ITALIA ALL-SHS (ITLMS.MI)	FTSE ITALIA MID CAP (ITMC.MI)
Mean -9.66E-05	Mean 0.000587
Median 0.004178	Median 0.004464
Maximum 0.098895	Maximum 0.099089
Minimum -0.166138	Minimum -0.118513
Std. Dev. 0.035876	Std. Dev. 0.030663
Skewness -0.778706	Skewness -0.542197
Kurtosis 4.902333	Kurtosis 4.677453
Jarque-Bera 78.32538	Jarque-Bera 51.70061
Probability 0.000000	Probability 0.000000
FTSE ITALIA STAR (ITSTAR.MI)	FTSE MIB (FTSEMIB.MI)
Mean 0.002418	Mean -0.000154
Median 0.005728	Median 0.003403
Maximum 0.065871	Maximum 0.104721
Minimum -0.127629	Minimum -0.169836
Std. Dev. 0.023588	Std. Dev. 0.037858
Skewness -1.120660	Skewness -0.726880
Kurtosis 6.484522	Kurtosis 4.790298
Jarque-Bera 223.8655	Jarque-Bera 69.36318
Probability 0.000000	Probability 0.000000

Table 4.1.3 Descriptive Analysis of Weekly indexes returns

The descriptive analysis of the index, on the basis of the weekly returns, highlights that all indexes have negative mean a part for FTSE IT MID CAP and FTSE ITALIA STAR indexes. The FTSE ITALIA STAR index has the highest value, whereas FTSE IT SMALL CAP index presents the lowest value. As happened for the daily data FTSE MIB index presents the highest volatility compared with other Italian Stock Exchange indexes, but now the difference from the standard deviation of the FTSE IT ALL-SHS index results hair's-breadth. Yet again FTSE IT MICRO CAP index shows the lowest volatility among Italian indexes. Weekly data attest that all the indexes present negative asymmetry. Even with less evidence, kurtosis values explain that the distributions of all the indexes are strongly centred with lights tails here as well. Jarque-Bera test suggest that all indexes (more or less at the same level) have been extracted by a sample not distributed such as a normal random variable. P-values are equal to zero for all indexes. Results show none of the indexes can be represented by a normal distribution.

Runs Test

ITMI.MI		ITSC.MI		ITLMS.MI		ITMC.MI		ITSTAR.MI		FTSEMIB.MI	
Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value
-3.86	0	-4.08	0	.68	.5	-1.25	.21	-1.19	.23	.06	.95

Table 4.1.4 Runs Test for Weekly returns on Italian Stock Exchange indexes

The p-value attests that FTSE IT MICRO CAP and FTSE IT SMALL CAP indexes are inconsistent at conventional level. The other indexes result consistent with a random process at the 5% significance level. Z-values are less than the critical value, hence the returns series appears to follow a random process, but for the FTSE IT MID CAP and FTSE ITALIA STAR indexes which present z-values higher than the critical one.

It is possible to affirm that only the FTSE IT ALL-SHS and the FTSE MIB indexes are supposed to be efficient on the basis of the runs test.

Unit Root test

Augmented Dickey-Fuller Test

LEVEL						
	ITMI.MI	ITSC.MI	ITLMS.MI	ITMC.MI	ITSTAR.MI	FTSEMIB.MI
t-Statistic	-1.212644	-1.347591	-2.176997	-1.523991	-0.346203	-2.176645
Prob.*	0.6699	0.6080	0.2153	0.5203	0.9148	0.2154

TEST CRITICAL VALUE						
1% level	-3.451214	-3.451214	-3.451214	-3.451214	-3.451146	-3.451146
5% level	-2.870621	-2.870621	-2.870621	-2.870621	-2.870591	-2.870591
10% level	-2.571679	-2.571679	-2.571679	-2.571679	-2.571663	-2.571663

*MacKinnon (1996) one-sided p-values.

Table 4.1.5 ADF Test for Weekly indexes log prices (level)

For what concerns weekly data, ADF statistic fluctuates from -0.346203 (FTSE IT MICRO CAP) to -2.176997 (FTSE ALL-SHS) and the associated one-sided *p*-value (for each index observations) is reliable high, hence p-values indicate that observations are consistent with the null hypothesis. This leads not to rejected the null unit root hypothesis at conventional level. In other words, market indexes suggest the presence of efficiency in the Italian market.

Philip-Perron Test

LEVEL						
	ITMI.MI	ITSC.MI	ITLMS.MI	ITMC.MI	ITSTAR.MI	FTSEMIB.MI
t-Statistic	-1.473871	-1.542083	-2.218229	-1.523991	-0.484485	-2.221724
Prob.*	0.5457	0.5110	0.2003	0.5203	0.8909	0.1990
TEST CRITICAL VALUE						
1% level	-3.451214	-3.451214	-3.451214	-3.451214	-3.451146	-3.451146
5% level	-2.870621	-2.870621	-2.870621	-2.870621	-2.870591	-2.870591
10% level	-2.571679	-2.571679	-2.571679	-2.571679	-2.571663	-2.571663

*MacKinnon (1996) one-sided p-values.

Table 4.1.6 PP Test for Weekly indexes returns (level)

Serial Correlation Test

Remembering that the absence of serial correlation in the residuals is certified by autocorrelations and partial autocorrelations at all lags equal to zero, and an insignificant Q-statistics with large p-values, it is possible to take a look at the current results:

FTSE IT MICRO CAP (ITMI.MI)	FTSE IT SMALL CAP (ITSC.MI)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.083	0.083	2.1686	0.141
		2	0.151	0.145	9.3107	0.010
		3	0.145	0.126	15.976	0.001
		4	-0.110	-0.155	19.784	0.001
		5	0.063	0.044	21.045	0.001
		6	0.045	0.062	21.687	0.001
		7	-0.037	-0.026	22.117	0.002
		8	0.184	0.152	33.012	0.000
		9	-0.119	-0.148	37.540	0.000
		10	-0.006	-0.017	37.553	0.000
		11	0.025	0.013	37.759	0.000
		12	-0.042	0.038	38.342	0.000
		13	-0.033	-0.086	38.708	0.000
		14	-0.064	-0.077	40.060	0.000
		15	-0.004	0.061	40.066	0.000
		16	0.075	0.078	41.941	0.000
		17	-0.007	0.021	41.958	0.001
		18	0.054	-0.005	42.910	0.001
		19	0.129	0.123	48.469	0.000
		20	0.017	0.012	48.564	0.000
		21	0.013	-0.025	48.619	0.001
		22	0.030	0.005	48.922	0.001
		23	0.090	0.103	51.673	0.001
		24	0.034	-0.010	52.060	0.001
		25	-0.051	-0.099	52.960	0.001
		26	0.018	0.004	53.072	0.001
		27	0.043	0.051	53.704	0.002
		28	-0.011	0.020	53.747	0.002
		29	0.055	0.031	54.806	0.003
		30	0.015	-0.000	54.888	0.004
		31	0.004	-0.026	54.892	0.005
		32	-0.025	-0.007	55.112	0.007
		33	-0.068	-0.012	56.724	0.006
		34	0.022	0.009	56.901	0.008
		35	0.041	0.020	57.501	0.010
		36	-0.014	0.007	57.567	0.013

FTSE ITALIA ALL-SHS (ITLMS.MI)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.149	0.149	7.0007	0.008
		2	0.009	-0.014	7.0257	0.030
		3	0.011	0.012	7.0646	0.070
		4	0.054	0.052	7.9877	0.092
		5	-0.019	-0.036	8.1043	0.151
		6	-0.054	-0.047	9.0376	0.171
		7	-0.003	0.012	9.0399	0.250
		8	-0.011	-0.016	9.0775	0.336
		9	-0.076	-0.071	10.946	0.279
		10	-0.052	-0.026	11.815	0.298
		11	-0.013	-0.004	11.866	0.374
		12	0.009	0.010	11.891	0.454
		13	0.050	0.057	12.694	0.472
		14	-0.048	-0.066	13.457	0.491
		15	-0.014	-0.005	13.521	0.562
		16	0.048	0.049	14.297	0.577
		17	0.021	-0.001	14.437	0.636
		18	0.018	0.019	14.546	0.693
		19	0.013	0.007	14.606	0.747
		20	0.034	0.017	14.996	0.777
		21	0.028	0.023	15.258	0.810
		22	0.039	0.045	15.767	0.827
		23	0.034	0.018	16.153	0.849
		24	-0.026	-0.041	16.379	0.874
		25	-0.008	0.006	16.403	0.902
		26	0.025	0.028	16.616	0.920
		27	0.048	0.054	17.420	0.920
		28	-0.002	-0.008	17.421	0.940
		29	-0.014	-0.016	17.488	0.954
		30	-0.006	0.001	17.498	0.966
		31	-0.083	-0.082	19.915	0.938
		32	-0.131	-0.102	25.894	0.768
		33	-0.081	-0.051	28.215	0.704
		34	0.016	0.031	28.310	0.742
		35	0.055	0.060	29.358	0.737
		36	0.011	0.015	29.401	0.774

FTSE ITALIA MID CAP (ITMC.MI)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.005	-0.005	0.0082	0.928
		2	0.017	0.017	0.1034	0.950
		3	0.038	0.038	0.5494	0.908
		4	-0.032	-0.032	0.8818	0.927
		5	-0.020	-0.021	1.0047	0.962
		6	-0.025	-0.026	1.2052	0.977
		7	-0.025	-0.023	1.4128	0.985
		8	-0.003	-0.002	1.4164	0.994
		9	-0.150	-0.149	8.6804	0.467
		10	-0.076	-0.080	10.524	0.396
		11	0.029	0.031	10.800	0.460
		12	-0.027	-0.015	11.038	0.526
		13	0.029	0.022	11.318	0.584
		14	0.067	0.056	12.807	0.542
		15	-0.001	-0.008	12.807	0.617
		16	0.015	0.002	12.885	0.681
		17	0.028	0.023	13.143	0.727
		18	-0.007	-0.025	13.160	0.782
		19	0.000	-0.023	13.160	0.830
		20	0.033	0.040	13.513	0.854
		21	-0.048	-0.046	14.297	0.857
		22	0.051	0.056	15.186	0.854
		23	0.011	0.038	15.228	0.886
		24	-0.046	-0.039	15.944	0.890
		25	-0.048	-0.058	16.727	0.891
		26	-0.052	-0.041	17.637	0.889
		27	-0.005	-0.005	17.644	0.914
		28	-0.026	-0.034	17.885	0.929
		29	-0.034	-0.023	18.275	0.938
		30	0.015	-0.001	18.357	0.952
		31	-0.025	-0.024	18.578	0.962
		32	-0.049	-0.033	19.408	0.961
		33	-0.065	-0.090	20.871	0.950
		34	0.055	0.032	21.944	0.945
		35	0.046	0.037	22.677	0.946
		36	0.036	0.022	23.140	0.952

FTSE ITALIA STAR (ITSTAR.MI)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.036	-0.036	0.4005	0.527
		2	0.020	0.019	0.5284	0.768
		3	0.037	0.039	0.9640	0.810
		4	-0.025	-0.022	1.1548	0.885
		5	-0.030	-0.033	1.4403	0.920
		6	-0.024	-0.027	1.6228	0.951
		7	-0.005	-0.004	1.6317	0.977
		8	0.093	0.096	4.4071	0.819
		9	-0.124	-0.118	9.3644	0.404
		10	-0.110	-0.128	13.304	0.207
		11	0.017	0.006	13.400	0.268
		12	0.036	0.060	13.817	0.313
		13	0.053	0.069	14.749	0.323
		14	0.042	0.034	15.335	0.356
		15	0.035	0.015	15.738	0.400
		16	0.059	0.044	16.902	0.392
		17	-0.027	0.004	17.142	0.445
		18	-0.007	0.002	17.159	0.512
		19	0.039	0.011	17.660	0.545
		20	0.048	0.039	18.438	0.559
		21	-0.034	-0.025	18.819	0.597
		22	0.064	0.080	20.206	0.570
		23	-0.037	-0.017	20.669	0.601
		24	-0.016	-0.015	20.756	0.653
		25	-0.023	-0.012	20.936	0.696
		26	-0.042	-0.038	21.542	0.713
		27	0.066	0.055	23.050	0.682
		28	-0.009	-0.012	23.076	0.729
		29	-0.024	-0.017	23.279	0.764
		30	0.019	-0.004	23.400	0.798
		31	-0.042	-0.032	24.014	0.810
		32	-0.004	0.002	24.018	0.844
		33	0.003	-0.006	24.022	0.873
		34	-0.006	-0.014	24.036	0.898
		35	0.052	0.018	24.976	0.895
		36	0.021	0.030	25.133	0.913

FTSE MIB (FTSEMIB.MI)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.052	0.052	0.8398	0.359
		2	0.078	0.076	2.7844	0.249
		3	0.008	0.001	2.8061	0.422
		4	0.011	0.004	2.8425	0.585
		5	0.003	0.001	2.8450	0.724
		6	-0.038	-0.040	3.3132	0.769
		7	-0.008	-0.005	3.3334	0.853
		8	0.073	0.080	5.0371	0.754
		9	-0.067	-0.074	6.4898	0.690
		10	-0.096	-0.103	9.5188	0.484
		11	0.029	0.051	9.7858	0.550
		12	-0.035	-0.026	10.198	0.599
		13	0.059	0.058	11.348	0.582
		14	0.066	0.077	12.798	0.542
		15	0.032	0.010	13.136	0.592
		16	0.048	0.019	13.892	0.607
		17	0.007	0.013	13.908	0.674
		18	-0.074	-0.077	15.717	0.612
		19	-0.002	-0.013	15.718	0.676
		20	0.028	0.051	15.979	0.718
		21	0.011	0.003	16.017	0.769
		22	0.093	0.084	18.964	0.648
		23	-0.027	-0.014	19.207	0.689
		24	-0.030	-0.050	19.518	0.724
		25	-0.034	-0.023	19.909	0.752
		26	-0.031	-0.002	20.246	0.780
		27	0.054	0.045	21.234	0.775
		28	0.004	-0.013	21.241	0.815
		29	-0.051	-0.060	22.156	0.814
		30	-0.000	-0.017	22.156	0.848
		31	-0.027	-0.002	22.418	0.869
		32	-0.092	-0.065	25.370	0.791
		33	-0.069	-0.067	27.026	0.759
		34	0.006	0.029	27.038	0.796
		35	0.031	0.014	27.389	0.817
		36	-0.008	-0.026	27.413	0.847

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.003	-0.003	0.0034	0.954
		2	0.025	0.025	0.1989	0.905
		3	0.039	0.039	0.6742	0.879
		4	-0.026	-0.027	0.8965	0.925
		5	-0.033	-0.035	1.2471	0.940
		6	-0.021	-0.021	1.3880	0.967
		7	-0.033	-0.030	1.7428	0.973
		8	-0.026	-0.023	1.9623	0.982
		9	-0.148	-0.148	9.1082	0.427
		10	-0.071	-0.074	10.735	0.379
		11	0.034	0.038	11.105	0.435
		12	-0.037	-0.027	11.557	0.482
		13	0.021	0.013	11.709	0.552
		14	0.081	0.067	13.897	0.457
		15	-0.007	-0.014	13.912	0.532
		16	0.021	0.005	14.053	0.595
		17	0.043	0.029	14.679	0.619
		18	-0.006	-0.025	14.690	0.683
		19	0.006	-0.014	14.700	0.741
		20	0.030	0.037	14.999	0.776
		21	-0.044	-0.041	15.649	0.789
		22	0.050	0.054	16.501	0.790
		23	0.013	0.044	16.562	0.830
		24	-0.054	-0.048	17.573	0.823
		25	-0.052	-0.061	18.494	0.821
		26	-0.050	-0.034	19.341	0.822
		27	-0.011	-0.007	19.379	0.856
		28	-0.025	-0.031	19.597	0.879
		29	-0.035	-0.025	20.031	0.892
		30	0.021	0.006	20.179	0.912
		31	-0.026	-0.027	20.424	0.926
		32	-0.036	-0.021	20.889	0.934
		33	-0.067	-0.100	22.468	0.917
		34	0.058	0.029	23.642	0.908
		35	0.040	0.039	24.215	0.915
		36	0.040	0.022	24.795	0.921

Table 4.1.7 Serial Correlation of Weekly Indexes Returns

The serial correlation test performed casts light on weekly data nature. None of the indexes show AC values equal to zero, but most of them are close to zero, especially in the first three lags. There is absence of serial correlation, so there is no possibility to reject the null hypothesis, a part for FTSE IT MICRO CAP that shows no reliable significance.

<u>Monthly analysis</u>

Descriptive Analysis

Hereunder there is the descriptive analysis of monthly data (Table 4.2.2). Indexes show both negative and positive mean as before. Here, the highest mean is represented by the FTSE ITALIA STAR index, while the lowest one by the FTSE IT SMALL CAP index. FTSE MIB, FTSE IT ALL-SHS and FTSE IT SMALL CAP indexes, in order of size, show the highest volatility compared with the others, proving a dispersion of data higher with respect to other indexes. The FTSE IT MICRO CAP index proves itself again to be the less volatile index. Skweness indicates that more than the half of the indexes present negative asymmetry, the remaining ones positive asymmetry. Kurtosis highlights, with less power than daily and weekly tests, that indexes are all centred with lights tails. Jarque-Bera test suggest that all indexes could be part of a sample distributed such as a normal random variable. P-values are significant at conventional level. So, results show the possibility that these indexes can be represented by a normal distribution.

FTSE IT MICRO CAP (ITMI.MI)		FTSE IT SMALL CAP (ITSC.MI)	
Mean	-0.000533	Mean	-0.003192
Median	-0.004399	Median	0.001138
Maximum	0.101259	Maximum	0.153825
Minimum	-0.106699	Minimum	-0.167443
Std. Dev.	0.042944	Std. Dev.	0.062911
Skewness	0.002743	Skewness	-0.066219
Kurtosis	2.557975	Kurtosis	3.194997
Jarque-Bera	0.586248	Jarque-Bera	0.166691
Probability	0.745929	Probability	0.920033
FTSE ITALIA ALL-SHS (ITLMS.MI)		FTSE ITALIA MID CAP (ITMC.MI)	
Mean	0.000204	Mean	0.003156
Median	0.001335	Median	0.007948
Maximum	0.175204	Maximum	0.140468
Minimum	-0.150522	Minimum	-0.130417
Std. Dev.	0.064445	Std. Dev.	0.052619
Skewness	-0.142062	Skewness	0.067841
Kurtosis	2.776273	Kurtosis	2.613736
Jarque-Bera	0.392341	Jarque-Bera	0.502829
Probability	0.821872	Probability	0.777700
FTSE ITALIA STAR (ITSTAR.MI)		FTSE MIB (FTSEMIB.MI)	
Mean	0.010833	Mean	-0.000323
Median	0.013298	Median	0.001949
Maximum	0.143101	Maximum	0.188966
Minimum	-0.109644	Minimum	-0.169271
Std. Dev.	0.044428	Std. Dev.	0.068631
Skewness	-0.022868	Skewness	-0.169041
Kurtosis	3.599380	Kurtosis	2.960027

Jarque-Bera	1.084045	Jarque-Bera	0.347693
Probability	0.581571	Probability	0.840426

Table 4.1.8 Descriptive Analysis of Monthly indexes returns

Runs test

ITMI.MI		ITSC.MI		ITLMS.MI		ITMC.MI		ITSTAR.MI		FTSEMIB.MI	
Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value
-.95	.34	.47	.63	0	1	-.95	34	-.47	.63	0	1

Table 4.1.9 Runs Test for Monthly returns on Italian Stock Exchange indexes

All the indexes based on monthly data appear to follow a random process at the 5% significance level. This means that – on the basis of the Runs test – all Italian indexes result efficient looking at month by month opportunities.

Unit Root test

Augmented Dickey-Fuller Test

LEVEL						
	ITMI.MI	ITSC.MI	ITLMS.MI	ITMC.MI	ITSTAR.MI	FTSEMIB.MI
t-Statistic	-1.636714	-1.233176	-1.910166	-1.290406	-1.196992	-1.900363
Prob.*	0.4587	0.6558	0.3259	0.6298	0.6715	0.3304
TEST CRITICAL VALUE						
1% level	-3.527045	-3.525618	-3.525618	-3.525618	-3.527045	-3.525618
5% level	-2.903566	-2.902953	-2.902953	-2.902953	-2.903566	-2.902953
10% level	-2.589227	-2.588902	-2.588902	-2.588902	-2.589227	-2.588902

*MacKinnon (1996) one-sided p-values.

Table 4.2.0 ADF Test for Monthly indexes returns (level)

Results are smaller with respect to the critical values and the associated one-sided *p*-value indicates that observations are consistent with the null hypothesis. This leads not to rejected the null unit root hypothesis at conventional level. In other words, market indexes suggest the presence of weak efficiency in the Italian market, even for FTSEMIB and ITLMS which show higher value than the values of the other indexes. This is confirmed by the PP test below too.

Philip-Perron Test

LEVEL						
	ITMI.MI	ITSC.MI	ITLMS.MI	ITMC.MI	ITSTAR.MI	FTSEMIB.MI
t-Statistic	-1.478253	-1.327966	-1.887157	-1.467209	-0.736188	-1.853117
Prob.*	0.5389	0.6123	0.3365	0.5444	0.8303	0.3524
TEST CRITICAL VALUE						
1% level	-3.525618	-3.525618	-3.525618	-3.525618	-3.525618	-3.525618
5% level	-2.902953	-2.902953	-2.902953	-2.902953	-2.902953	-2.902953
10% level	-2.588902	-2.588902	-2.588902	-2.588902	-2.588902	-2.588902

*MacKinnon (1996) one-sided p-values.

Table 4.2.1 PP Test for Monthly indexes log prices (level)

Serial Correlation Test

FTSE IT MICRO CAP (ITMI.MI)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.257	0.257	4.9629	0.026
		2	0.097	0.033	5.6852	0.058
		3	-0.058	-0.097	5.9445	0.114
		4	0.139	0.187	7.4582	0.114
		5	0.074	0.005	7.8878	0.163
		6	0.116	0.069	8.9676	0.175
		7	0.021	0.000	9.0033	0.252
		8	-0.083	-0.130	9.5714	0.296
		9	-0.133	-0.083	11.067	0.271
		10	-0.105	-0.070	12.005	0.285
		11	0.020	0.055	12.042	0.361
		12	-0.065	-0.083	12.418	0.413
		13	-0.038	0.014	12.549	0.483
		14	-0.074	0.002	13.049	0.523
		15	-0.027	-0.010	13.118	0.593
		16	-0.075	-0.038	13.653	0.625
		17	-0.032	-0.029	13.752	0.685
		18	-0.049	-0.038	13.992	0.730
		19	0.011	0.026	14.005	0.783
		20	-0.026	-0.022	14.075	0.827
		21	-0.161	-0.183	16.795	0.723
		22	-0.176	-0.103	20.114	0.576
		23	-0.147	-0.079	22.458	0.493
		24	-0.039	-0.015	22.629	0.542
		25	-0.062	-0.040	23.067	0.574
		26	-0.062	-0.041	23.519	0.603
		27	-0.099	-0.019	24.690	0.592
		28	-0.180	-0.163	28.618	0.432
		29	-0.092	-0.015	29.666	0.431
		30	0.011	-0.015	29.681	0.482
		31	0.067	-0.017	30.272	0.503
		32	-0.043	-0.069	30.519	0.542

FTSE IT SMALL CAP (ITSC.MI)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.139	0.139	1.4415	0.230
		2	-0.051	-0.071	1.6361	0.441
		3	-0.016	0.002	1.6550	0.647
		4	0.089	0.089	2.2696	0.686
		5	0.014	-0.013	2.2858	0.808
		6	0.078	0.091	2.7828	0.836
		7	-0.100	-0.128	3.6048	0.824
		8	-0.142	-0.112	5.2818	0.727
		9	-0.063	-0.037	5.6155	0.778
		10	0.010	-0.010	5.6248	0.846
		11	-0.083	-0.075	6.2312	0.858
		12	0.064	0.109	6.5977	0.883
		13	-0.012	-0.022	6.6103	0.921
		14	-0.075	-0.057	7.1215	0.930
		15	0.037	0.061	7.2471	0.950
		16	-0.007	-0.083	7.2522	0.968
		17	-0.053	-0.033	7.5233	0.976
		18	0.080	0.082	8.1616	0.976
		19	0.069	0.027	8.6384	0.979
		20	-0.032	-0.010	8.7407	0.986
		21	-0.043	-0.031	8.9331	0.990
		22	-0.058	-0.089	9.2933	0.992
		23	-0.046	-0.022	9.5239	0.994
		24	0.073	0.056	10.117	0.994
		25	-0.002	-0.048	10.118	0.996
		26	-0.257	-0.203	17.789	0.883
		27	-0.161	-0.090	20.848	0.793
		28	-0.214	-0.269	26.379	0.552
		29	-0.033	0.012	26.515	0.598
		30	0.001	-0.036	26.515	0.649
		31	-0.032	-0.054	26.650	0.690
		32	-0.161	-0.073	30.120	0.562

FTSE ITALIA ALL-SHS (ITLMS.MI)

FTSE ITALIA MID CAP (ITMC.MI)

Lag	AC	PAC	Q-Stat	Prob
1	0.066	0.066	0.3267	0.568
2	-0.237	-0.242	4.5868	0.101
3	0.101	0.146	5.3771	0.146
4	0.082	0.000	5.9023	0.207
5	-0.109	-0.064	6.8491	0.232
6	-0.052	-0.029	7.0705	0.314
7	-0.076	-0.131	7.5410	0.375
8	-0.081	-0.065	8.0869	0.425
9	0.062	0.050	8.4142	0.493
10	0.060	0.033	8.7260	0.558
11	-0.005	0.037	8.7283	0.647
12	-0.076	-0.093	9.2394	0.682
13	-0.026	-0.048	9.3012	0.750
14	-0.007	-0.056	9.3056	0.811
15	0.074	0.087	9.8125	0.831
16	0.002	0.006	9.8128	0.876
17	-0.118	-0.080	11.167	0.848
18	0.137	0.153	13.015	0.791
19	0.011	-0.122	13.028	0.837
20	-0.072	0.022	13.558	0.852
21	0.072	0.054	14.093	0.866
22	-0.006	-0.054	14.097	0.898
23	-0.097	0.000	15.126	0.890
24	-0.064	-0.129	15.574	0.903
25	-0.087	-0.122	16.424	0.902
26	-0.190	-0.199	20.606	0.762
27	0.039	0.050	20.790	0.796
28	-0.159	-0.286	23.864	0.689
29	-0.050	0.045	24.179	0.720
30	0.155	0.042	27.226	0.611
31	0.044	-0.075	27.473	0.648
32	-0.165	-0.133	31.120	0.511

Lag	AC	PAC	Q-Stat	Prob
1	0.156	0.156	1.8313	0.176
2	-0.076	-0.102	2.2653	0.322
3	0.142	0.177	3.8171	0.282
4	0.169	0.111	6.0497	0.195
5	-0.049	-0.072	6.2371	0.284
6	0.046	0.079	6.4061	0.379
7	0.000	-0.081	6.4061	0.493
8	-0.101	-0.087	7.2590	0.509
9	0.040	0.078	7.3917	0.596
10	0.061	0.006	7.7085	0.657
11	0.003	0.051	7.7093	0.739
12	-0.039	-0.034	7.8459	0.797
13	-0.031	-0.061	7.9323	0.848
14	-0.076	-0.071	8.4636	0.864
15	0.021	0.036	8.5061	0.902
16	-0.069	-0.089	8.9547	0.915
17	-0.145	-0.080	11.003	0.856
18	-0.002	0.052	11.004	0.894
19	-0.110	-0.162	12.212	0.876
20	-0.085	0.025	12.959	0.879
21	-0.041	-0.051	13.139	0.904
22	-0.128	-0.145	14.898	0.867
23	-0.062	0.082	15.320	0.883
24	-0.010	-0.074	15.330	0.911
25	-0.007	0.040	15.335	0.933
26	-0.188	-0.167	19.431	0.818
27	-0.069	-0.051	19.987	0.831
28	-0.143	-0.178	22.459	0.760
29	-0.023	0.055	22.526	0.798
30	0.054	0.069	22.898	0.819
31	-0.028	-0.058	23.001	0.849
32	-0.206	-0.132	28.650	0.637

FTSE ITALIA STAR (ITSTAR.MI)

FTSE MIB (FTSEMIB.MI)

Lag	AC	PAC	Q-Stat	Prob
1	0.292	0.292	6.3887	0.011
2	-0.041	-0.138	6.5148	0.038
3	0.095	0.166	7.2111	0.065
4	0.055	-0.040	7.4506	0.114
5	-0.072	-0.062	7.8630	0.164
6	0.021	0.068	7.9003	0.245
7	-0.118	-0.198	9.0384	0.250
8	-0.173	-0.047	11.528	0.174
9	0.087	0.153	12.167	0.204
10	0.008	-0.110	12.172	0.274
11	-0.080	0.036	12.732	0.311
12	0.073	0.064	13.211	0.354
13	0.013	-0.090	13.226	0.431
14	-0.054	0.039	13.489	0.488
15	0.083	0.032	14.131	0.516
16	-0.001	-0.075	14.131	0.589
17	-0.119	-0.013	15.512	0.559
18	0.039	0.031	15.660	0.616
19	0.028	-0.024	15.742	0.674
20	-0.074	0.004	16.300	0.698
21	-0.027	-0.060	16.379	0.748
22	-0.018	-0.010	16.413	0.795
23	-0.114	-0.064	17.825	0.767
24	0.027	0.042	17.904	0.808
25	-0.022	-0.085	17.957	0.844
26	-0.247	-0.187	25.038	0.517
27	-0.243	-0.172	32.029	0.231
28	-0.193	-0.180	36.540	0.129
29	-0.050	0.117	36.852	0.150
30	0.007	-0.053	36.858	0.181
31	0.015	0.023	36.887	0.215
32	-0.079	-0.058	37.713	0.224

Lag	AC	PAC	Q-Stat	Prob
1	0.056	0.056	0.2358	0.627
2	-0.259	-0.263	5.3609	0.069
3	0.107	0.151	6.2432	0.100
4	0.096	0.005	6.9705	0.137
5	-0.103	-0.051	7.8179	0.167
6	-0.061	-0.037	8.1228	0.229
7	-0.077	-0.134	8.6061	0.282
8	-0.065	-0.057	8.9558	0.346
9	0.066	0.049	9.3247	0.408
10	0.043	0.025	9.4834	0.487
11	0.014	0.065	9.5013	0.576
12	-0.082	-0.113	10.099	0.607
13	-0.038	-0.044	10.232	0.675
14	0.007	-0.058	10.236	0.745
15	0.065	0.073	10.625	0.779
16	-0.002	0.021	10.625	0.832
17	-0.113	-0.082	11.859	0.809
18	0.145	0.166	13.920	0.734
19	0.011	-0.128	13.932	0.788
20	-0.079	0.020	14.565	0.801
21	0.078	0.060	15.197	0.813
22	0.002	-0.055	15.198	0.854
23	-0.100	0.010	16.290	0.843
24	-0.070	-0.144	16.833	0.856
25	-0.092	-0.127	17.796	0.851
26	-0.184	-0.205	21.700	0.705
27	0.060	0.059	22.127	0.731
28	-0.163	-0.279	25.361	0.608
29	-0.062	0.033	25.830	0.635
30	0.168	0.054	29.395	0.497
31	0.044	-0.074	29.647	0.536
32	-0.169	-0.137	33.454	0.397

Table 4.2.2 Serial Correlation of Monthly Indexes Returns

All data indexes show large p-values with significant Q-statistic results and autocorrelation values close to zero. There is absence of serial correlation, and so the null hypothesis results to be respected. Be careful, serial correlation test has been performed with log return data.

Companies Analysis

Purpose of the analysis on Companies: although the analysis over indexes looks at the whole market, it is interesting to look at specific companies as well. If it could be proved that even companies which form the market indexes are subjected to the efficient market hypothesis, hence it is possible to affirm the EMH holds for the Italian market as whole.

4.1.4 Data

As done before for the indexes, now the first step in order to examine specific companies of the Italian Market is defining data. Data collected for the study of the companies consist of observations for the period January 1, 2009-December 31, 2014.

This empirical analysis of this study uses data of adjusted close prices for eight companies quoted on the FTSE MIB index of the Italian Stock Exchange: BMPS (BANCA MONTE PASCHI SIENA); ENEL.MI; ENI.MI; FNC.MI (FINMECCANICA); ISP.MI (INTESA SAN PAOLO); MS.MI (MEDIASET); TIT.MI (TELECOM ITALIA); UCG.MI (UNICREDIT). This companies have been chosen on the basis of their actual financial situation (especially to observe the trends generated by BMPS), as well as the opportunity to look at big companies operating in different industries. The choice comes from my personal belief that the behaviour of these companies do not get too away from other companies of the FTSE MIB, indeed these companies have a long existence, as well as being well renowned in the Country. Moreover these companies did not enjoy merger and acquisition over time (i.e., FCA is not part of the sample because trends would be distorted)

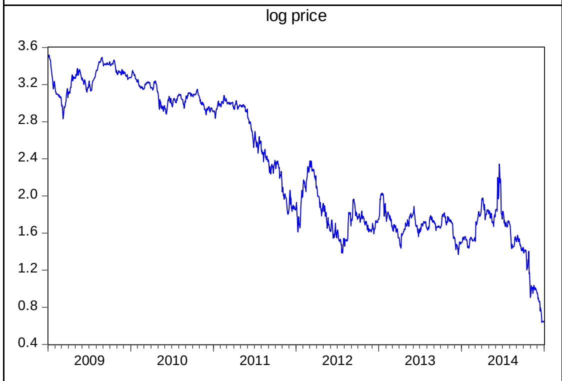
Index	Notations	Sample Period	Observations		
			Daily	Weekly	Monthly
BANCA MONTE PASCHI SIENA	BMPS	1/1/2009-31/12/2014	1566	314	73
ENEL	ENEL.MI	1/1/2009-31/12/2014	1566	314	73
ENI	ENI.MI	1/1/2009-31/12/2014	1566	314	73
FINMECCANICA	FNC.MI	1/1/2009-31/12/2014	1566	314	73
INTESA SAN PAOLO	ISP.MI	1/1/2009-31/12/2014	1566	314	73
MEDIASET	MS.MI	1/1/2009-31/12/2014	1566	314	73
TELECOM	TIT.MI	1/1/2009-	1566	314	73

		31/12/2014			
ITALIA UNICREDIT	UCG.MI	1/1/2009-31/12/2014	1566	314	73

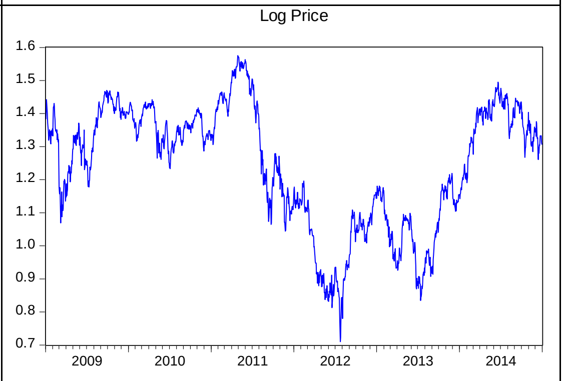
Table 4.2.3 Description of Data Samples (Companies)

Hereinafter I drew companies graphs divided on the basis of days, weeks and months during the six years above defined. Log prices are used in the analysis.

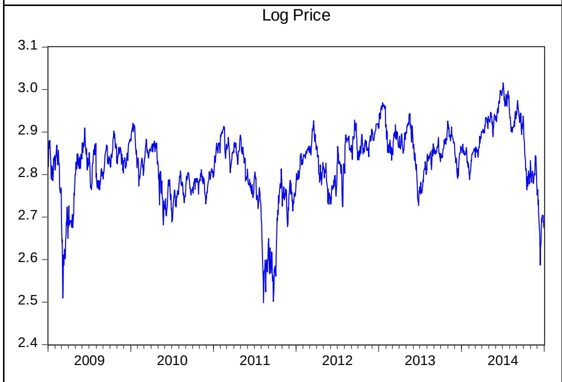
BMPS



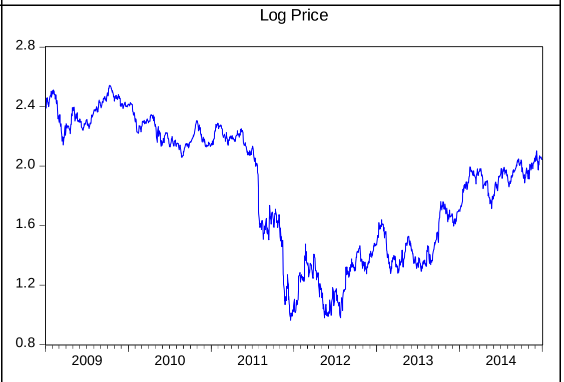
ENEL.MI



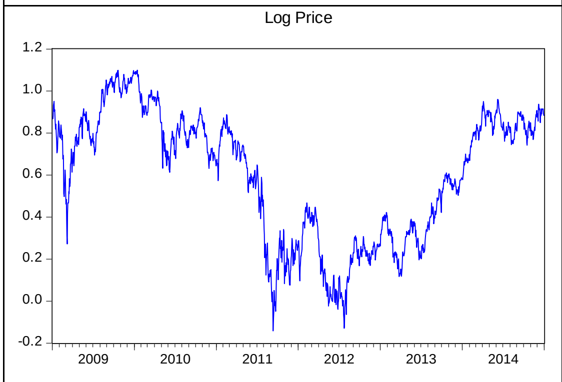
ENI.MI



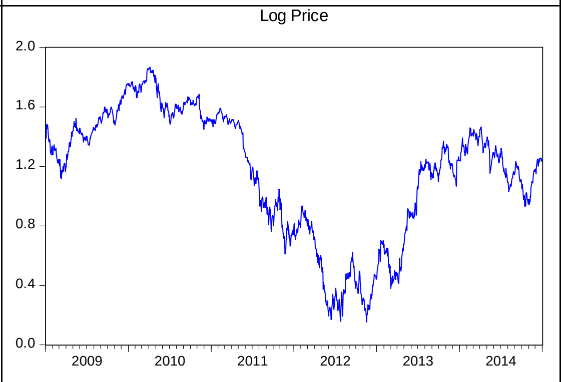
FNC.MI



ISP.MI

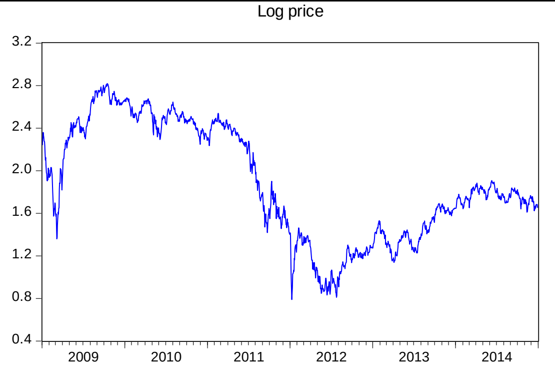


MS.MI



UCG.MI

TIT.MI



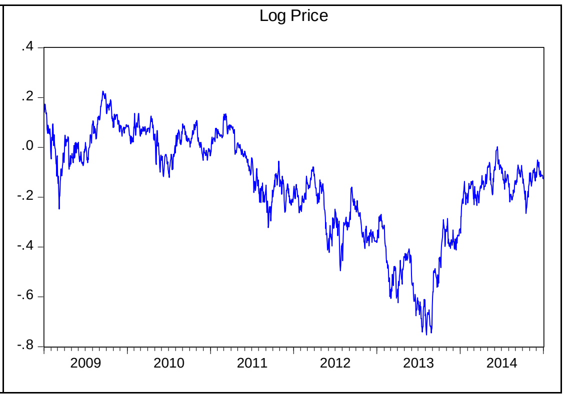
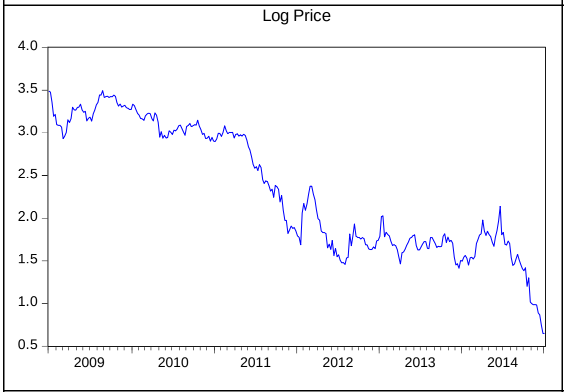
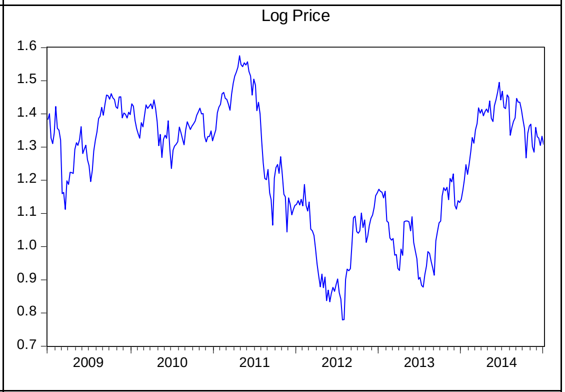


Table 4.2.4 Time Series Plots of Daily Prices of FTSE MIB Selected Companies

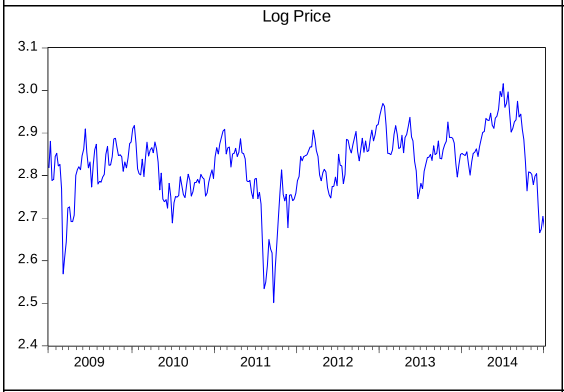
The daily graphic analysis leads to make some considerations. BMPS shows weak appearance a negative trend that approximately starts in 2010 and causes a reliable slowdown in 2011. Indeed it is well known what is the situation of the Bank nowadays. Other indexes, on the other hand, suggest that the changes of trends are casual, and they appear to have permanent effect on following values. This could mean there exist presence of unit roots in the time series relatives to selected companies' prices.

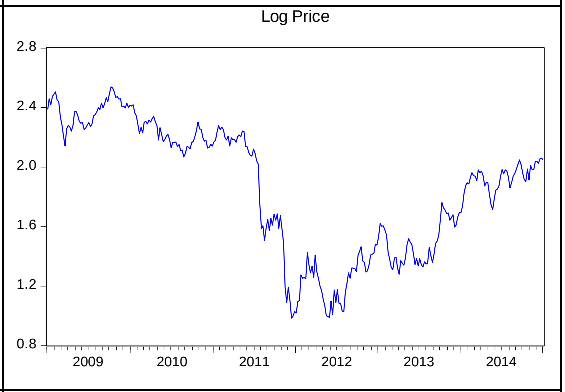
BMPS	ENEL.MI



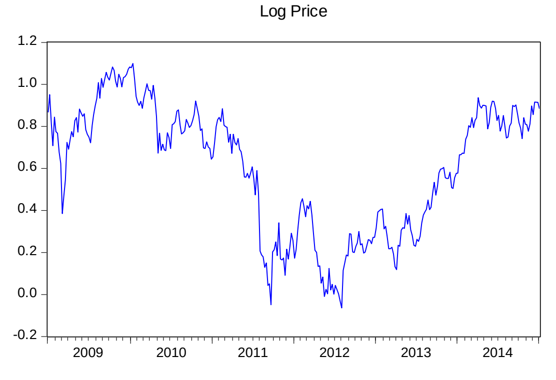


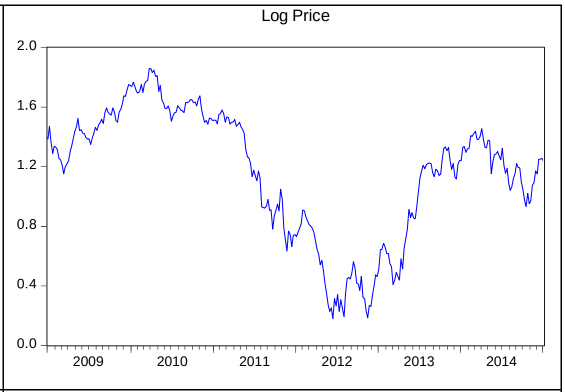
ENI.MI	FNC.MI



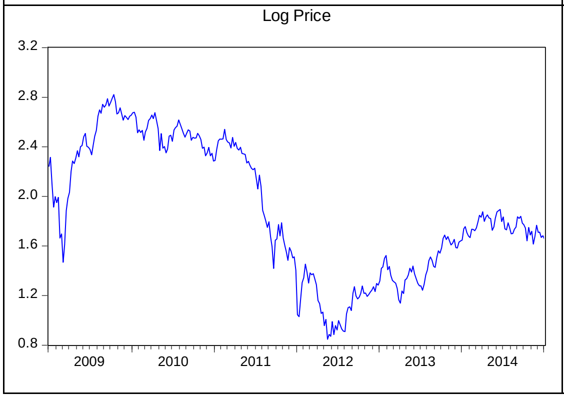


ISP.MI	MS.MI





UCG.MI	TIT.MI



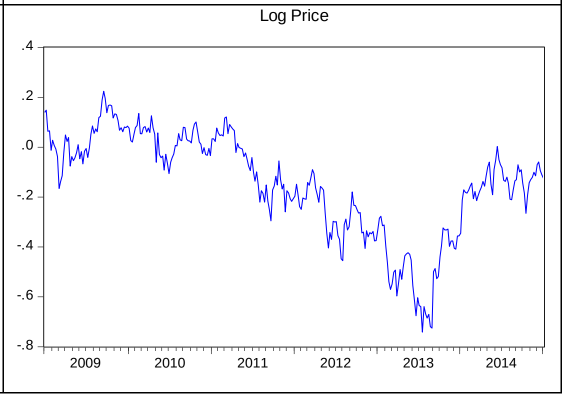
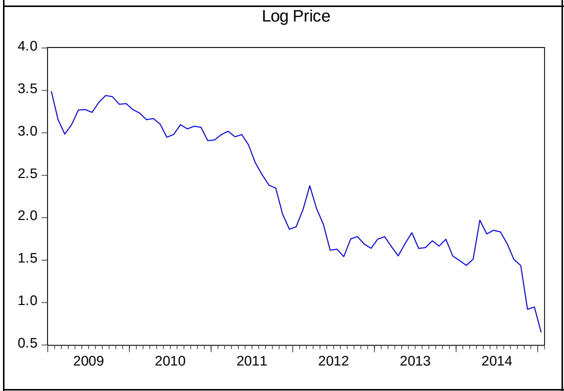
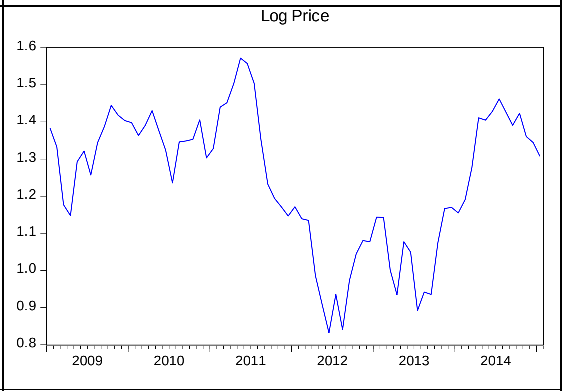


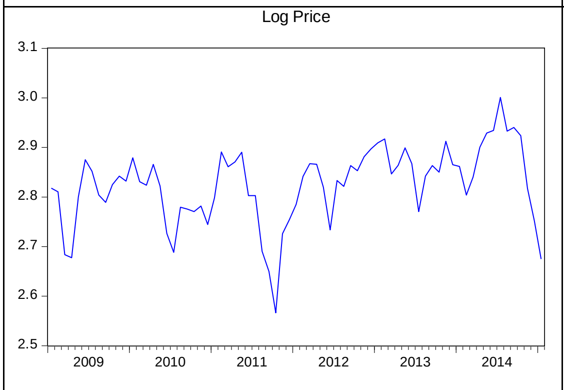
Table 4.2.5 Time Series Plots of Weekly Prices of FTSE MIB Selected Companies

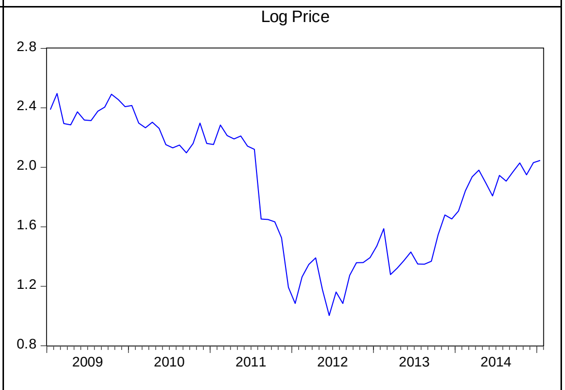
BMPS	ENEL.MI



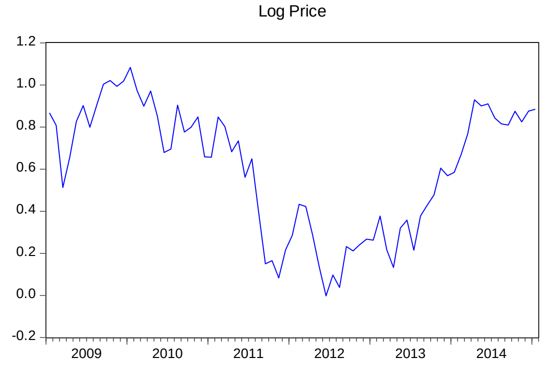


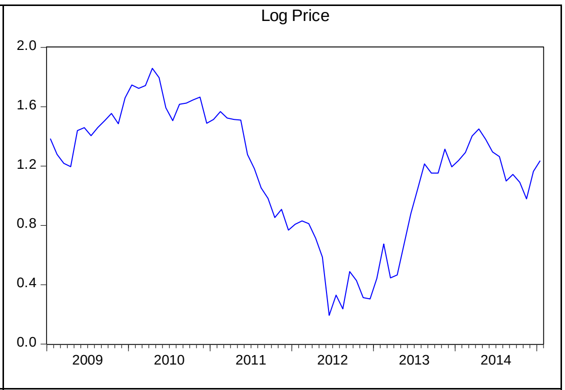
ENI.MI	FNC.MI



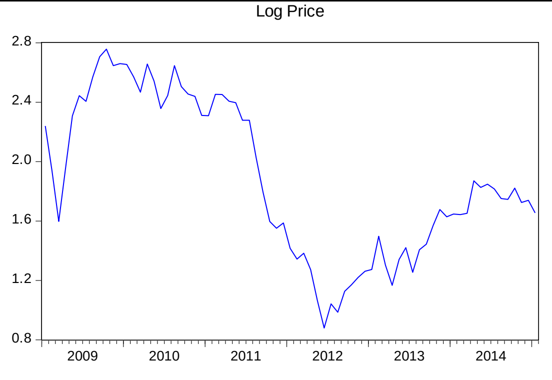


ISP.MI	MS.MI





UCG.MI	TIT.MI



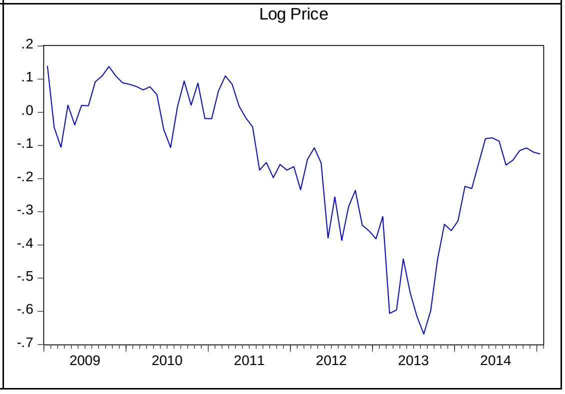
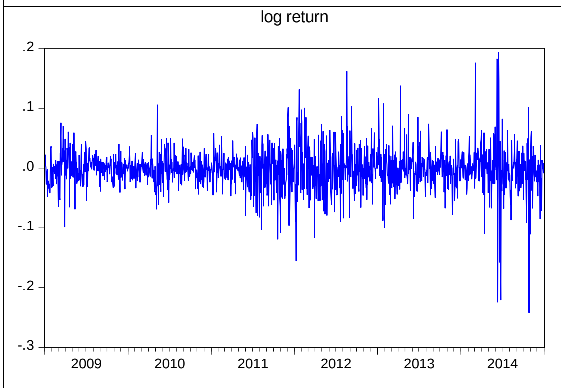


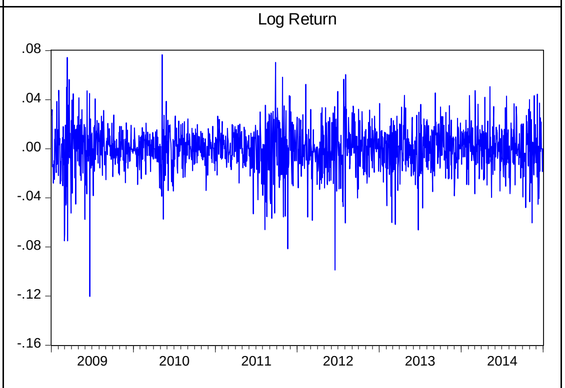
Table 4.2.6 Time Series Plots of Monthly Prices of FTSE MIB Selected Companies

Although there are some differences, it is quite evident that daily, weekly and monthly data of the same company show the same trend over time. It is remarkable to underline that Intesa San Paolo does not show any trends in any timeline.

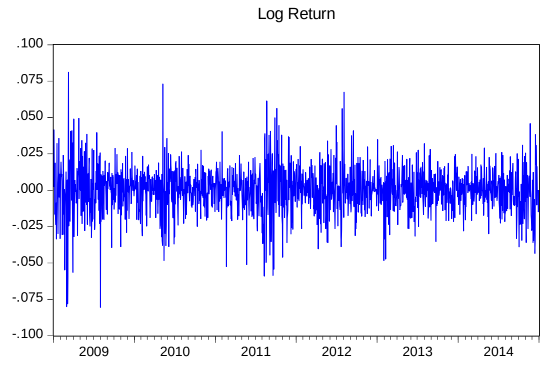
It is possible to examine companies' trends looking at log returns.

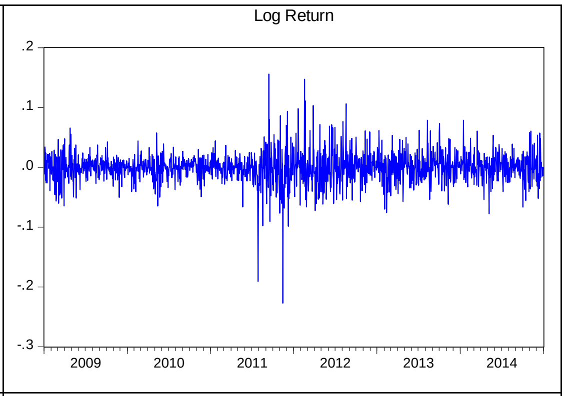
BMPS	ENEL.MI



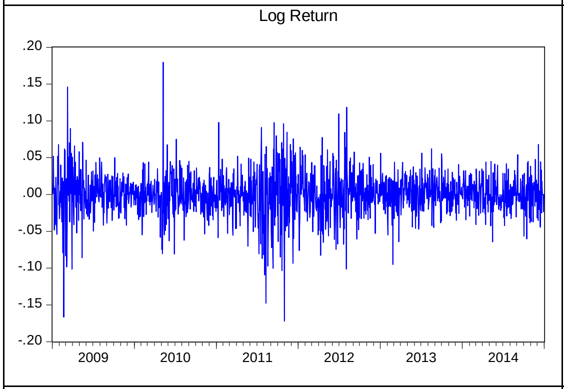


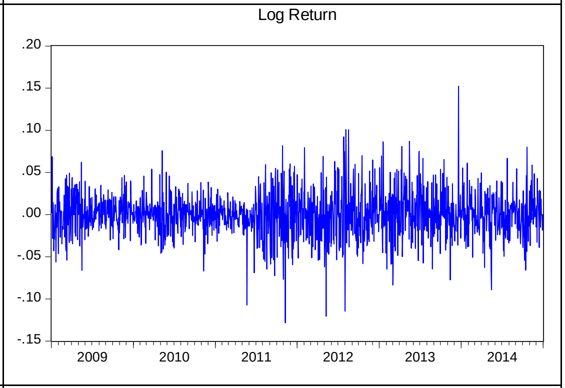
ENI.MI	FNC.MI



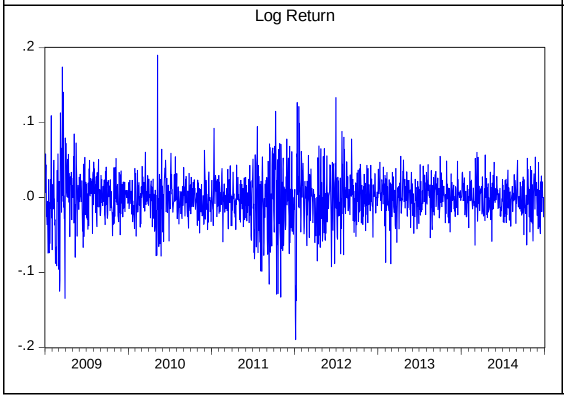


ISP.MI	MS.MI





UCG.MI	TIT.MI



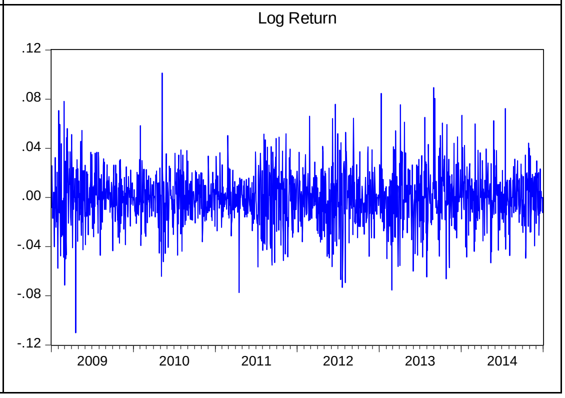
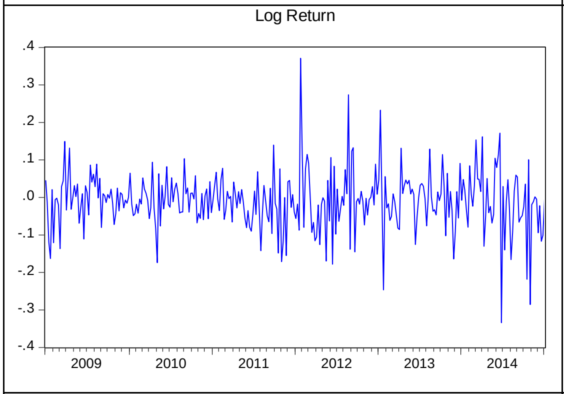
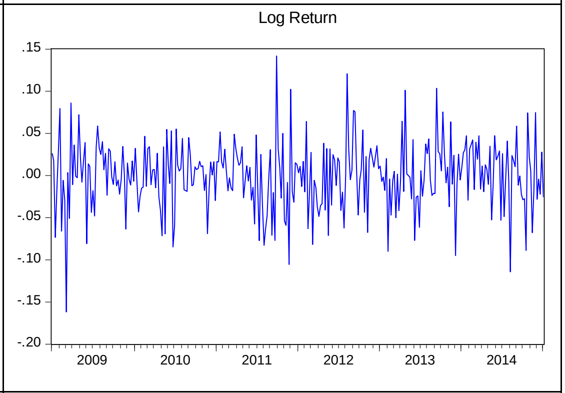


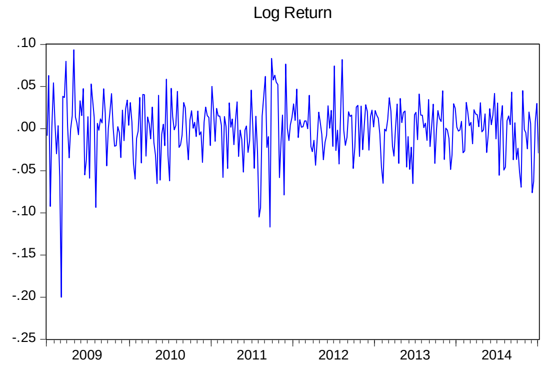
Table 4.2.7 Time Series Plots of Daily Log Returns of FTSE MIB Selected Companies

BMPS	ENEL.MI

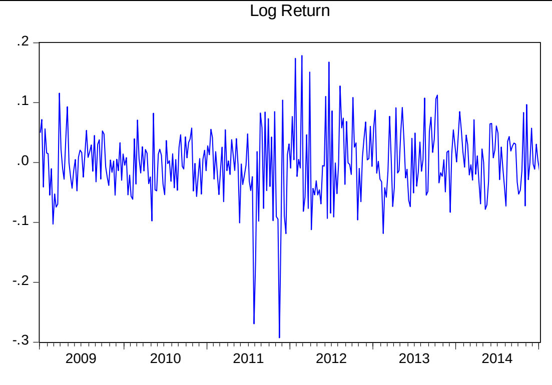




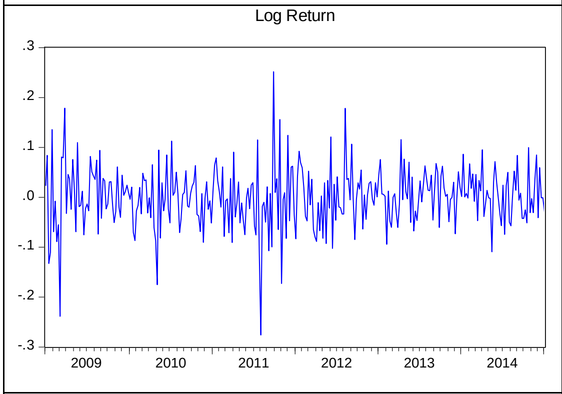
ENI.MI	FNC.MI



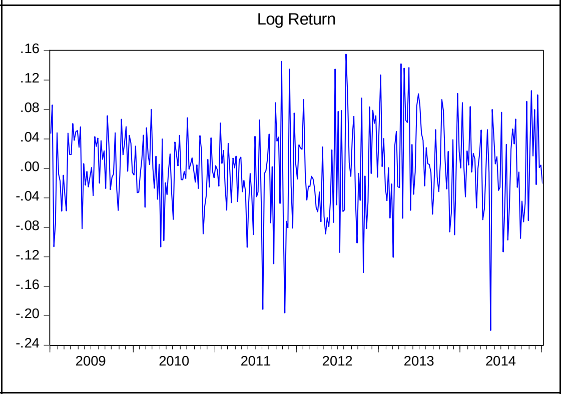
ISP.MI



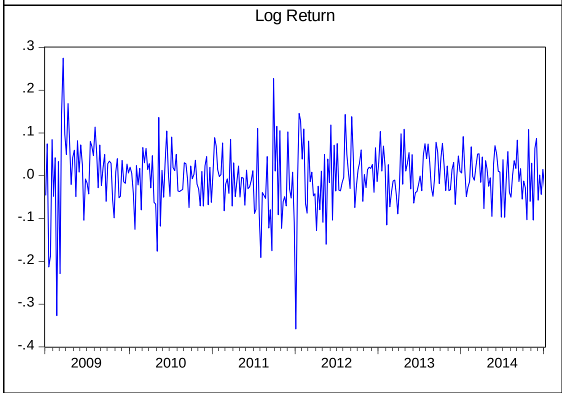
MS.MI



UCG.MI



TIT.MI



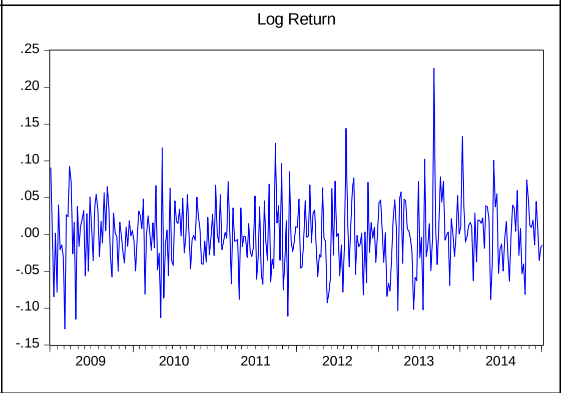
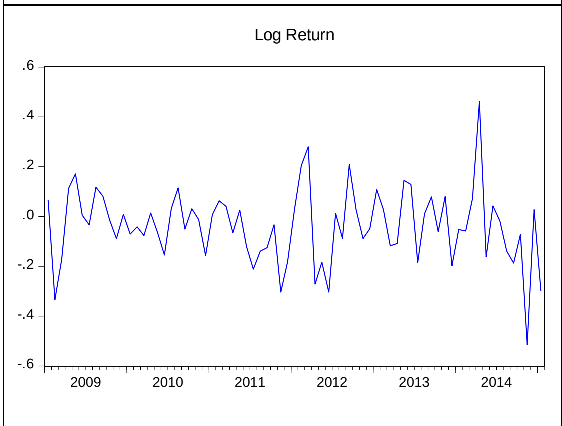


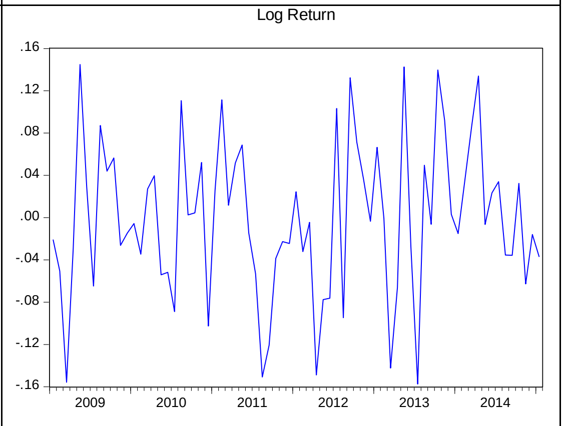
Table 4.2.8 Time Series Plots of Weekly Log Returns of FTSE MIB Selected Companies

BMPS

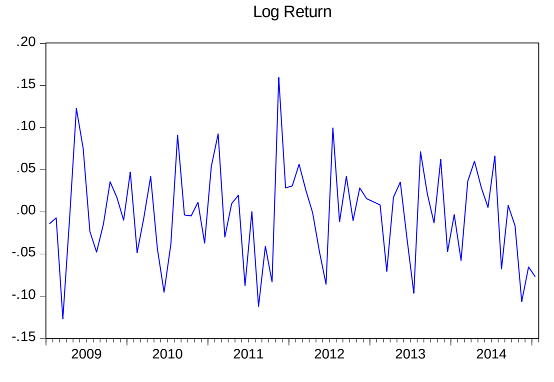
ENEL.MI

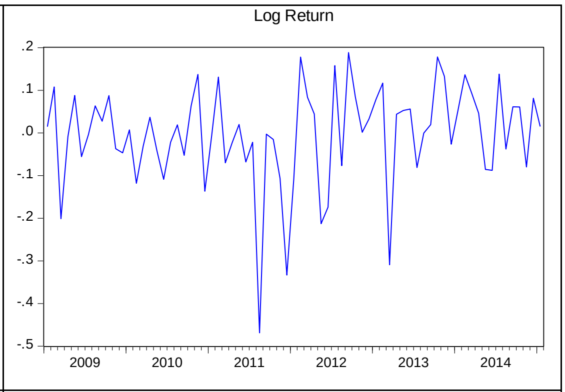


ENI.MI



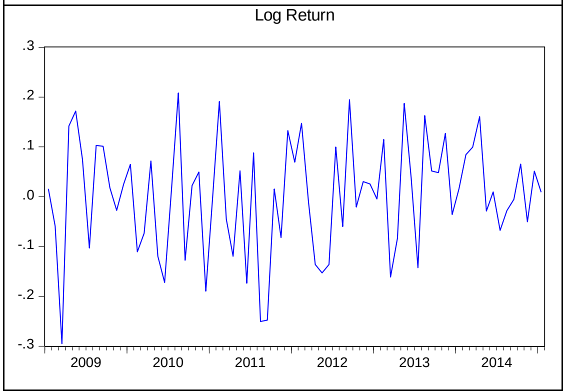
FNC.MI

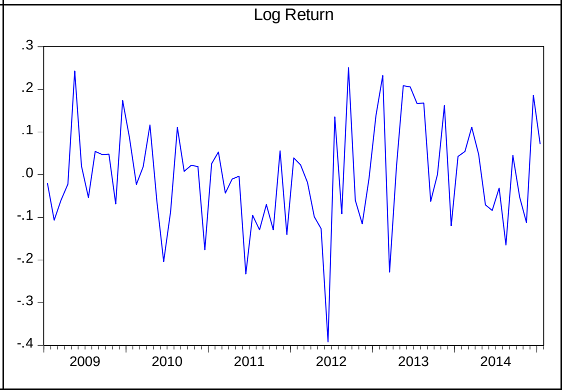




ISP.MI

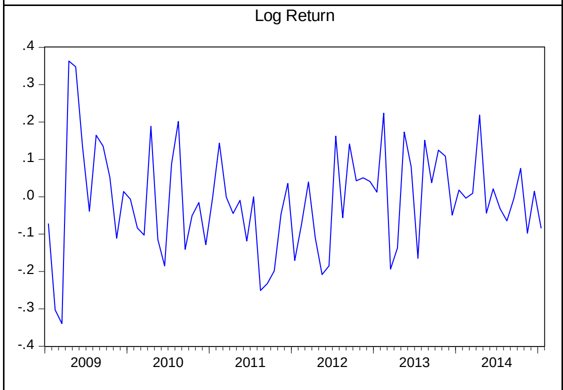
MS.MI





UCG.MI

TIT.MI



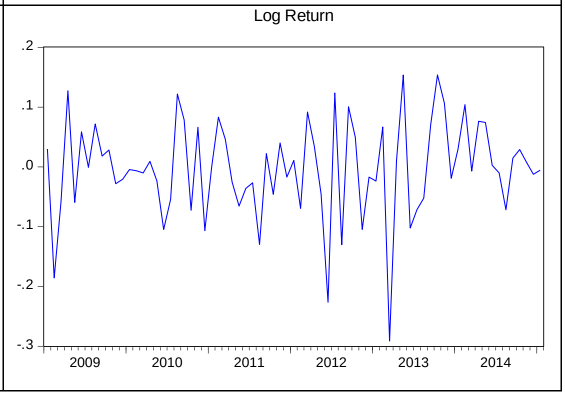


Table 4.2.9 Time Series Plots of Monthly Log Returns of FTSE MIB Selected Companies

It appears evident the presence of an high level of volatility affecting all the companies selected, more or less at the same level.

4.1.5 Weak Hypothesis

$$\begin{cases} H_0: The\ Italian\ Stock\ Market\ is\ weak - form\ efficient \\ H_1: The\ Italian\ Stock\ Market\ does\ not\ follow\ a\ random\ walk \end{cases}$$

4.1.6 Methodology and Results

In order to verify the hypothesis above, it has been used some statistical methods: descriptive analysis; the serial correlation test; the runs test; the sign test; the Augmented Dickey-Fuller and the Phillips-Perron unit root tests. In the following part it is possible to appreciate results of the analysis:

<u>Daily analysis</u>

Descriptive Analysis

BMPS		ENEL.MI	
Mean	13.22980	Mean	3.521919
Median	8.170000	Median	3.669000
Maximum	33.73470	Maximum	4.832000
Minimum	1.888100	Minimum	2.034000
Std. Dev.	9.011182	Std. Dev.	0.623629
Skewness	0.524339	Skewness	-0.247208
Kurtosis	1.744747	Kurtosis	2.018937
Jarque-Bera	174.5688	Jarque-Bera	78.75230
Probability	0.000000	Probability	0.000000
ENI.MI		**FNC.MI**	
Mean	16.91433	Mean	6.966502
Median	17.10000	Median	7.052500
Maximum	20.41000	Maximum	12.72000
Minimum	12.17000	Minimum	2.620000
Std. Dev.	1.319303	Std. Dev.	2.773127
Skewness	-0.609348	Skewness	0.115006
Kurtosis	3.998725	Kurtosis	1.736534
Jarque-Bera	161.9942	Jarque-Bera	107.6137
Probability	0.000000	Probability	0.000000
ISP.MI		**MS.MI**	
Mean	1.899712	Mean	3.447743
Median	1.993200	Median	3.446000
Maximum	3.003600	Maximum	6.485000
Minimum	0.868000	Minimum	1.166000
Std. Dev.	0.545722	Std. Dev.	1.309733
Skewness	-0.016783	Skewness	0.051758
Kurtosis	1.817425	Kurtosis	2.091111

Jarque-Bera 91.32456 Probability 0.000000	Jarque-Bera 54.60088 Probability 0.000000
UCG.MI	TIT.MI
Mean 7.543875 Median 5.898750 Maximum 16.78220 Minimum 2.204400 Std. Dev. 3.942104 Skewness 0.535372 Kurtosis 1.906951 Jarque-Bera 152.7663 Probability 0.000000	Mean 0.877705 Median 0.882500 Maximum 1.253000 Minimum 0.471000 Std. Dev. 0.168754 Skewness -0.287508 Kurtosis 2.387494 Jarque-Bera 46.05394 Probability 0.000000

Table 4.3.0 Descriptive Analysis of Daily Companies Returns

The descriptive analysis of the selected companies, on the basis of the daily returns, underlines that half companies show negative mean and half present a positive one. MS.MI represents the highest mean among these companies, while UCG.MI has the lowest one. Results from standard deviations confirm the hypothesis of high volatility made before. ENI and Finmeccanica seem to be the companies with most dispersion of returns with respect to their mean, whereas Telecom Italia presents the lowest standard deviation value, so the lowest volatility among the selected sample. Finmeccanica, Intesa San Paolo and Telecom Italia presents negative value for skewness. Moreover Mediaset, Banca Monte Paschi di Siena and Intesa San Paolo are centred stronger than the other observed companies. Jarque-Bera test suggest that the most part of the companies have been extracted by a sample not distributed such as a normal random variable, a part from a weak result concerning Finmeccanica. FNC.MI is also the only company to show significance on the basis of a p-value of 0.848705. Results suggest the only company that could be represented by a normal distribution would be Finmeccanica, but it does not appear to reach all the owed properties.

Runs test

Now it is possible to look at runs test result for companies daily returns as well:

BMPS.MI		ENEL.MI		ENI.MI		FNC.MI		ISP.MI		MS.MI		UCG.MI		TIT.MI	
Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value

-2.28	.02	1.93	.05	1.14	.25	.28	.78	1.36	.17	-2.01	.04	.12	.9	.08	.94

Table 4.3.1 Runs Test for Daily returns on FTSE MIB Selected Companies

BMPS, MS.MI and TIT.MI are the only companies that seem not to follow some randomness processes, but first two cited companies show dat not really significance. By the way, this leads to think that the other companies are supposed to be efficient under the weak form.

Unit Root test

In order to join more reliable results, ADF and PP tests, with their relatives first differences, have been performed. These tests are based on log prices.

Augmented Dickey-Fuller Test

LEVEL								
	BMPS.MI	ENEL.MI	ENI.MI	FNC.MI	ISP.MI	MS.MI	UCG.MI	TIT.MI
t-Statistic	-0.392914	-2.041856	-3.711379	-1.444246	-1.884979	-1.247856	-1.389292	-2.366591
Prob.*	0.9080	0.2689	0.0041	0.5617	0.3396	0.6555	0.5890	0.1515
TEST CRITICAL VALUE								
1% level	-3.434325	-3.434323	-3.434323	-3.434323	-3.434323	-3.434323	-3.434325	-3.434323
5% level	-2.863183	-2.863182	-2.863182	-2.863182	-2.863182	-2.863182	-2.863183	-2.863182
10% level	-2.567693	-2.567692	-2.567692	-2.567692	-2.567692	-2.567692	-2.567693	-2.567692

*MacKinnon (1996) one-sided p-values.

Table 4.3.2 ADF Test for Daily FTSE MIB Selected Companies (level)

Here, there is something that immediately appears evident, ENI is on the left of the critical values. This leads to think that ENI does not appear weak efficient considering daily prices. The result could be an open door for investors in order to beat the market. By the way, p-value over ENI's results does not lead to any significant levels. Remains the fact that result for ENI suggest the absence of a unit root, so the rejection of the null hypothesis. Moreover, also Telecom appears to be weakly smaller than its critical values.

Philip-Perron Test

LEVEL								
	BMPS.MI	ENEL.MI	ENI.MI	FNC.MI	ISP.MI	MS.MI	UCG.MI	TIT.MI
t-Statistic	-0.249340	-1.993124	-3.813543	-1.463946	-1.688596	-1.264650	-1.320413	-2.236335

Prob.*	0.9296	0.2900	0.0028	0.5519	0.4369	0.6479	0.6220	0.1935
TEST CRITICAL VALUE								
1% level	-3.434323	-3.434323	-3.434323	-3.434323	-3.434323	-3.434323	-3.434323	-3.434323
5% level	-2.863182	-2.863182	-2.863182	-2.863182	-2.863182	-2.863182	-2.863182	-2.863182
10% level	-2.567692	-2.567692	-2.567692	-2.567692	-2.567692	-2.567692	-2.567692	-2.567692

*MacKinnon (1996) one-sided p-values.

Table 4.3.3 PP Test for Daily FTSE MIB Selected Companies (level)

The PP leads exactly to the same results of the ADF test.

Serial Correlation Test

$$\begin{cases} H_0: Data\ are\ independently\ distributed\ (the\ correlations\ are\ equal\ to\ zero, so\ any \\ observed\ correlations\ resilt\ from\ randomness) \\ H_1: The\ data\ are\ not\ independently\ distributed\ (serial\ correlation) \end{cases}$$

It is helpful to repeat that no serial correlation in residuals means that the autocorrelations and partial autocorrelations at all lags should be nearly zero, and all Q-statistics should be insignificant with large p-values. The Ljung-Box test has been carried out on the basis of log return data.

BMPS

Lag	AC	PAC	Q-Stat	Prob
1	0.100	0.100	15.631	0.000
2	-0.021	-0.031	16.318	0.000
3	-0.064	-0.059	22.740	0.000
4	0.011	0.023	22.929	0.000
5	0.005	-0.002	22.963	0.000
6	-0.005	-0.009	23.002	0.001
7	-0.029	-0.026	24.373	0.001
8	-0.006	-0.000	24.421	0.002
9	0.056	0.055	29.308	0.001
10	0.030	0.016	30.754	0.001
11	-0.018	-0.020	31.260	0.001
12	-0.013	-0.001	31.525	0.002
13	-0.019	-0.018	32.100	0.002
14	-0.020	-0.021	32.743	0.003
15	0.036	0.040	34.793	0.003
16	0.048	0.042	38.511	0.001
17	0.029	0.022	39.857	0.001
18	-0.021	-0.024	40.569	0.002
19	0.029	0.036	41.913	0.002
20	-0.014	-0.019	42.206	0.003
21	-0.005	-0.004	42.252	0.004
22	-0.050	-0.042	46.153	0.002
23	-0.017	-0.005	46.623	0.003
24	-0.010	-0.012	46.791	0.004
25	0.019	0.007	47.343	0.004
26	-0.001	-0.007	47.346	0.006
27	0.011	0.015	47.548	0.009
28	0.026	0.025	48.609	0.009
29	0.027	0.022	49.752	0.010
30	0.010	0.011	49.923	0.013
31	-0.016	-0.014	50.343	0.015
32	-0.015	-0.010	50.703	0.019
33	-0.030	-0.028	52.104	0.018
34	-0.006	-0.006	52.158	0.024
35	0.033	0.032	53.909	0.021
36	-0.043	-0.056	56.819	0.015

ENEL.MI

Lag	AC	PAC	Q-Stat	Prob
1	-0.041	-0.041	2.6781	0.102
2	0.005	0.003	2.7198	0.257
3	0.004	0.004	2.7399	0.433
4	-0.013	-0.012	2.9865	0.560
5	-0.038	-0.040	5.3177	0.378
6	0.041	0.038	7.9197	0.244
7	-0.017	-0.013	8.3497	0.303
8	0.003	0.002	8.3670	0.398
9	-0.010	-0.011	8.5098	0.484
10	-0.014	-0.015	8.8114	0.550
11	0.052	0.054	13.035	0.291
12	-0.044	-0.043	16.161	0.184
13	0.042	0.040	18.981	0.124
14	-0.007	-0.006	19.062	0.163
15	0.008	0.009	19.164	0.206
16	0.034	0.038	20.982	0.179
17	-0.008	-0.012	21.074	0.223
18	-0.035	-0.028	22.992	0.191
19	0.008	-0.000	23.084	0.234
20	0.000	0.005	23.084	0.285
21	-0.033	-0.031	24.776	0.257
22	0.029	0.020	26.116	0.247
23	-0.025	-0.018	27.105	0.252
24	0.031	0.026	28.593	0.236
25	0.017	0.023	29.065	0.261
26	0.028	0.025	30.319	0.255
27	-0.000	0.002	30.319	0.300
28	-0.001	-0.003	30.320	0.348
29	-0.015	-0.010	30.664	0.381
30	-0.021	-0.025	31.344	0.399
31	-0.011	-0.010	31.548	0.439
32	0.023	0.023	32.407	0.447
33	-0.018	-0.020	32.943	0.470
34	-0.023	-0.016	33.777	0.479
35	0.018	0.009	34.289	0.502
36	-0.030	-0.025	35.721	0.482

ENI.MI	FNC.MI

ENI.MI

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.017	-0.017	0.4357	0.509
		2	-0.003	-0.004	0.4542	0.797
		3	0.008	0.008	0.5490	0.908
		4	-0.019	-0.018	1.0902	0.896
		5	-0.019	-0.019	1.6533	0.895
		6	0.030	0.030	3.1116	0.795
		7	0.028	0.029	4.3671	0.737
		8	-0.016	-0.014	4.7458	0.784
		9	-0.016	-0.017	5.1289	0.823
		10	-0.038	-0.039	7.4286	0.684
		11	-0.002	-0.001	7.4383	0.763
		12	-0.041	-0.042	10.143	0.603
		13	-0.016	-0.020	10.552	0.648
		14	-0.068	-0.071	17.845	0.214
		15	-0.003	-0.004	17.854	0.270
		16	0.005	0.006	17.899	0.330
		17	0.031	0.033	19.470	0.302
		18	-0.015	-0.016	19.830	0.342
		19	-0.015	-0.016	20.191	0.383
		20	-0.031	-0.030	21.669	0.359
		21	0.009	0.012	21.797	0.411
		22	0.006	0.001	21.850	0.469
		23	-0.051	-0.059	25.991	0.301
		24	0.055	0.043	30.731	0.162
		25	0.020	0.021	31.343	0.178
		26	-0.024	-0.023	32.229	0.186
		27	-0.033	-0.038	33.980	0.167
		28	0.031	0.022	35.542	0.155
		29	-0.021	-0.014	36.277	0.166
		30	-0.001	-0.002	36.279	0.199
		31	0.008	0.002	36.380	0.232
		32	0.024	0.020	37.311	0.238
		33	-0.017	-0.018	37.789	0.260
		34	-0.026	-0.029	38.912	0.258
		35	0.035	0.032	40.837	0.229
		36	0.009	0.015	40.974	0.261

FNC.MI

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.017	0.017	0.4463	0.504
		2	0.012	0.011	0.6555	0.721
		3	-0.000	-0.001	0.6557	0.884
		4	0.015	0.015	0.9964	0.910
		5	-0.037	-0.038	3.1993	0.669
		6	-0.007	-0.006	3.2841	0.772
		7	0.035	0.036	5.1728	0.639
		8	-0.024	-0.026	6.1020	0.636
		9	0.033	0.035	7.8554	0.549
		10	0.009	0.007	7.9861	0.630
		11	-0.004	-0.006	8.0072	0.713
		12	0.037	0.040	10.124	0.605
		13	0.013	0.009	10.393	0.662
		14	-0.015	-0.016	10.753	0.705
		15	0.036	0.040	12.824	0.616
		16	-0.002	-0.008	12.830	0.685
		17	0.054	0.057	17.440	0.425
		18	-0.013	-0.014	17.718	0.474
		19	0.016	0.010	18.145	0.513
		20	0.045	0.050	21.334	0.378
		21	-0.007	-0.012	21.406	0.434
		22	0.011	0.011	21.614	0.483
		23	0.021	0.025	22.319	0.501
		24	-0.042	-0.053	25.068	0.402
		25	-0.020	-0.011	25.710	0.423
		26	-0.028	-0.031	26.989	0.410
		27	0.002	-0.003	26.996	0.464
		28	0.044	0.052	30.076	0.360
		29	-0.015	-0.029	30.414	0.394
		30	-0.007	-0.010	30.484	0.441
		31	-0.045	-0.041	33.678	0.339
		32	-0.045	-0.060	36.958	0.251
		33	-0.080	-0.067	47.186	0.052
		34	-0.026	-0.029	48.308	0.053
		35	-0.005	-0.010	48.353	0.066
		36	0.016	0.023	48.747	0.076

ISP.MI	MS.MI

ISP.MI

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.006	-0.006	0.0488	0.825
		2	-0.044	-0.044	3.0357	0.219
		3	-0.056	-0.056	7.9050	0.048
		4	-0.036	-0.039	9.9760	0.041
		5	-0.054	-0.060	14.535	0.013
		6	0.041	0.033	17.141	0.009
		7	0.016	0.007	17.533	0.014
		8	-0.006	-0.010	17.588	0.025
		9	0.025	0.026	18.577	0.029
		10	-0.028	-0.028	19.850	0.031
		11	0.032	0.039	21.484	0.029
		12	0.033	0.033	23.163	0.026
		13	0.018	0.019	23.668	0.034
		14	-0.022	-0.013	24.449	0.040
		15	-0.028	-0.026	25.676	0.042
		16	0.018	0.026	26.216	0.051
		17	0.041	0.041	28.868	0.036
		18	-0.013	-0.017	29.145	0.047
		19	-0.030	-0.029	30.560	0.045
		20	-0.005	-0.006	30.600	0.061
		21	-0.017	-0.014	31.068	0.073
		22	0.031	0.030	32.644	0.067
		23	-0.008	-0.018	32.741	0.086
		24	-0.008	-0.013	32.835	0.108
		25	-0.009	-0.008	32.962	0.132
		26	-0.030	-0.030	34.350	0.126
		27	-0.013	-0.008	34.626	0.149
		28	0.034	0.023	36.419	0.132
		29	0.030	0.020	37.856	0.126
		30	-0.018	-0.016	38.368	0.141
		31	0.043	0.049	41.390	0.101
		32	-0.016	-0.004	41.778	0.116
		33	-0.013	-0.009	42.065	0.134
		34	-0.057	-0.059	47.351	0.064
		35	0.020	0.019	47.996	0.071
		36	-0.038	-0.036	50.340	0.057

MS.MI

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.031	0.031	1.5058	0.220
		2	-0.021	-0.022	2.1704	0.338
		3	-0.046	-0.044	5.4276	0.143
		4	-0.041	-0.039	8.1139	0.087
		5	0.019	0.020	8.6915	0.122
		6	0.026	0.021	9.7609	0.135
		7	0.063	0.059	16.007	0.025
		8	0.046	0.044	19.307	0.013
		9	-0.000	0.004	19.307	0.023
		10	-0.036	-0.028	21.400	0.018
		11	0.011	0.020	21.582	0.028
		12	-0.011	-0.012	21.760	0.040
		13	0.048	0.043	25.423	0.020
		14	-0.019	-0.030	26.019	0.026
		15	0.021	0.021	26.705	0.031
		16	0.044	0.043	29.731	0.019
		17	0.024	0.028	30.670	0.022
		18	-0.022	-0.023	31.451	0.026
		19	-0.002	0.004	31.461	0.036
		20	-0.006	-0.007	31.512	0.049
		21	0.047	0.046	35.021	0.028
		22	0.015	0.006	35.365	0.035
		23	0.018	0.016	35.879	0.042
		24	-0.049	-0.057	39.739	0.023
		25	0.018	0.031	40.269	0.027
		26	0.007	0.005	40.348	0.036
		27	0.006	0.006	40.398	0.047
		28	0.004	-0.009	40.422	0.061
		29	0.044	0.043	43.462	0.041
		30	-0.031	-0.038	44.997	0.039
		31	-0.043	-0.031	47.995	0.026
		32	-0.051	-0.054	52.132	0.014
		33	-0.006	-0.005	52.191	0.018
		34	0.011	-0.007	52.402	0.023
		35	0.031	0.032	53.973	0.021
		36	-0.001	-0.015	53.975	0.028

UCG.MI	TIT.MI

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.093	0.093	13.656	0.000
		2	0.042	0.033	16.409	0.000
		3	-0.014	-0.022	16.738	0.001
		4	-0.036	-0.034	18.730	0.001
		5	-0.076	-0.069	27.809	0.000
		6	0.007	0.023	27.890	0.000
		7	0.021	0.024	28.606	0.000
		8	0.004	-0.004	28.633	0.000
		9	0.037	0.031	30.773	0.000
		10	0.022	0.013	31.546	0.000
		11	0.018	0.016	32.060	0.001
		12	-0.035	-0.036	33.946	0.001
		13	-0.006	0.000	34.010	0.001
		14	-0.039	-0.030	36.425	0.001
		15	-0.029	-0.021	37.715	0.001
		16	0.044	0.051	40.780	0.001
		17	0.080	0.068	50.806	0.000
		18	0.005	-0.015	50.849	0.000
		19	-0.028	-0.039	52.107	0.000
		20	0.000	0.007	52.107	0.000
		21	-0.038	-0.022	54.417	0.000
		22	-0.031	-0.017	55.981	0.000
		23	-0.016	-0.013	56.383	0.000
		24	-0.018	-0.020	56.901	0.000
		25	-0.024	-0.021	57.853	0.000
		26	0.012	0.006	58.088	0.000
		27	0.025	0.017	59.055	0.000
		28	0.041	0.038	61.753	0.000
		29	-0.003	-0.011	61.767	0.000
		30	-0.019	-0.019	62.351	0.000
		31	0.020	0.037	62.969	0.001
		32	-0.009	-0.002	63.096	0.001
		33	-0.006	-0.013	63.145	0.001
		34	-0.004	-0.011	63.169	0.002
		35	0.016	0.018	63.573	0.002
		36	-0.022	-0.021	64.362	0.003

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.013	-0.013	0.2738	0.601
		2	-0.010	-0.010	0.4267	0.808
		3	-0.052	-0.053	4.7523	0.191
		4	-0.030	-0.032	6.1970	0.185
		5	-0.005	-0.007	6.2351	0.284
		6	-0.004	-0.007	6.2570	0.395
		7	0.007	0.003	6.3307	0.502
		8	-0.008	-0.009	6.4238	0.600
		9	-0.017	-0.018	6.8744	0.650
		10	-0.036	-0.037	8.8952	0.542
		11	-0.014	-0.017	9.2241	0.601
		12	-0.013	-0.017	9.5007	0.660
		13	0.046	0.041	12.899	0.456
		14	-0.016	-0.019	13.289	0.504
		15	0.005	0.002	13.329	0.577
		16	-0.016	-0.013	13.733	0.619
		17	0.014	0.014	14.032	0.665
		18	-0.023	-0.024	14.883	0.670
		19	-0.031	-0.034	16.448	0.627
		20	-0.010	-0.014	16.608	0.678
		21	-0.010	-0.014	16.764	0.725
		22	-0.016	-0.022	17.161	0.754
		23	-0.005	-0.007	17.198	0.799
		24	-0.019	-0.023	17.762	0.814
		25	0.041	0.038	20.447	0.723
		26	0.015	0.011	20.820	0.751
		27	-0.030	-0.032	22.299	0.722
		28	0.070	0.069	30.144	0.356
		29	-0.015	-0.012	30.494	0.390
		30	0.008	0.002	30.589	0.436
		31	-0.037	-0.032	32.820	0.378
		32	0.036	0.037	34.865	0.333
		33	0.028	0.028	36.100	0.326
		34	-0.004	-0.005	36.123	0.370
		35	-0.003	0.001	36.140	0.415
		36	-0.073	-0.068	44.708	0.151

Table 4.3.4 Serial Correlation of Daily FTSE MIB Selected Companies

A part for BMPS and UCG companies show some low p-values, leading to reject the absence of serial correlation, and so the null hypothesis, if considered with the AC and PAC value which differ from zero (even if really close to it). On the other hand, almost all the companies do not reject the null hypothesis and so are consistent with the efficient market hypothesis.

<u>Weekly analysis</u>

Descriptive Analysis

BMPS		ENEL.MI	
Mean	13.23605	Mean	3.526465
Median	8.143300	Median	3.686500
Maximum	32.96120	Maximum	4.832000
Minimum	1.912500	Minimum	2.180000
Std. Dev.	9.053442	Std. Dev.	0.625748
Skewness	0.519649	Skewness	-0.255377
Kurtosis	1.736595	Kurtosis	2.040991
Jarque-Bera	35.01534	Jarque-Bera	15.44576

Probability	0.000000	Probability	0.000443
ENI.MI		FNC.MI	
Mean	16.92000	Mean	6.972296
Median	17.11000	Median	7.075000
Maximum	20.41000	Maximum	12.67000
Minimum	12.20000	Minimum	2.678000
Std. Dev.	1.304258	Std. Dev.	2.778483
Skewness	-0.553892	Skewness	0.113001
Kurtosis	4.087784	Kurtosis	1.740975
Jarque-Bera	31.53682	Jarque-Bera	21.40722
Probability	0.000000	Probability	0.000022
ISP.MI		MS.MI	
Mean	1.902262	Mean	3.450897
Median	2.001200	Median	3.463000
Maximum	3.003600	Maximum	6.415000
Minimum	0.938000	Minimum	1.197000
Std. Dev.	0.543226	Std. Dev.	1.311780
Skewness	-0.030356	Skewness	0.048622
Kurtosis	1.817917	Kurtosis	2.091260
Jarque-Bera	18.32985	Jarque-Bera	10.92806
Probability	0.000105	Probability	0.004236
UCG.MI		TIT.MI	
Mean	7.545173	Mean	0.878432
Median	5.883450	Median	0.880000
Maximum	16.78220	Maximum	1.251000
Minimum	2.335600	Minimum	0.476700
Std. Dev.	3.934684	Std. Dev.	0.168408
Skewness	0.533833	Skewness	-0.300358
Kurtosis	1.906341	Kurtosis	2.377461
Jarque-Bera	30.56267	Jarque-Bera	9.791765
Probability	0.000000	Probability	0.007477

Table 4.3.5 Descriptive Analysis of Weekly FTSE MIB Selected Companies

The descriptive analysis of the selected companies, on the basis of the weekly returns, highlights the clear contrast from BMPS.MI to UCG.MI in terms of mean. The daily returns high volatility is confirmed by weekly evidences too. ENI and Finmeccanica again with most dispersion than others. Moreover Mediaset, Banca Monte Paschi di Siena, Unicredit and Intesa San Paolo are centred stronger than the other observed companies. Jarque-Bera test suggest that the most part of the companies have been extracted by a sample not distributed such as a normal random variable. FNC.MI confirms to be an exception.

Runs Test

BMPS		ENEL.MI		ENI.MI		FNC.MI		ISP.MI		MS.MI		UCG.MI		TIT.MI	
Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value
.11	.91	-.23	.82	-.11	.91	.9	.37	0	1	-1.58	.11	.34	.73	1.13	.26

Table 4.3.6 Runs Test for Weekly returns on FTSE MIB Selected Companies

All companies appear to follow a random order process. Hence, for what concerns weekly analysis, the whole selected sample of campanies appear to be weak form efficient.

Unit Root test

Augmented Dickey-Fuller Test

LEVEL								
	BMPS.MI	ENEL.MI	ENI.MI	FNC.MI	ISP.MI	MS.MI	UCG.MI	TIT.MI
t-Statistic	-0.205830	-1.964814	-3.766310	-1.454239	-1.747778	-1.237516	-1.250745	-2.289314
Prob.*	0.9347	0.3025	0.0036	0.5556	0.4062	0.6589	0.6530	0.1761
TEST CRITICAL VALUE								
1% level	-3.451078	-3.451078	-3.451078	-3.451078	-3.451078	-3.451078	-3.451078	-3.451078
5% level	-2.870561	-2.870561	-2.870561	-2.870561	-2.870561	-2.870561	-2.870561	-2.870561
10% level	-2.571647	-2.571647	-2.571647	-2.571647	-2.571647	-2.571647	-2.571647	-2.571647

*MacKinnon (1996) one-sided p-values.

Table 4.3.7 ADF Test for Weekly FTSE MIB Selected Companies (level)

Philip-Perron Test

LEVEL								
	BMPS.MI	ENEL.MI	ENI.MI	FNC.MI	ISP.MI	MS.MI	UCG.MI	TIT.MI
t-Statistic	-0.245977	-2.012348	-3.726090	-1.561244	-1.678354	-1.363130	-1.279372	-2.113676
Prob.*	0.9294	0.2815	0.0042	0.5012	0.4413	0.6005	0.6400	0.2395
TEST CRITICAL VALUE								
1% level	-3.451078	-3.451078	-3.451078	-3.451078	-3.451078	-3.451078	-3.451078	-3.451078
5% level	-2.870561	-2.870561	-2.870561	-2.870561	-2.870561	-2.870561	-2.870561	-2.870561
10% level	-2.571647	-2.571647	-2.571647	-2.571647	-2.571647	-2.571647	-2.571647	-2.571647

*MacKinnon (1996) one-sided p-values.

Table 4.3.8 PP Test for Weekly FTSE MIB Selected Companies (level)

Again, weekly data show positive results to confirm the null hypothesis for all the company selected but ENI.

Serial Correlation Test

BMPS

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.060	-0.060	1.1583	0.282
		2	0.071	0.068	2.7778	0.249
		3	0.026	0.035	3.0010	0.391
		4	0.010	0.008	3.0313	0.553
		5	0.023	0.020	3.1955	0.670
		6	0.007	0.008	3.2134	0.782
		7	-0.050	-0.053	4.0275	0.777
		8	-0.014	-0.023	4.0929	0.849
		9	-0.130	-0.127	9.5666	0.387
		10	-0.056	-0.069	10.607	0.389
		11	0.092	0.106	13.350	0.271
		12	-0.056	-0.025	14.392	0.276
		13	0.070	0.063	16.027	0.248
		14	0.001	0.016	16.027	0.312
		15	-0.100	-0.111	19.317	0.200
		16	-0.010	-0.045	19.349	0.251
		17	-0.004	-0.007	19.354	0.309
		18	0.076	0.076	21.315	0.264
		19	-0.010	-0.009	21.352	0.318
		20	-0.020	0.002	21.484	0.369
		21	0.048	0.054	22.255	0.385
		22	-0.004	-0.006	22.260	0.444
		23	0.004	0.003	22.265	0.504
		24	0.009	-0.039	22.294	0.562
		25	-0.004	-0.019	22.301	0.618
		26	-0.046	-0.035	23.035	0.631
		27	0.026	0.041	23.268	0.671
		28	-0.072	-0.039	25.049	0.625
		29	-0.020	-0.042	25.191	0.668
		30	0.045	0.066	25.911	0.680
		31	-0.053	-0.055	26.888	0.678
		32	0.037	0.016	27.371	0.700
		33	0.020	0.049	27.505	0.737
		34	-0.044	-0.057	28.182	0.748
		35	-0.004	-0.033	28.187	0.786
		36	0.072	0.086	30.060	0.746

ENEL.MI

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.063	-0.063	1.2685	0.260
		2	0.064	0.060	2.5618	0.278
		3	-0.021	-0.014	2.7074	0.439
		4	-0.012	-0.018	2.7567	0.599
		5	0.104	0.105	6.2369	0.284
		6	-0.081	-0.069	8.3716	0.212
		7	-0.039	-0.062	8.8618	0.263
		8	-0.043	-0.035	9.4506	0.306
		9	0.015	0.016	9.5206	0.391
		10	-0.026	-0.035	9.7425	0.463
		11	-0.112	-0.108	13.853	0.241
		12	-0.015	-0.020	13.931	0.305
		13	0.096	0.112	16.949	0.202
		14	0.045	0.044	17.610	0.225
		15	0.097	0.093	20.717	0.146
		16	-0.040	-0.013	21.253	0.169
		17	0.044	0.020	21.888	0.189
		18	-0.039	-0.068	22.406	0.214
		19	0.020	0.006	22.543	0.258
		20	-0.003	0.004	22.546	0.312
		21	-0.003	0.018	22.550	0.368
		22	-0.015	-0.031	22.626	0.423
		23	0.033	0.055	22.987	0.462
		24	-0.095	-0.078	26.048	0.351
		25	0.016	0.023	26.133	0.401
		26	-0.084	-0.073	28.591	0.330
		27	-0.002	-0.015	28.593	0.381
		28	-0.042	-0.074	29.202	0.402
		29	-0.009	-0.005	29.231	0.453
		30	-0.000	-0.025	29.231	0.505
		31	-0.010	0.022	29.269	0.555
		32	0.008	-0.014	29.293	0.604
		33	-0.026	-0.006	29.538	0.640
		34	0.023	-0.002	29.734	0.677
		35	-0.011	-0.014	29.775	0.718
		36	0.114	0.092	34.408	0.544

ENI.MI

FNC.MI

Lag	AC	PAC	Q-Stat	Prob
1	0.015	0.015	0.0699	0.791
2	-0.104	-0.104	3.4929	0.174
3	-0.088	-0.085	5.9393	0.115
4	-0.076	-0.086	7.7794	0.100
5	-0.035	-0.053	8.1696	0.147
6	0.043	0.019	8.7787	0.186
7	0.079	0.057	10.778	0.149
8	-0.087	-0.097	13.260	0.103
9	0.068	0.085	14.784	0.097
10	-0.103	-0.115	18.241	0.051
11	-0.002	0.017	18.242	0.076
12	-0.016	-0.040	18.327	0.106
13	0.049	0.036	19.117	0.120
14	-0.036	-0.056	19.545	0.145
15	-0.020	-0.011	19.680	0.185
16	0.014	-0.009	19.750	0.232
17	0.003	0.027	19.752	0.287
18	0.090	0.060	22.465	0.212
19	-0.089	-0.078	25.110	0.157
20	-0.034	-0.034	25.492	0.183
21	-0.049	-0.037	26.312	0.195
22	0.086	0.067	28.852	0.149
23	-0.009	-0.026	28.879	0.184
24	-0.027	-0.040	29.126	0.215
25	0.039	0.034	29.651	0.238
26	-0.050	-0.033	30.519	0.247
27	-0.083	-0.098	32.922	0.200
28	-0.068	-0.057	34.550	0.183
29	0.099	0.050	37.940	0.124
30	-0.010	-0.026	37.972	0.150
31	-0.049	-0.098	38.816	0.158
32	-0.132	-0.135	44.920	0.064
33	-0.025	-0.022	45.143	0.077
34	0.022	-0.022	45.312	0.093
35	0.047	-0.007	46.100	0.099
36	0.073	0.024	48.019	0.087

ISP.MI

Lag	AC	PAC	Q-Stat	Prob
1	0.011	0.011	0.0370	0.847
2	0.138	0.138	6.0727	0.048
3	-0.001	-0.003	6.0728	0.108
4	0.074	0.056	7.8191	0.098
5	-0.043	-0.044	8.4048	0.135
6	-0.098	-0.117	11.470	0.075
7	-0.089	-0.079	14.048	0.050
8	-0.027	-0.003	14.286	0.075
9	-0.016	0.013	14.369	0.110
10	-0.097	-0.081	17.415	0.066
11	-0.079	-0.078	19.434	0.054
12	0.008	0.016	19.455	0.078
13	-0.030	-0.028	19.742	0.102
14	0.033	0.034	20.094	0.127
15	0.125	0.143	25.281	0.046
16	0.039	0.006	25.777	0.057
17	0.129	0.074	31.316	0.018
18	-0.118	-0.154	35.999	0.007
19	0.138	0.100	42.407	0.002
20	-0.036	-0.002	42.836	0.002
21	0.120	0.111	47.689	0.001
22	0.077	0.144	49.685	0.001
23	0.072	0.044	51.472	0.001
24	-0.042	-0.084	52.069	0.001
25	0.025	0.019	52.288	0.001
26	-0.009	0.031	52.315	0.002
27	-0.095	-0.058	55.421	0.001
28	-0.008	0.047	55.446	0.002
29	-0.028	0.005	55.715	0.002
30	-0.095	-0.118	58.862	0.001
31	0.043	0.034	59.512	0.002
32	-0.086	-0.049	62.105	0.001
33	-0.041	-0.018	62.685	0.001
34	-0.001	-0.001	62.685	0.002
35	-0.051	-0.043	63.604	0.002
36	0.133	0.078	69.963	0.001

MS.MI

Lag	AC	PAC	Q-Stat	Prob
1	-0.108	-0.108	3.6835	0.055
2	0.081	0.071	5.7908	0.055
3	-0.058	-0.043	6.8577	0.077
4	0.057	0.042	7.9063	0.095
5	-0.079	-0.063	9.9006	0.078
6	0.033	0.011	10.250	0.115
7	-0.026	-0.008	10.468	0.164
8	-0.065	-0.082	11.859	0.158
9	-0.096	-0.102	14.834	0.096
10	-0.024	-0.043	15.027	0.131
11	-0.006	-0.002	15.037	0.181
12	-0.023	-0.026	15.213	0.230
13	0.075	0.069	17.073	0.196
14	0.062	0.075	18.332	0.192
15	0.017	0.018	18.423	0.241
16	0.042	0.039	18.999	0.269
17	0.031	0.019	19.326	0.310
18	-0.028	-0.039	19.586	0.357
19	-0.027	-0.040	19.824	0.405
20	-0.001	-0.011	19.825	0.469
21	-0.027	-0.018	20.066	0.517
22	0.033	0.057	20.429	0.556
23	-0.023	0.010	20.615	0.605
24	-0.105	-0.106	24.379	0.440
25	-0.010	-0.009	24.415	0.496
26	-0.037	-0.036	24.880	0.526
27	-0.017	-0.049	24.978	0.576
28	-0.008	-0.021	24.998	0.628
29	-0.021	-0.051	25.157	0.670
30	0.008	-0.002	25.182	0.716
31	0.009	0.016	25.210	0.758
32	0.018	0.010	25.329	0.792
33	-0.020	-0.038	25.473	0.822
34	0.087	0.077	28.153	0.749
35	-0.029	-0.021	28.446	0.776
36	0.116	0.086	33.275	0.599

UCG.MI

Lag	AC	PAC	Q-Stat	Prob
1	0.003	0.003	0.0020	0.964
2	0.064	0.064	1.3240	0.516
3	0.086	0.086	3.7029	0.295
4	0.008	0.004	3.7214	0.445
5	0.040	0.030	4.2470	0.514
6	-0.081	-0.090	6.3753	0.382
7	-0.024	-0.031	6.5669	0.475
8	-0.001	0.003	6.5674	0.584
9	-0.021	-0.003	6.7143	0.667
10	-0.070	-0.066	8.3071	0.599
11	-0.034	-0.027	8.6905	0.650
12	-0.036	-0.032	9.1202	0.693
13	0.040	0.053	9.6469	0.723
14	0.080	0.095	11.773	0.625
15	0.044	0.051	12.411	0.648
16	0.008	-0.021	12.432	0.714
17	0.068	0.040	13.962	0.670
18	-0.030	-0.051	14.270	0.711
19	-0.016	-0.026	14.353	0.763
20	0.023	0.027	14.534	0.802
21	-0.013	0.002	14.592	0.843
22	0.111	0.108	18.778	0.659
23	0.039	0.059	19.308	0.683
24	0.008	0.008	19.329	0.734
25	0.105	0.093	23.128	0.570
26	-0.042	-0.043	23.725	0.592
27	0.003	-0.021	23.729	0.645
28	0.057	0.046	24.855	0.636
29	0.032	0.043	25.214	0.667
30	-0.045	-0.066	25.931	0.679
31	0.012	0.016	25.984	0.722
32	-0.053	-0.040	26.990	0.718
33	-0.030	-0.013	27.303	0.746
34	0.068	0.101	28.937	0.714
35	-0.048	-0.014	29.760	0.719
36	0.040	0.006	30.324	0.735

TIT.MI

Lag	AC	PAC	Q-Stat	Prob
1	-0.021	-0.021	0.1386	0.710
2	0.107	0.106	3.7679	0.152
3	-0.074	-0.071	5.5359	0.137
4	0.036	0.023	5.9599	0.202
5	-0.054	-0.038	6.8801	0.230
6	0.031	0.019	7.1930	0.303
7	0.017	0.032	7.2873	0.400
8	-0.073	-0.087	9.0310	0.340
9	-0.058	-0.059	10.119	0.341
10	0.015	0.031	10.188	0.424
11	-0.072	-0.072	11.893	0.372
12	-0.037	-0.047	12.354	0.418
13	0.025	0.038	12.558	0.482
14	0.024	0.021	12.757	0.546
15	0.076	0.080	14.656	0.476
16	0.025	0.018	14.871	0.534
17	0.097	0.076	18.017	0.388
18	0.008	0.027	18.036	0.453
19	0.035	0.011	18.452	0.492
20	0.014	0.012	18.517	0.553
21	-0.008	-0.016	18.538	0.615
22	0.075	0.084	20.470	0.554
23	0.064	0.077	21.885	0.527
24	-0.113	-0.129	26.251	0.341
25	-0.050	-0.040	27.126	0.350
26	-0.000	0.053	27.126	0.403
27	0.008	0.012	27.149	0.456
28	-0.032	-0.025	27.511	0.491
29	-0.017	-0.036	27.606	0.539
30	0.025	0.038	27.822	0.580
31	-0.061	-0.032	29.124	0.563
32	0.025	-0.020	29.347	0.601
33	-0.053	-0.068	30.334	0.601
34	0.063	0.068	31.719	0.580
35	-0.050	-0.041	32.610	0.584
36	0.089	0.031	35.413	0.496

Lag	AC	PAC	Q-Stat	Prob
1	-0.081	-0.081	2.0697	0.150
2	-0.024	-0.031	2.2574	0.323
3	-0.080	-0.086	4.3195	0.229
4	-0.031	-0.047	4.6289	0.328
5	-0.008	-0.021	4.6521	0.460
6	0.039	0.028	5.1531	0.524
7	-0.045	-0.047	5.7955	0.564
8	-0.010	-0.020	5.8282	0.666
9	-0.030	-0.032	6.1242	0.727
10	-0.021	-0.034	6.2682	0.792
11	-0.034	-0.048	6.6538	0.826
12	-0.050	-0.070	7.4692	0.825
13	-0.021	-0.042	7.6207	0.867
14	0.005	-0.018	7.6284	0.908
15	0.085	0.068	10.019	0.819
16	-0.003	-0.002	10.021	0.866
17	0.032	0.031	10.353	0.888
18	-0.031	-0.017	10.683	0.907
19	-0.004	-0.007	10.688	0.934
20	-0.007	-0.011	10.703	0.954
21	0.088	0.074	13.312	0.897
22	0.036	0.051	13.750	0.910
23	0.026	0.035	13.978	0.927
24	-0.048	-0.022	14.777	0.927
25	0.024	0.036	14.980	0.942
26	0.002	0.025	14.981	0.958
27	-0.045	-0.039	15.670	0.959
28	-0.091	-0.089	18.560	0.911
29	0.035	0.026	18.990	0.922
30	-0.012	-0.015	19.044	0.939
31	0.052	0.038	19.997	0.936
32	-0.043	-0.035	20.642	0.939
33	-0.136	-0.131	27.147	0.753
34	0.076	0.070	29.208	0.702
35	-0.007	-0.013	29.226	0.743
36	0.042	0.006	29.843	0.755

Table 4.3.9 Serial Correlation of Weekly FTSE MIB Selected Companies

Weekly data tested for serial correlation confirm the companies selected cannot be identify in a random process, but the results lead to suppose an approximation to the random walk exists, and so there exist the possibility of presence of weak form efficiency too.

Monthly analysis

Descriptive Analysis

BMPS		ENEL.MI	
Mean	13.24745	Mean	3.529714
Median	8.131900	Median	3.680000
Maximum	32.78930	Maximum	4.816000
Minimum	1.912500	Minimum	2.298000
Std. Dev.	9.154201	Std. Dev.	0.625372
Skewness	0.521662	Skewness	-0.198198
Kurtosis	1.764007	Kurtosis	2.106198
Jarque-Bera	7.957619	Jarque-Bera	2.907869
Probability	0.018708	Probability	0.233649
ENI.MI		FNC.MI	

Mean	16.89986	Mean	6.997973
Median	17.00000	Median	7.025000
Maximum	20.10000	Maximum	12.13000
Minimum	13.02000	Minimum	2.728000
Std. Dev.	1.269989	Std. Dev.	2.793289
Skewness	-0.478323	Skewness	0.096703
Kurtosis	3.489197	Kurtosis	1.664729
Jarque-Bera	3.511554	Jarque-Bera	5.536911
Probability	0.172773	Probability	0.062759
ISP.MI		MS.MI	
Mean	1.908696	Mean	3.456899
Median	1.952000	Median	3.440000
Maximum	2.954300	Maximum	6.415000
Minimum	0.997500	Minimum	1.214000
Std. Dev.	0.539197	Std. Dev.	1.319629
Skewness	-0.070197	Skewness	0.073947
Kurtosis	1.720163	Kurtosis	2.152369
Jarque-Bera	5.042147	Jarque-Bera	2.251899
Probability	0.080373	Probability	0.324344
UCG.MI		TIT.MI	
Mean	7.511841	Mean	0.882500
Median	6.021000	Median	0.891000
Maximum	15.75130	Maximum	1.150000
Minimum	2.408900	Minimum	0.512500
Std. Dev.	3.878725	Std. Dev.	0.169978
Skewness	0.520571	Skewness	-0.378028
Kurtosis	1.853851	Kurtosis	2.277711
Jarque-Bera	7.292801	Jarque-Bera	3.325522
Probability	0.026085	Probability	0.189615

Table 4.4.0 Descriptive Analysis of Monthly Companies Returns

It is evident that monthly observation suggest more for normality. P-values suggest more significance in results but standard deviations confirm a tendency of almost all companies to suffer a certain volatility. Distributions also appear to be less centred than observed in the previous examinations.

Runs test

BMPS		ENEL.MI		ENI.MI		FNC.MI		ISP.MI		MS.MI		UCG.MI		TIT.MI	
Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value	Z	P-value
.12	.9	-1.06	.29	-.12	.91	-.59	.56	.59	.55	-.82	.41	-.59	.56	.12	.9

Table 4.4.1 Runs Test for Monthly returns on FTSE MIB Selected Companies

Monthly analysis gives back same results as weekly gave before. This means all companies are supposed to be weak form efficient.

Unit Root test

Augmented Dickey-Fuller Test

LEVEL								
	BMPS.MI	ENEL.MI	ENI.MI	FNC.MI	ISP.MI	MS.MI	UCG.MI	TIT.MI
t-Statistic	-0.104127	-1.778844	-3.054587	-1.432481	-1.608144	-1.253222	-1.174932	-1.992398
Prob.*	0.9444	0.3880	0.0347	0.5618	0.4733	0.6469	0.6811	0.2896
TEST CRITICAL VALUE								
1% level	-3.524233	-3.524233	-3.524233	-3.524233	-3.524233	-3.524233	-3.524233	-3.524233
5% level	-2.902358	-2.902358	-2.902358	-2.902358	-2.902358	-2.902358	-2.902358	-2.902358
10% level	-2.588587	-2.588587	-2.588587	-2.588587	-2.588587	-2.588587	-2.588587	-2.588587

*MacKinnon (1996) one-sided p-values.

Table 4.4.2 ADF Test for Monthly FTSE MIB Selected Companies (level)

Philip-Perron Test

LEVEL								
	BMPS.MI	ENEL.MI	ENI.MI	FNC.MI	ISP.MI	MS.MI	UCG.MI	TIT.MI
t-Statistic	-0.179464	-1.929321	-3.250374	-1.432481	-1.569088	-1.302700	-1.258365	-1.904737
Prob.*	0.9355	0.3173	0.0211	0.5618	0.4931	0.6242	0.6446	0.3284
TEST CRITICAL VALUE								
1% level	-3.524233	-3.524233	-3.524233	-3.524233	-3.524233	-3.524233	-3.524233	-3.524233
5% level	-2.902358	-2.902358	-2.902358	-2.902358	-2.902358	-2.902358	-2.902358	-2.902358
10% level	-2.588587	-2.588587	-2.588587	-2.588587	-2.588587	-2.588587	-2.588587	-2.588587

*MacKinnon (1996) one-sided p-values.

Table 4.4.3 PP Test for Monthly FTSE MIB Selected Companies (level)

Monthly data seem to suggest more tendency not to refuse the null hypothesis with respect both to daily and weekly ones. Indeed, ENI shows weak efficiency at 1% significant level on the basis of the MacKinnon one-sided p-values.

Serial Correlation Test

Even monthly data give back results similar to the previous ones, excluding a strongly existence of weak form efficiency into selected companies.

Finally the analysis to test the weak-form efficiency focuses on two anomalies established during years: the day of the week effect and the January effect.

The Day Of The Week Effect

The most violations of the efficient market hypothesis have been identified in calendar anomalies. Hereinafter will be examined the day of the week effect for each Italian Stock Exchange index. Be a matter of days, it follows that the object of the examination are the daily returns for the whole period of mine investigation (2009-2014). The purpose is to find out whether there is any statistical significant difference among index returns on different days of the week.
The starting point would be the following regression:

$$R_t = \mu + b_2 D_2 + b_3 D_3 + b_4 D_4 + b_5 D_5 + \varepsilon_t \quad (31)$$

where D_1 is the dummy variable for Tuesday (that means $D_1 = 1$ if the observation is on Monday, $D_1 = 0$ otherwise), D_2 is the dummy variable for Wednesday, D_3 is the dummy variable for Thursday, and finally D_4 is the dummy variable for Friday. The intercept μ represents the rate of change of Monday, while b_n is the difference between the average rate of daily change and μ. The null hypothesis is the following:

$$H_0: b_1 = b_2 = b_3 = b_4 = 0$$

So the index will be proved subjected to the weak-form efficiency whether coefficient will result equal to zero, otherwise the null hypothesis would not be proved consistent with the data.

Now let's see in the deep how each index behaves:

FTSE IT MICRO CAP

Dependent Variable: LOG_RETURNS
Method: Least Squares
Sample: 1/05/2009 12/30/2014
Included observations: 1519

Variable	Coefficient	Std. Error	t-Statistic	Prob.
@WEEKDAY=2	9.39E-05	0.000642	0.146288	0.8837
@WEEKDAY=3	-0.000307	0.000643	-0.477448	0.6331
@WEEKDAY=4	-0.000463	0.000643	-0.720526	0.4713
@WEEKDAY=5	0.000814	0.000646	1.260045	0.2078
C	-5.00E-05	0.000456	-0.109635	0.9127

R-squared	0.003098	Mean dependent var	-2.53E-05
Adjusted R-squared	0.000464	S.D. dependent var	0.007917
S.E. of regression	0.007915	Akaike info criterion	-6.836798
Sum squared resid	0.094851	Schwarz criterion	-6.819267
Log likelihood	5197.548	Hannan-Quinn criter.	-6.830271
F-statistic	1.176099	Durbin-Watson stat	1.973705
Prob(F-statistic)	0.319464		

Table 4.4.4 Day of the Week FTSE IT MICRO CAP

FTSE IT SMALL CAP

Dependent Variable: LOG_RETURNS
Method: Least Squares
Sample: 1/02/2009 12/30/2014
Included observations: 1520

Variable	Coefficient	Std. Error	t-Statistic	Prob.
@WEEKDAY=2	-0.000567	0.000973	-0.582465	0.5603
@WEEKDAY=3	0.000392	0.000974	0.402608	0.6873
@WEEKDAY=4	-0.000935	0.000974	-0.960794	0.3368
@WEEKDAY=5	-0.000700	0.000978	-0.716457	0.4738
C	0.000212	0.000691	0.306028	0.7596

R-squared	0.001654	Mean dependent var	-0.000151
Adjusted R-squared	-0.000982	S.D. dependent var	0.011987
S.E. of regression	0.011993	Akaike info criterion	-6.005779

Sum squared resid	0.217889	Schwarz criterion	-5.988258
Log likelihood	4569.392	Hannan-Quinn criter.	-5.999256
F-statistic	0.627327	Durbin-Watson stat	1.611672
Prob(F-statistic)	0.643045		

Table 4.4.5 Day of the Week FTSE IT SMALL CAP

FTSE IT ALL-SHS

Dependent Variable: LOG_RETURNS
Method: Least Squares
Sample: 1/02/2009 12/30/2014
Included observations: 1520

Variable	Coefficient	Std. Error	t-Statistic	Prob.
@WEEKDAY=2	0.002333	0.001310	1.781403	0.0750
@WEEKDAY=3	0.002804	0.001312	2.137177	0.0327
@WEEKDAY=4	0.001898	0.001311	1.447882	0.1479
@WEEKDAY=5	0.001692	0.001316	1.285152	0.1989
C	-0.001741	0.000931	-1.870898	0.0616

R-squared	0.003463	Mean dependent var	9.64E-06
Adjusted R-squared	0.000832	S.D. dependent var	0.016156
S.E. of regression	0.016149	Akaike info criterion	-5.410658
Sum squared resid	0.395087	Schwarz criterion	-5.393137
Log likelihood	4117.100	Hannan-Quinn criter.	-5.404135
F-statistic	1.316142	Durbin-Watson stat	1.976480
Prob(F-statistic)	0.261748		

Table 4.4.6 Day of the Week FTSE IT ALL-SHS CAP

FTSE IT MID CAP

Dependent Variable: LOG_RETURNS
Method: Least Squares
Sample: 1/02/2009 12/30/2014
Included observations: 1520

Variable	Coefficient	Std. Error	t-Statistic	Prob.
@WEEKDAY=2	0.001059	0.001059	0.999494	0.3177
@WEEKDAY=3	0.001793	0.001061	1.690432	0.0912
@WEEKDAY=4	0.001704	0.001060	1.607391	0.1082
@WEEKDAY=5	0.001671	0.001064	1.569929	0.1166

C	-0.001098	0.000753	-1.458998	0.1448

R-squared	0.002656	Mean dependent var	0.000149
Adjusted R-squared	0.000023	S.D. dependent var	0.013058
S.E. of regression	0.013058	Akaike info criterion	-5.835595
Sum squared resid	0.258312	Schwarz criterion	-5.818074
Log likelihood	4440.052	Hannan-Quinn criter.	-5.829072
F-statistic	1.008753	Durbin-Watson stat	1.856060
Prob(F-statistic)	0.401651		

Table 4.4.7 Day of the Week FTSE IT MID CAP

FTSE ITALIA STAR

Dependent Variable: LOG_RETURNS
Method: Least Squares
Sample: 1/02/2009 12/30/2014
Included observations: 1548

Variable	Coefficient	Std. Error	t-Statistic	Prob.
@WEEKDAY=2	0.002310	0.001368	1.688386	0.0915
@WEEKDAY=3	0.002814	0.001372	2.050137	0.0405
@WEEKDAY=4	0.001876	0.001372	1.367162	0.1718
@WEEKDAY=5	0.001593	0.001371	1.161814	0.2455
C	-0.001732	0.000968	-1.788810	0.0738

R-squared	0.003124	Mean dependent var	-1.50E-05
Adjusted R-squared	0.000540	S.D. dependent var	0.017078
S.E. of regression	0.017073	Akaike info criterion	-5.299419
Sum squared resid	0.449762	Schwarz criterion	-5.282156
Log likelihood	4106.750	Hannan-Quinn criter.	-5.292998
F-statistic	1.208892	Durbin-Watson stat	1.989917
Prob(F-statistic)	0.305067		

Table 4.4.8 Day of the Week FTSE ITALIA STAR

FTSE MIB

Dependent Variable: LOG_RETURNS
Method: Least Squares
Sample: 1/02/2009 12/30/2014
Included observations: 1548

Variable	Coefficient	Std. Error	t-Statistic	Prob.
@WEEKDAY=2	0.008162	0.025134	0.324731	0.7454

@WEEKDAY=3	0.008666	0.025215	0.343670	0.7311
@WEEKDAY=4	0.037988	0.025215	1.506538	0.1321
@WEEKDAY=5	0.001167	0.025195	0.046320	0.9631
C	-0.007584	0.017787	-0.426376	0.6699

R-squared	0.001946	Mean dependent var	0.003577
Adjusted R-squared	-0.000641	S.D. dependent var	0.313571
S.E. of regression	0.313671	Akaike info criterion	0.522282
Sum squared resid	151.8152	Schwarz criterion	0.539545
Log likelihood	-399.2461	Hannan-Quinn criter.	0.528703
F-statistic	0.752084	Durbin-Watson stat	2.003083
Prob(F-statistic)	0.556596		

Table 4.4.9 Day of the Week FTSE MIB

It is possible to look at the summarised results below:

Index	μ	Prob.	D_2	Prob.	D_3	Prob.	D_4	Prob.	D_5	Prob.
ITMI.MI	-0.00005	0.9127	0.0000939	0.8837	-0.000307	0.6331	-0.000463	0.4713	0.000814	0.2078
ITSC.MI	0.000212	0.7596	-0.000567	0.5603	0.000392	0.6873	-0.000935	0.3368	-0.000700	0.4738
ITLMS.MI	-0.001741	0.0616	0.002333	0.0750	0.002804	0.0327	0.001898	0.1479	0.001692	0.1989
ITMC.MI	-0.001098	0.1448	0.001059	0.3177	0.001793	0.0912	0.001704	0.1082	0.001671	0.1166
ITSTAR.MI	-0.001732	0.0738	0.002310	0.0915	0.002814	0.0405	0.001876	0.1718	0.001593	0.2455
FTSEMIB.MI	-0.007584	0.6699	0.008162	0.7454	0.008666	0.7311	0.037988	0.1321	0.001167	0.9631

Table 4.5.0 Italian Stock Exchange Day of the week effect

It appears clear that none of the indexes present coefficients equal to zero, but they are all close to it. Monday rates appears different from each other, furthermore they result negative, a part for the FTSE IT SMALL CAP index. The fact that results show values close to zero, with p-value that suggest as a good probability for those coefficients to be zero, allows not to reject the null hypothesis. Hence all the indexes could be considered efficient under the weak efficient form.

Index	F-statistic	Prob (F-statistic)
ITMI.MI	1.176099	0.319464
ITSC.MI	0.627327	0.643045
ITLMS.MI	1.316142	0.261748
ITMC.MI	1.008753	0.401651
ITSTAR.MI	1.208892	0.305067
FTSEMIB.MI	0.752084	0.556596

Table 4.5.1 Italian Stock Exchange Day of the week effect

In order to assess, easier and for sure, the proof of the weak efficiency under the day of the week effect, the above table summarise results for the F-statistic and their relatives p-values. Thanks to p-values it is easy to notice that F-statistics suggest all the indexes are efficient under the weak-form. Indeed probabilities show value higher than the α. This means that all indexes appear to follow a RW at 5% significance level.

The January Effect

Another important effect, as it has possible to see in the present work, is the January effect. In order to test the presence of this effect into the Italian market, it has been performed a regression as follow:

$$R_t = \mu + \beta' D_t + \varepsilon_t \qquad (32)$$

Where D_t is a dummy for the month of January[34].

Now, let's proceed:

FTSE IT MICRO CAP

Dependent Variable: LOG_RETURNS
Method: Least Squares
Sample: 2009M01 2014M12
Included observations: 72

Variable	Coefficient	Std. Error	t-Statistic	Prob.
JANUARY	0.005325	0.018431	0.288899	0.7735
C	-0.000977	0.005321	-0.183545	0.8549

R-squared	0.001191	Mean dependent var	-0.000533
Adjusted R-squared	-0.013078	S.D. dependent var	0.042944
S.E. of regression	0.043224	Akaike info criterion	-3.417448
Sum squared resid	0.130783	Schwarz criterion	-3.354208
Log likelihood	125.0281	Hannan-Quinn criter.	-3.392272
F-statistic	0.083463	Durbin-Watson stat	1.474034
Prob(F-statistic)	0.773512		

[34] Data consist of monthly returns

Table 4.5.2 January effect FTSE IT MICRO CAP

FTSE IT SMALL CAP

Dependent Variable: LOG_RETURNS
Method: Least Squares
Sample: 2009M01 2014M12
Included observations: 72

Variable	Coefficient	Std. Error	t-Statistic	Prob.
JANUARY	0.039244	0.026606	1.475016	0.1447
C	-0.006462	0.007680	-0.841367	0.4030

R-squared	0.030144	Mean dependent var	-0.003192
Adjusted R-squared	0.016289	S.D. dependent var	0.062911
S.E. of regression	0.062397	Akaike info criterion	-2.683229
Sum squared resid	0.272533	Schwarz criterion	-2.619988
Log likelihood	98.59624	Hannan-Quinn criter.	-2.658052
F-statistic	2.175671	Durbin-Watson stat	1.742760
Prob(F-statistic)	0.144692		

Table 4.5.3 January effect FTSE IT SMALL CAP

FTSE IT ALL-SHS

Dependent Variable: LOG_RETURNS
Method: Least Squares
Sample: 2009M01 2014M12
Included observations: 72

Variable	Coefficient	Std. Error	t-Statistic	Prob.
JANUARY	0.016954	0.027601	0.614262	0.5410
C	-0.001209	0.007968	-0.151773	0.8798

R-squared	0.005361	Mean dependent var	0.000204
Adjusted R-squared	-0.008848	S.D. dependent var	0.064445
S.E. of regression	0.064730	Akaike info criterion	-2.609811
Sum squared resid	0.293295	Schwarz criterion	-2.546570
Log likelihood	95.95318	Hannan-Quinn criter.	-2.584634
F-statistic	0.377318	Durbin-Watson stat	1.826567
Prob(F-statistic)	0.541034		

Table 4.5.4 January effect FTSE IT ALL-SHS

FTSE IT MID CAP

Dependent Variable: LOG_RETURNS

Method: Least Squares

Sample: 2009M01 2014M12

Included observations: 72

Variable	Coefficient	Std. Error	t-Statistic	Prob.
JANUARY	0.029832	0.022313	1.336952	0.1856
C	0.000670	0.006441	0.104031	0.9174

R-squared	0.024899	Mean dependent var	0.003156
Adjusted R-squared	0.010969	S.D. dependent var	0.052619
S.E. of regression	0.052329	Akaike info criterion	-3.035136
Sum squared resid	0.191685	Schwarz criterion	-2.971895
Log likelihood	111.2649	Hannan-Quinn criter.	-3.009959
F-statistic	1.787440	Durbin-Watson stat	1.682741
Prob(F-statistic)	0.185567		

Table 4.5.5 January effect FTSE IT MID CAP

FTSE ITALIA STAR

Dependent Variable: LOG_RETURNS

Method: Least Squares

Sample: 2009M01 2014M12

Included observations: 72

Variable	Coefficient	Std. Error	t-Statistic	Prob.
JANUARY	0.015438	0.018990	0.812983	0.4190
C	0.009547	0.005482	1.741517	0.0860

R-squared	0.009354	Mean dependent var	0.010833
Adjusted R-squared	-0.004798	S.D. dependent var	0.044428
S.E. of regression	0.044534	Akaike info criterion	-3.357725
Sum squared resid	0.138832	Schwarz criterion	-3.294484
Log likelihood	122.8781	Hannan-Quinn criter.	-3.332548
F-statistic	0.660941	Durbin-Watson stat	1.421767
Prob(F-statistic)	0.418985		

Table 4.5.6 January effect FTSE ITALIA STAR

FTSE MIB

Dependent Variable: LOG_RETURNS

Method: Least Squares

Sample: 2009M01 2014M12

Included observations: 72

Variable	Coefficient	Std. Error	t-Statistic	Prob.
JANUARY	0.016320	0.029408	0.554946	0.5807
C	-0.001683	0.008489	-0.198303	0.8434

R-squared	0.004380	Mean dependent var	-0.000323
Adjusted R-squared	-0.009843	S.D. dependent var	0.068631
S.E. of regression	0.068968	Akaike info criterion	-2.482955
Sum squared resid	0.332964	Schwarz criterion	-2.419714
Log likelihood	91.38639	Hannan-Quinn criter.	-2.457779
F-statistic	0.307965	Durbin-Watson stat	1.846195
Prob(F-statistic)	0.580700		

Table 4.5.7 January effect FTSE MIB

Hereinafter it possible to appreciate the whole analysis under all the indexes levels:

Index	*January*	Prob.	*Other Months*	Prob.
ITMI.MI	0.005325	0.7735	-0.000977	0.8549
ITSC.MI	0.039244	0.1447	-0.006462	0.4030
ITLMS.MI	0.016954	0.5410	-0.001209	0.8798
ITMC.MI	0.029832	0.1856	0.000670	0.9174
ITSTAR.MI	0.015438	0.4190	0.009547	0.0860
FTSEMIB.MI	0.016320	0.5807	-0.001683	0.8434

Table 4.5.8 The January Effect (Italian Stock Exchange)

The coefficient relatives to January (dummy variable for January) measures the difference between the intercept value on January and the intercept value of months different from January. The second coefficient measures the value of the intercept for the other months. The coefficient of January does not seem to reliably differ from zero, this leads to understand that the intercept on January does not suffer changes with respect to values assumed during the other months. Therefore the effect seems not to be present in the Italian market.

4.1.7 Semi-Strong Hypothesis

The semi-strong form of market efficiency occurs when prices immediately reflect all public available information, and so, there exists no possibility to beat the market by predicting future price movements.

Before assessing the semi-strong efficiency of Italian companies, an example of semi-strong efficiency is reported in the following rows as an additional explanation of the theory:

Mario Rossi held 100 shares of FCA. He had purchased them on 1 January 2015 for 9,60 € per share. FCA is a company that appears among the main worldwide car manufacturers. Mario is not an active investor so he does not checks the stock performance daily. On 12 January 2015 he discovered that FCA has incurred in some trade union troubles by an article published on 11 January 2012 by Il Sole 24 Ore. According to the article, FCA is wasting labour time because of an all-out strike. Total outstanding shares of FCA are 1,2 billion. Mario sold off his holding for 8,5 € per share in the opening hours of 13 January 2012. Hence, he minimized his loss. Unfortunately, towards the end of 15 January 2015, the company's stock price had climbed to 10,7 € per share. The market seems to be semi-strong form efficient because had adjusted itself to the public information on 12 January 2015 as soon as the market came to know about it and changed on 15 January 2015 when FCA solved its problems as was shown by a tweet of the FCA CEO Sergio Marchionne.

4.1.1 Methodology

The idea on the basis of this analysis is that if some anomalies affect the Italian market, the market would result not semi-strong efficient.

The analysis tries to the presence of the Dividend Yield influence over market prices, in order to study the possibility of the presence of this anomaly and to verify the existence of semi-strong efficiency into the market.

Dividend Yield

As introduced, another good expedient to keep tracks of stocks behaviours is testing for dividends. The dividend yield consists in the ratio of the total amount of dividends paid out by a company in the last year, over the last month. It is possible to analyse the effect of the dividend yield on some companies on the basis of the following regression:

$$R_t = \mu + \delta' F_{t-1} + \varepsilon_t \qquad (33)$$

Dividends Yield has been calculated as the ratio between the last dividend paid out and daily prices. So I constructed a dummy for the month of January and I verified results of the coefficient.

BMPS.MI

Dependent Variable: LOG_RETURNS
Method: Least Squares
Sample: 2/02/2009 1/29/2010
Included observations: 257

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DUMDATA4	-0.002624	0.222452	-0.011795	0.9906
C	0.000375	0.062056	0.006049	0.9952

R-squared	0.000001	Mean dependent var	0.000171
Adjusted R-squared	-0.003921	S.D. dependent var	0.953477
S.E. of regression	0.955344	Akaike info criterion	2.754261
Sum squared resid	232.7340	Schwarz criterion	2.781880
Log likelihood	-351.9226	Hannan-Quinn criter.	2.765368
F-statistic	0.000139	Durbin-Watson stat	2.979286
Prob(F-statistic)	0.990598		

Table 4.5.9 Dividend Yield effect BMPS

Results from the regression above suggest that dividend yields do not help investors to forecast future prices because the coefficient is not really different from zero, as suggested by a reliable p-value. This means in turn that dividend yields do not appear to influence returns. R-squared is really low, as confirmed by the F-statistic at 10% significance level. This means that dividends do not help to explain returns, suggesting that returns are difficult to forecast and leading not to reject the null hypothesis. Hence the Italian market could be considered semi-strong form efficient.

The year 2010 was characterized by no dividends for BMPS.

ENI

Dividends Yield has been calculated as the ratio between the total dividend paid out of the previous year (0,5 + 0,65 for the period 2009) and daily prices.

Dependent Variable: LOG_RETURN
Method: Least Squares
Sample (adjusted): 2/02/2010 1/31/2011
Included observations: 260 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIVIDEND_YIELD	-0.344979	0.133404	-2.585972	0.0103
C	0.134424	0.051959	2.587088	0.0102

R-squared	0.025265	Mean dependent var	7.63E-05
Adjusted R-squared	0.021487	S.D. dependent var	0.013986
S.E. of regression	0.013835	Akaike info criterion	-5.715604
Sum squared resid	0.049381	Schwarz criterion	-5.688214
Log likelihood	745.0285	Hannan-Quinn criter.	-5.704593
F-statistic	6.687249	Durbin-Watson stat	2.019524
Prob(F-statistic)	0.010259		

Table 4.6.0 Dividend Yield effect ENI

Results from the regression above suggest that there exists the possibility that dividend yields help investors to forecast future prices because the coefficient is different from zero. On the other hand, the p-value does not suggest considerable reliability results at 5% significance level. Moreover, neither the F-statistic is considerable significant at 5% statistical level, and the R-squared and the Adjusted R-squared indicate that the relation between returns and dividend yields is not considerable. This leads not to reject the null hypothesis, hence the Italian market could be considered semi-strong form efficient.

Dependent Variable: LOG_RETURN
Method: Least Squares
Sample (adjusted): 2/02/2010 1/31/2011
Included observations: 260 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIVIDEND_YIELD	-0.344979	0.133404	-2.585972	0.0103
C	0.134424	0.051959	2.587088	0.0102

R-squared	0.025265	Mean dependent var	7.63E-05
Adjusted R-squared	0.021487	S.D. dependent var	0.013986
S.E. of regression	0.013835	Akaike info criterion	-5.715604
Sum squared resid	0.049381	Schwarz criterion	-5.688214
Log likelihood	745.0285	Hannan-Quinn criter.	-5.704593
F-statistic	6.687249	Durbin-Watson stat	2.019524
Prob(F-statistic)	0.010259		

Table 4.6.1 Dividend Yield effect ENI

It is possible to notice the same results for the period from February, 2 2010 to January, 29 2011. The results obtained lead to strongly reject the possibility that dividend yields could help investors to forecast future returns. Hence, ENI seems to be part of a semi-strong efficient market.

MEDIASET

Dependent Variable: LOG_RETURN
Method: Least Squares
Sample (adjusted): 2/03/2009 1/29/2010
Included observations: 259 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIVIDEND_YIELDS	-0.051800	0.040719	-1.272147	0.2045
C	0.015168	0.010690	1.418819	0.1572

R-squared	0.006258	Mean dependent var	0.001654
Adjusted R-squared	0.002391	S.D. dependent var	0.019309
S.E. of regression	0.019285	Akaike info criterion	-5.051238
Sum squared resid	0.095586	Schwarz criterion	-5.023772
Log likelihood	656.1353	Hannan-Quinn criter.	-5.040195
F-statistic	1.618358	Durbin-Watson stat	2.299076
Prob(F-statistic)	0.204471		

Table 4.6.2 Dividend Yield effect MS

Dependent Variable: LOG_RETURN
Method: Least Squares
Sample: 2/01/2010 1/31/2011
Included observations: 261

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIVIDEND_YIELD	-0.279377	0.190149	-1.469250	0.1430
C	0.026833	0.018692	1.435572	0.1523

R-squared	0.008266	Mean dependent var	-0.000575
Adjusted R-squared	0.004437	S.D. dependent var	0.019105
S.E. of regression	0.019063	Akaike info criterion	-5.074506
Sum squared resid	0.094120	Schwarz criterion	-5.047192
Log likelihood	664.2231	Hannan-Quinn criter.	-5.063527
F-statistic	2.158694	Durbin-Watson stat	1.956005
Prob(F-statistic)	0.142979		

Table 4.6.3 Dividend Yield effect MS

Both in 2009 and 2010, Mediaset issued dividends. Although coefficients differ from zero, especially in the second case, results do not seem to suggest any affection over returns by dividends. Indeed R^2 and AdjR^2 do not suggest the possibility that this model help finding relation among returns and dividends.

FINMECCANICA

Dependent Variable: LOG_RETURN
Method: Least Squares
Sample (adjusted): 2/03/2009 1/31/2012
Included observations: 781 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIVIDEND_YIELD	-0.029201	0.014072	-2.075073	0.0383
C	0.003806	0.002759	1.379388	0.1682

R-squared	0.005497	Mean dependent var	-0.001614
Adjusted R-squared	0.004220	S.D. dependent var	0.024917
S.E. of regression	0.024865	Akaike info criterion	-4.548184
Sum squared resid	0.481617	Schwarz criterion	-4.536249
Log likelihood	1778.066	Hannan-Quinn criter.	-4.543593
F-statistic	4.305928	Durbin-Watson stat	1.899479
Prob(F-statistic)	0.038307		

Table 4.6.4 Dividend Yield effect FNC

TELECOM

Dependent Variable: LOG_RETURN
Method: Least Squares
Date: 09/25/15 Time: 11:56
Sample (adjusted): 2/03/2009 1/31/2014
Included observations: 1303 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIVIDEND_YIELD	3.27E-05	0.000135	0.242430	0.8085
C	-0.000114	0.000627	-0.182593	0.8551

R-squared	0.000045	Mean dependent var	-0.000118
Adjusted R-squared	-0.000723	S.D. dependent var	0.022609
S.E. of regression	0.022617	Akaike info criterion	-4.738691
Sum squared resid	0.665502	Schwarz criterion	-4.730752
Log likelihood	3089.257	Hannan-Quinn criter.	-4.735713

F-statistic	0.058772	Durbin-Watson stat	2.002185
Prob(F-statistic)	0.808485		

Table 4.6.5 Dividend Yield effect TIT

The last two cases examined (Finmeccanica and Telecom) clearly suggest that there exists no influence carried out by dividends over returns, as confirmed by reliable p-values and despite the use of larger samples.

5. The ways we access the market

Whomver decides to approach with financial markets would face different opportunities. If we just think to the Italian Stock Exchange “Borsa Italiana”, there is a wide world of opportunities. ETFs, ETC, ETM, Mutual Funds, Derivatives, as well as CW, Bonds and Certificates are the main part of the huge panorama of the Italian Financial Market. Among these multiple choices of the market, I find interesting to focus on ETFs, which are raising instruments in the Italian and worldwide panorama.

5.1 Exchange-Traded Funds

Exchange Traded Funds (ETFs) are funds (or Sicav[35]) that track indexes like the FTSE MIB, NASDAQ-100 Index, S&P 500, Dow Jones, etc.[36] ETFs are represented as stocks into any Stock Exchange, that means they are negotiated as a stock as well. ETFs allow to achieve a yield equal to the benchmark in use. This is possible by means of a passive funds management style. Another feature of ETFs is represented by the capability to show prices adjusted for NAV (Net Asset Value)[37] [38]. ETFs seem to appear as index funds, but they do not try to outperform their corresponding index, that is a feature of an active management strategy. Therefore ETFs do not try to beat the market, they try to be the market. As a consequence, administrative costs of an ETF are supposed to be less than other managed funds because they incur in less management fees[39].

The origin of ETFs is ascribed to some Canadian instruments (i.e. the Toronto 100 Index Participation Units - HIPs) by A. Seddik Meziani, but the creator of ETFs is worldwide

[35] http://www.borsaitaliana.it/etf/formazione/cosaeunetf/coseunetf.htm
[36] http://www.nasdaq.com/investing/etfs/what-are-ETFs.aspx#ixzz3lnDzfJKm
[37] The Nav represents the mutual fund’s price per share or the exchange-traded fund’s per share value. The NAV is calculated as the total value of all the securities in its portfolio, divided by the number of fund shares outstanding - http://www.investopedia.com/terms/n/nav.asp
[38] http://www.borsaitaliana.it/etf/formazione/cosaeunetf/coseunetf.htm
[39] http://www.nasdaq.com/investing/etfs/what-are-ETFs.aspx#ixzz3lnDzfJKm

represented by Nathan Most. The first recognized ETF was the Standard & Poor's Depositary Receipts (SPDR), also known as "Spider", based on the S&P500 index. Then, the Barclays Global Investor fascinated by the success obtained by ETFs in the late 90s, created the World Equity Benchmark Shares (WEBS), instruments able to replicate any national Stock Exchange. This leads to the creation of sector ETFs as well [40]. In 2003, the ETF S&P/MIB Master Unit was born, it was the first ETF over an Italian Stock Exchange index[41]. In the same year, the Active ETF raised up in the NYSE[42], but here the focus is completely concentred over the traditional concept of ETFs.

ETFs are generally divided in: Management Investment Trust, Unit Investment Trust and Grantor Trust. Most of the ETFs are structured on the basis of the first typology (MIT, ed.). In this kind of ETF, managers coordinate activities relative to the underlying. The primary characteristic of MIT typology is the possibility not to hold each stocks of the underlying (the index). Unit Investment Trust differs from Management Investment Trust because of the less flexibility (i.e. no derivatives allowed) and less fees. Finally Grantor Trust is the less manageable typology, because it is not allowed to hold less stocks than those in the portfolios. In the Italian Stock Exchange exists a regulated electronic market dedicated to ETFs, the ETFplus[43]. The ETFplus consists of: ETFs, structured ETFs, Active ETFs, Exchange Traded Commodities (ETC) and Exchange Traded notes (ETN) [44]. It has already been stated the meaning of ETFs, while structured ETFs add to the normal activity of an ETF, the possibility to access investment strategies on the basis of a leveraged ETF or a short ETF (this kind of ETF works on falls of the market). On the other hand ETC and ETN are instruments based on derivatives and bonds[45]. Again, this work is focused just on ETF itself.

5.2 Testing the weak form of EMH through the Exchange-traded Funds in Italy

Given that ETFs represent one of the best ways for an investor to access the market, the last analysis performed in this work tries to verify the efficiency of the Italian ETFs operating in the ETFplus market. There exist proofs of the presence of weak form efficiency into the US

[40] Strategie basate su indicatori fondamentali e di volatilità: un'applicazione al mercato europeo degli ETF settoriali, Matteo Paolini, 2010

[41] Comunicato Stampa, Lyxor AM lancia il primo ETF sull'indice S&P/MIB in Borsa Italiana, 10 Novembre 2003

[42] Active ETFs track indexes created by financial managers - Strategie basate su indicatori fondamentali e di volatilità: un'applicazione al mercato europeo degli ETF settoriali, Matteo Paolini, 2010

[43] Strategie basate su indicatori fondamentali e di volatilità: un'applicazione al mercato europeo degli ETF settoriali, Matteo Paolini, 2010

[44] http://www.borsaitaliana.it/etf/formazione/segmentazioneemicrostrutturamercatoetfplus/etfplussegmentazioneemicrostruttura.htm

[45] http://www.borsaitaliana.it/etf/formazione/segmentazioneemicrostrutturamercatoetfplus/etfplussegmentazioneemicrostruttura.htm

ETF market[46], this would lead to think there would be in the Italian one as weel. “So, are the Italian ETFs weak form efficient?” This is the question I would like to answer at the end of this investigation.

ETFs were born to replicate Index’s performance. The purpose of the management is to make that total return performance of an ETF trails the total return performance of the benchmark in order to minimize the differential of the return (Tracking Error)[47]. So, the first step in order to consider whether Italian ETFs are parts of an efficient market, is to evaluate ETFs’ performance with respect to their underlying indexes.
ETFs’ performance has been tested by means of several indicators, Ursula Marchioni of iShares states that there exist two most important indicators: the tracking difference (TD) and the aforementioned tracking error (TE)[48].

Tracking Difference

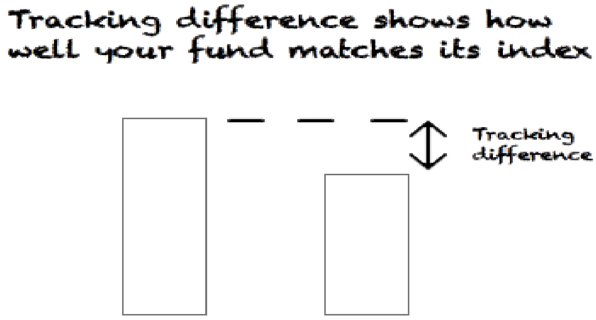


Figure 5.1 How good is your tracker? Use tracking difference to find out!, The Accumulator, 2011

Tracking difference shows how a product’s performance compares with that of its benchmark over a significant period of time[49]. Tracking difference results can appear positive or negative, underlying the extent to which an ETF outperforms or underperforms its index. The TD is computed as the difference between the NAV (total return) and the total return of the index (or benchmark). Because the NAV of ETFs total return includes some expenses, tracking difference typically is negative[50].

Tracking Errors

The first step is to verify how well ETFs track their indexes. In our case Italian ETFs with available data track all the same index (FTSE MIB). Therefore, following the three estimation process of the Tracking Error known in literature[51] [52], I calculated the TE of four Italian ETFs

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[46] Testing weak-form e ciency of exchange traded funds market, Gerasimos G. Rompotis, National and Kapodistrian University of Athens, July 2011
[47] http://www.borsaitaliana.it/etf/formazione/modalitadireplicaetf/modalitadireplicaetf.htm
[48] How to evaluate ETFs through tracking error and difference, Ursula Marchioni. iShares, 2013
[49] Understanding tracking difference and tracking error, Vanguard Investments Hong Kong Limited, 2014
[50] Understanding tracking difference and tracking error, Vanguard Investments Hong Kong Limited, 2014
[51] Tracking S&P 500 index funds. Journal of Portfolio Management, Frino, Gallagher, 2001.

to verify that they follow their indexes at significant level. The tracking errors measure the difference in performance between the ETF and their benchmark indices[53]. In other words, tracking errors indicate how much variability exists among the individual data points of the ETF average tracking difference over a given period of time. Therefore, commonly, TE is defined as the volatility of the differences in returns between an ETF and its underlying index. Hence, there exist two possibilities: the TE is consistently low, and so, the ETF has been tracking its underlying index (or benchmark) equally well[54]; the TE is not that low, and so it did not track the ETF consistently.

The three ways to calculate the tracking errors are the following:

- The first tracking error is the average of the funds absolute return differences between the ETF and index, or the mean absolute deviation (MAD):

$$TE_1 = \frac{1}{T}\sum_{t=1}^{T}\left|r_{F,t} - r_{l,t}\right| \tag{34}$$

- The second TE is the standard deviation of return differences between the ETF and the index:

$$TE_2 = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(RD_T - \overline{RD})^2} \tag{35}$$

- The last tracking error is calculated as the standard error of a regression of the ETF returns on the benchmark returns.

$TE_3 =$ *Standard Error* resulted by the following regression:

$$r_{F,t} = \alpha + \beta r_{l,t} + u_t \tag{36}$$

Where $r_{F,t}$ and $r_{l,t}$ are, respectively, the logarithmic daily return calculated on the NAV of the ETF considered, and the log daily return of the Index considered. RD_T it the absolute

[52] Measuring the tracking error of exchange traded funds: an unobserved components approach, Giuliano De Rossi, Quantitative analyst, UBS Investment Research, 2012
[53] The performance and tracking ability of Exchange Traded Funds, Lars Bassie, Tilburg University – Finance Department, 2012
[54] Tracking difference and tracking error of ETFs, Investor Education Centre, Hong Kong

difference between $r_{F,t}$ and $r_{I,t}$. The β coefficient of TE_3 measures the co-movement of the returns of the ETF with the benchmark index. The closer this beta coefficient is to 1, the better it performs in tracking the index.

The indicator designed to assess Italian ETFs performance is the TE. Following the three methods and using daily NAV (Net Asset Value) and Daily Log Returns, I computed TEs. The period of observation fluctuates from October, 22 2010 to September, 9 2015. Results are the following:

ETF	INDEX	Tracking Error	Tracking Error 2	Tracking Error 3
AM FT MIB UCITS ETF (FMI.MI)	FTSE MIB	0,017804065	0,015602427	0,027962
DBXT FTSE MIB 1D (XMIB.MI)	FTSE MIB	0,017196159	0,023187612	0,026852
FTSE MIB EUR (IMIB.MI)	FTSE MIB	0,017410839	0,022848089	0,027057
L UC ETF FTS MIB (ETFMIB.MI)	FTSE MIB	0,016827193	0,023198928	0,027283

Table 5.1 Tracking Errors over daily ETFs

The table above leads to observe that tracking errors of the selected ETFs fluctuate around a value 1-3 per cent depending of the estimation process. This leads to think that ETFs well represent the FTSE MIB index, because the deviation from index values is meaningless (0,027962 in the worst case). Results state that selected ETFs track FTSE MIB index at a remarkable level. In other terms, it is possible to affirm that the ETFs performances correspond to FTSE MIB index. Although the evidences suggest that assesses these ETFs is unnecessary once that FTSE MIB index has been already tested.

Information Ratio

Another way to assess the efficiency of ETFs, in terms of trailing indexes, is to compute the Information Ratio (IR).

The IR is an indicator calculated as the ratio between the return differentials and the Tracking Error.

The formula to calculate the IR is the following:

$$IR = \frac{R_P - R_B}{TE_{P,B}} \tag{37}$$

Where R_P is the ETF return, R_B is the index (or benchmark) return and $TE_{P,B}$ is the tracking error volatility. This indicator includes the weight of return differentials, given the possibility to check the management capability to outperform the index with respect to the risk (the contingent gap between ETF and index).

ETF	INDEX	IR (using TE)	IR (using TE 2)	IR (using TE 3)
AM FT MIB UCITS ETF (FMI.MI)	FTSE MIB	-4,88165709	-5,570501537	-3,108266282
DBXT FTSE MIB 1D (XMIB.MI)	FTSE MIB	-1,96499468	-1,457259223	-1,258392697
FTSE MIB EUR (IMIB.MI)	FTSE MIB	0,801776152	0,61097432	0,515932877
L UC ETF FTS MIB (ETFMIB.MI)	FTSE MIB	-0,288829199	-0,2095004	-0,178139676

Table 5.2 Information Ratio over Daily ETFs

The IR adjust for return differential, so it gives a better answer with respect of the TE. Table 5.2 underlines the underperformance of three ETFs, with remarkable evidences for the AM FT MIB UCITS ETF, while FTSE MIB EUR shows even positive IR values. As a consequence there exists the possibility that IMIB represents an ETF that outperforms the market. However values are close to zero, that means ETFs well represent their index. This does not hold for AM FT MIB UCITS ETF.

Testing the efficiency of ETFs would be an additional useless work on the basis of TE results. On the other hand, the information ratios suggest the possibility that there exist something wrong with these ETFs, hence an analysis for the weak-form efficiency have been performed in the following paragraphs.

5.3 Weak Hypothesis

Purpose of the analysis: An index is a mathematical construct, so it may not be invested in directly. Exchange-traded funds attempt to track an index in order to transform it into a good that could be object of investment. The aim of the following analysis is to verify the presence of weak efficiency into the ETFplus to verify if these instruments are able to give investors a “cleaning” way to access the market. Therefore the null hypothesis stated is that the prices of ETFs considered follow a random walk. Hereinafter, the two hypothesis that could be proved:

$$\begin{cases} H_0\text{: the prices of the Italian ETFs are random over the period of the study} - weak - form\ efficiency \\ H_1\text{: the prices of the Italian ETFs are not random over the period of the study} - inefficiency \end{cases}$$

5.4 Data

The analysis relative to the ETFs has been realized by means of Standard Italian ETFs data obtained by Yahoo finance [55]. There exist seven ETFs belonging to the Italian Stock Exchange, but I kept out the Lyxor ETF FTSE Italia Mid Cap D-EUR A/I (ITAMID.MI) because of the small presence of data.

Therefore, ETFs considered are: Amundi FTSE MIB Ucits ETF (FMI.MI), Amundi MSCI Italy Ucits ETF (CI1.MI), Db X-Trackers FTSE MIB Ucits ETF (Dr) (XMIB.MI), IShares FTSE MIB Ucits ETF (CSMIB.MI), Lyxor Ucits ETF FTSE MIB (ETFMIB.MI) and Powershares FTSE Rafi Italy 30 Ucits ETF (PTI.MIB). Even though some of the ETFs' data considered are available since 2007, 2008 and 2003, it is not the same for the others. Therefore, the analysis concerns the period from September, 9 2010 to September, 9 2015.

5.5 Methodology and Results

The analysis follows the guideline of the previous investigations over the Italian market. Autocorrelation test, ADF and PP tests have been carried out to reach the purpose established before.

Here an overview of the characteristics of the Italian ETFs selected:

Name	Symbol	Issuer	Benchmark	Daily	Weekly	Monthly
AMUNDI FTSE MIB UCITS ETF	FMI	AMUNDI	FTSE MIB TR	1224	260	60
AMUNDI MSCI ITALY UCITS ETF	CI1	AMUNDI	MSCI ITALY TRN	929	240	60
DB X-TRACKERS FTSE MIB UCITS ETF (DR)	XMIB	DB-X-TRACKERS	FTSE MIB	1245	261	60
LYXOR UCITS ETF FTSE MIB	ETFMIB	LYXOR INTERNATIONAL ASSET MANAGEMENT S.A	FTSE MIB TRN	1252	261	60
ISHARES FTSE MIB UCITS ETF (ACC)	CSMIB	ISHARES VII	FTSE MIB TR	1186	259	60
POWERSHARES	PTI	POWERSHARES	FTSE RAFI	614	172	60

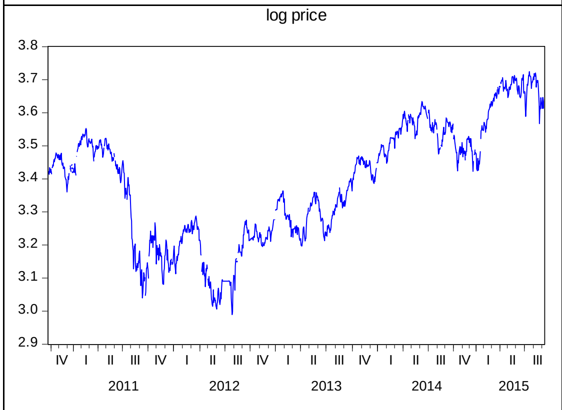
55 http://www.borsaitaliana.it/etf/etf/home.htm

FTSE RAFI ITALY 30 UCITS ETF	GLOBAL FUNDS IRELAND PLC	ITALY 30

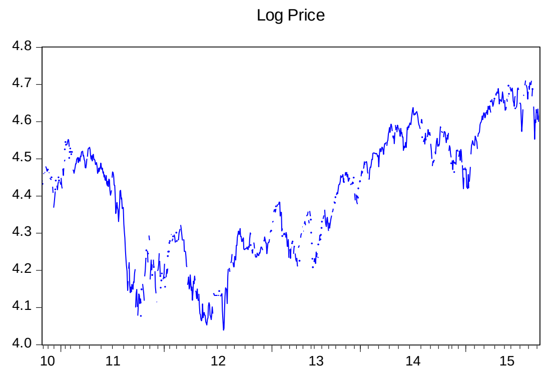
Table 5.3 Profiles of ETFs

Profiles of ETFs underline a lack of available data, not observed before, over Powershares FTSE RAFI ITALY and AMUNDI MSCI ITALY UCITS ETF. Hereinafter it is possible see whether this would lead to inconsistent results.

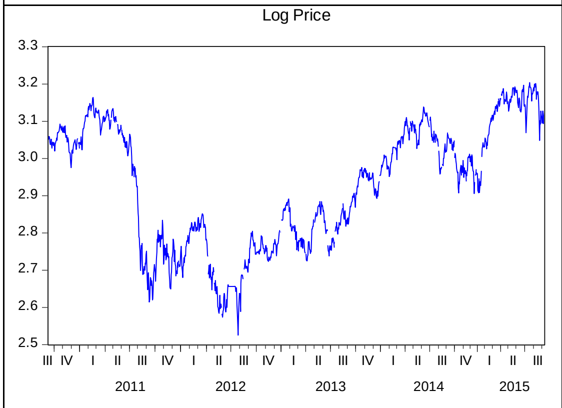
FMI



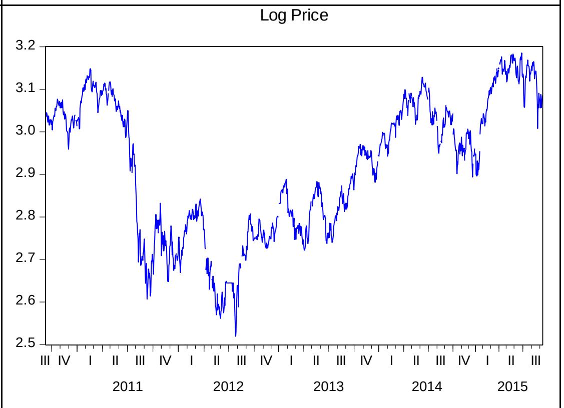
CI1



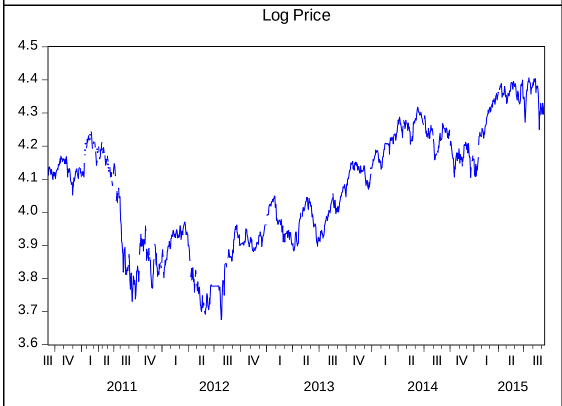
XMIB



ETFMIB



CSMIB



PTI

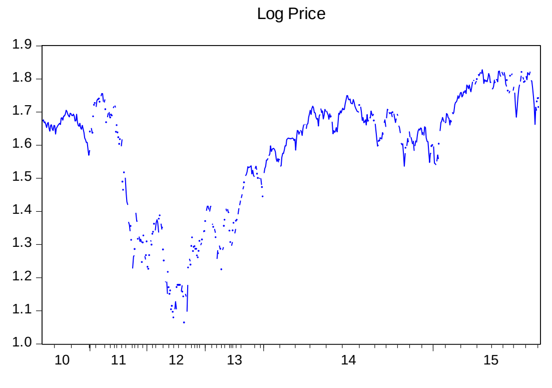
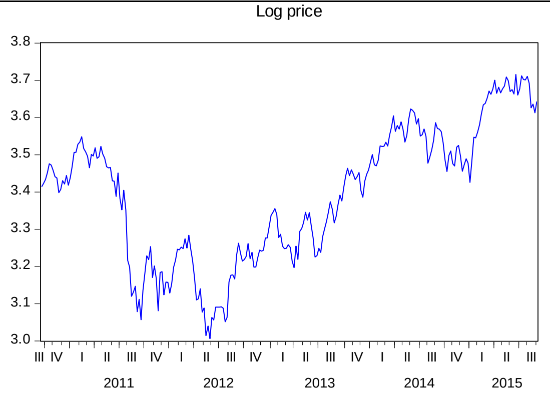
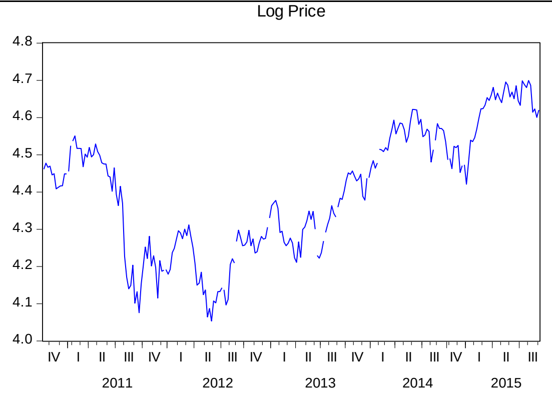
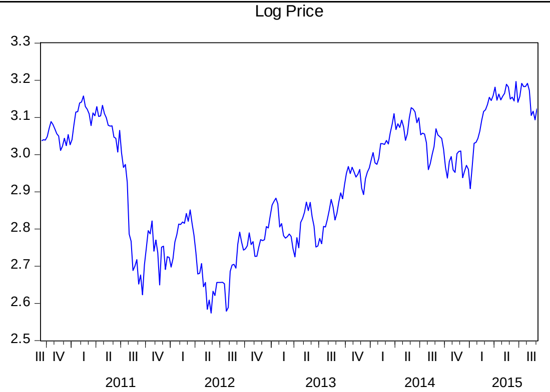
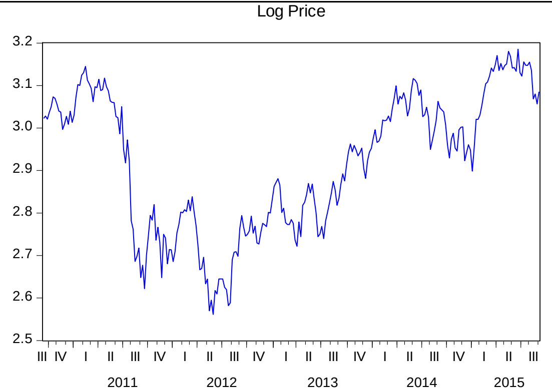


Table 5.4 Time Series Plots of Daily Prices (ETFs)

FMI	CI1
	

XMIB	ETFMIB
	

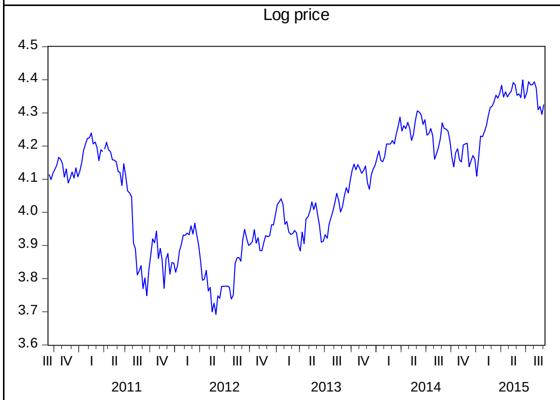
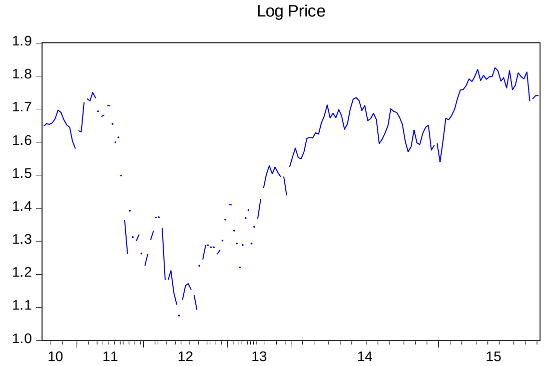
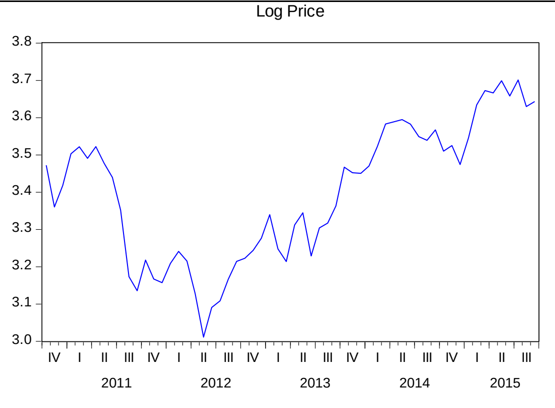
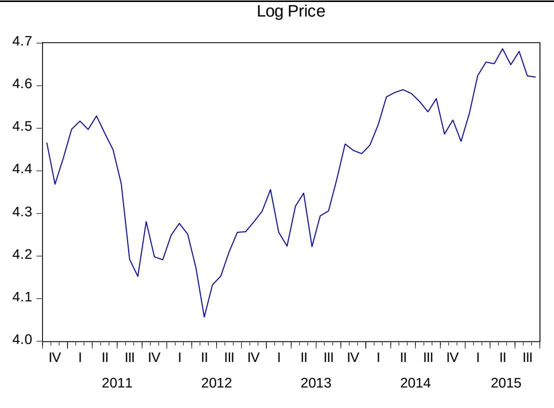
CSMIB	PTI
	

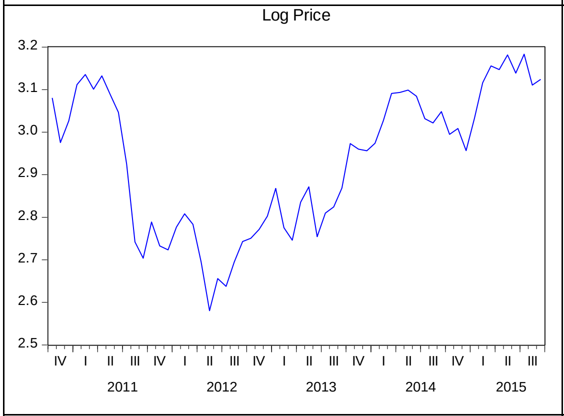
Table 5.5 Time Series Plots of Weekly Prices (ETFs)

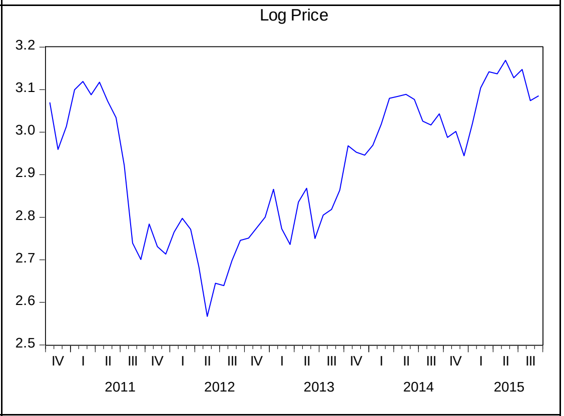
FMI	CI1



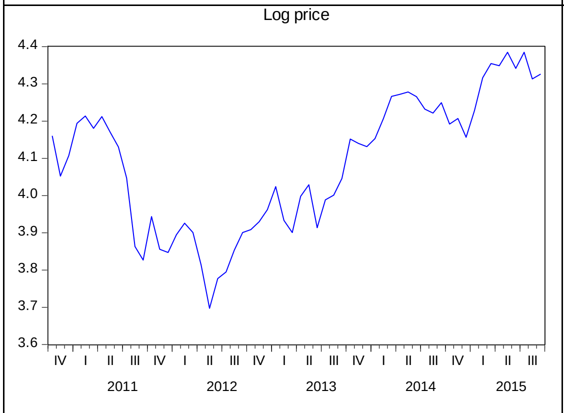


XMIB	ETFMIB





CSMIB	PTI



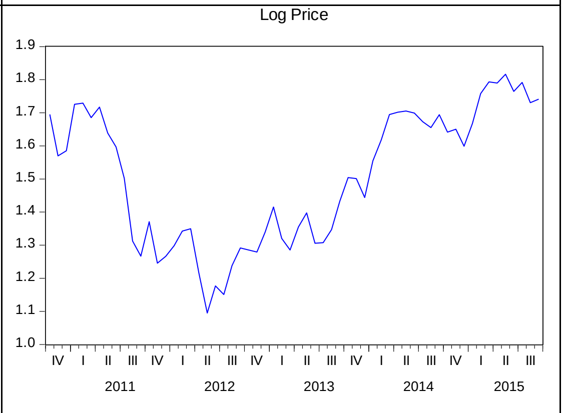
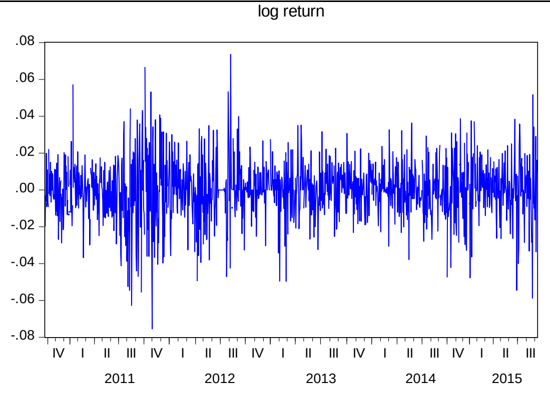


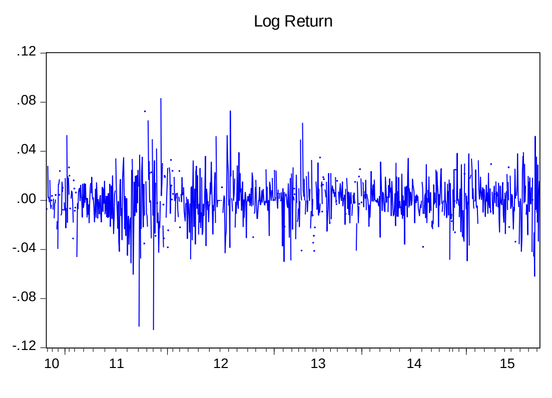
Table 5.6 Time Series Plots of Monthly Prices (ETFs)

All the plots of ETFs show similar evidences despite the use of different benchmarks. This would mean that all the benchmark used could reliably represent the underlying portfolio.

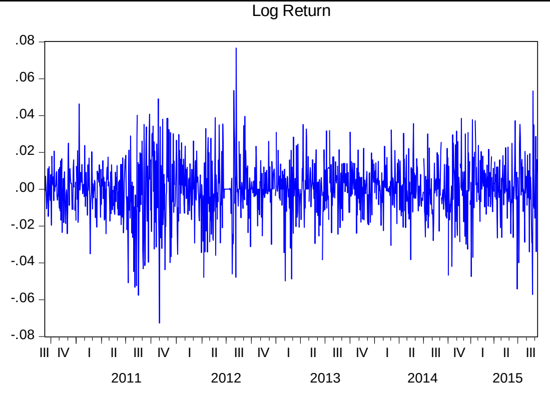
FMI	CI1



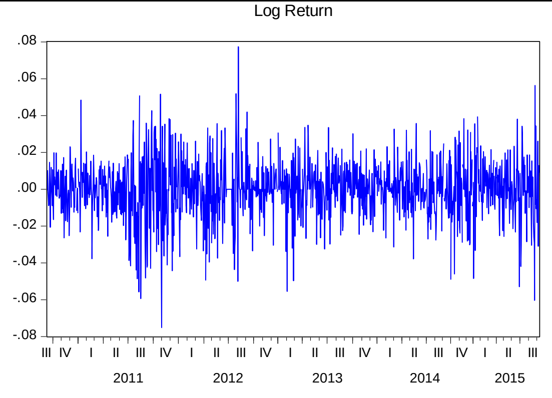
XMIB



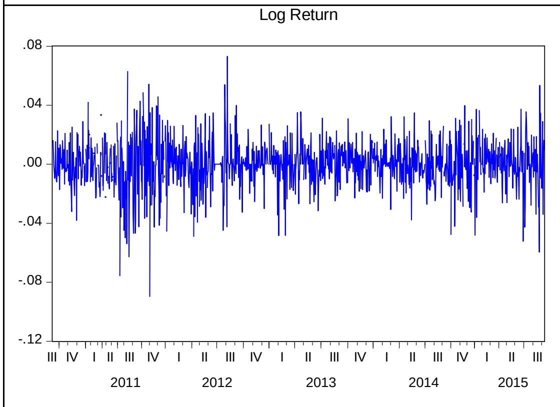
ETFMIB



CSMIB



PTI



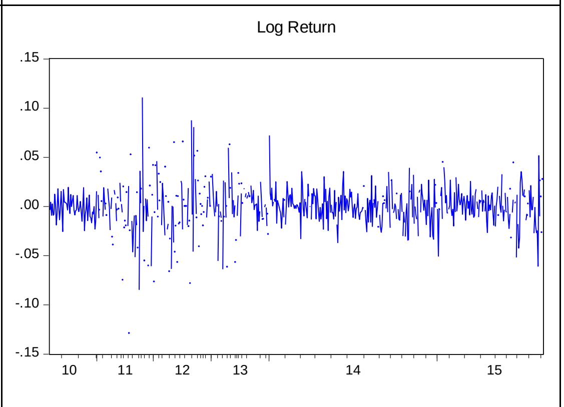


Table 5.7 Time Series Plots of Daily Log Returns (ETFs)

FMI	CI1

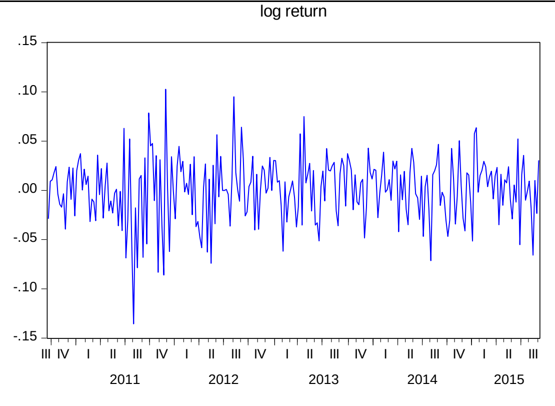
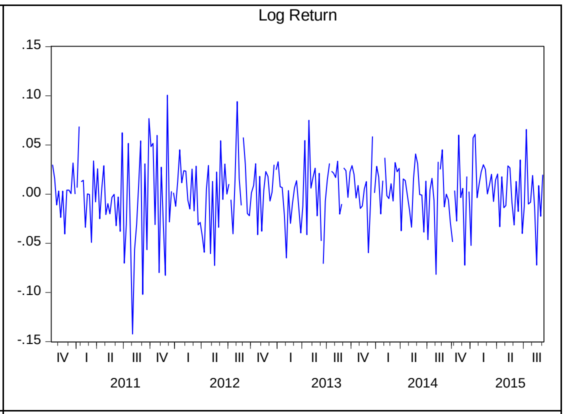
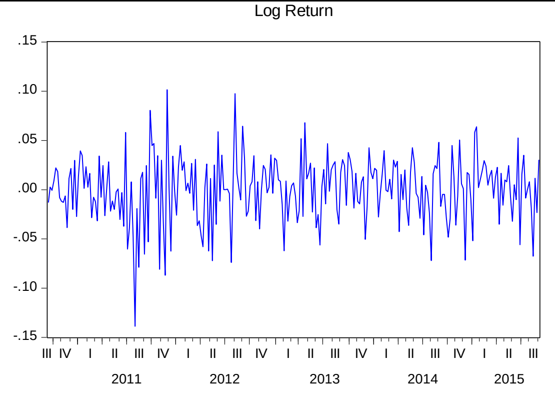
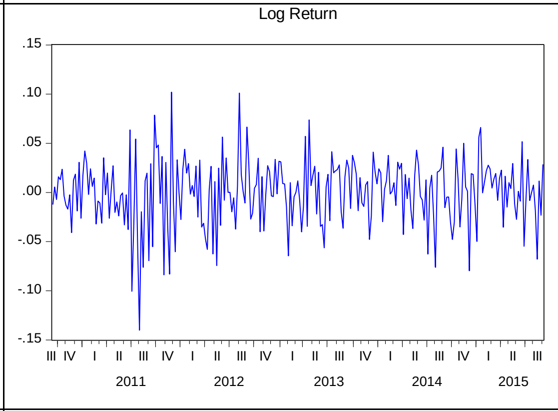
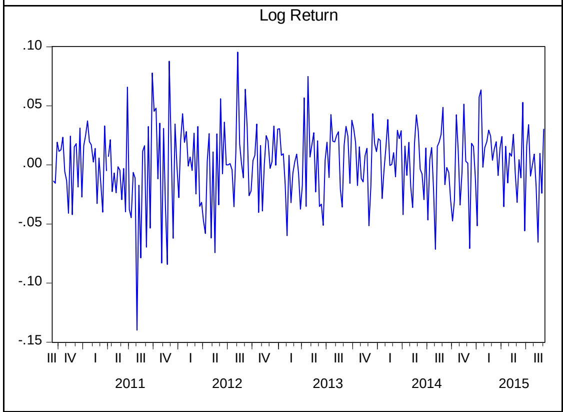
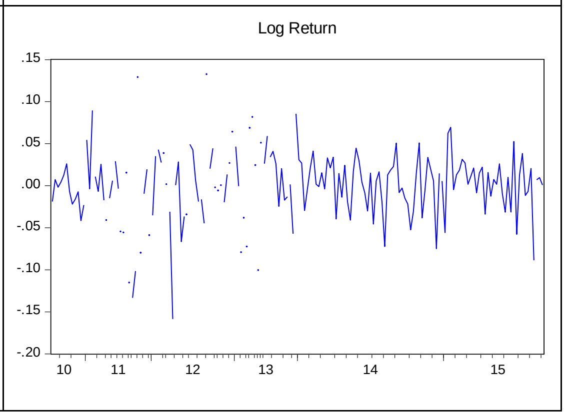
	
XMIB	ETFMIB
	
CSMIB	PTI
	

Table 5.8 Time Series Plots of Weekly Log Returns (ETFs)

FMI	CI1

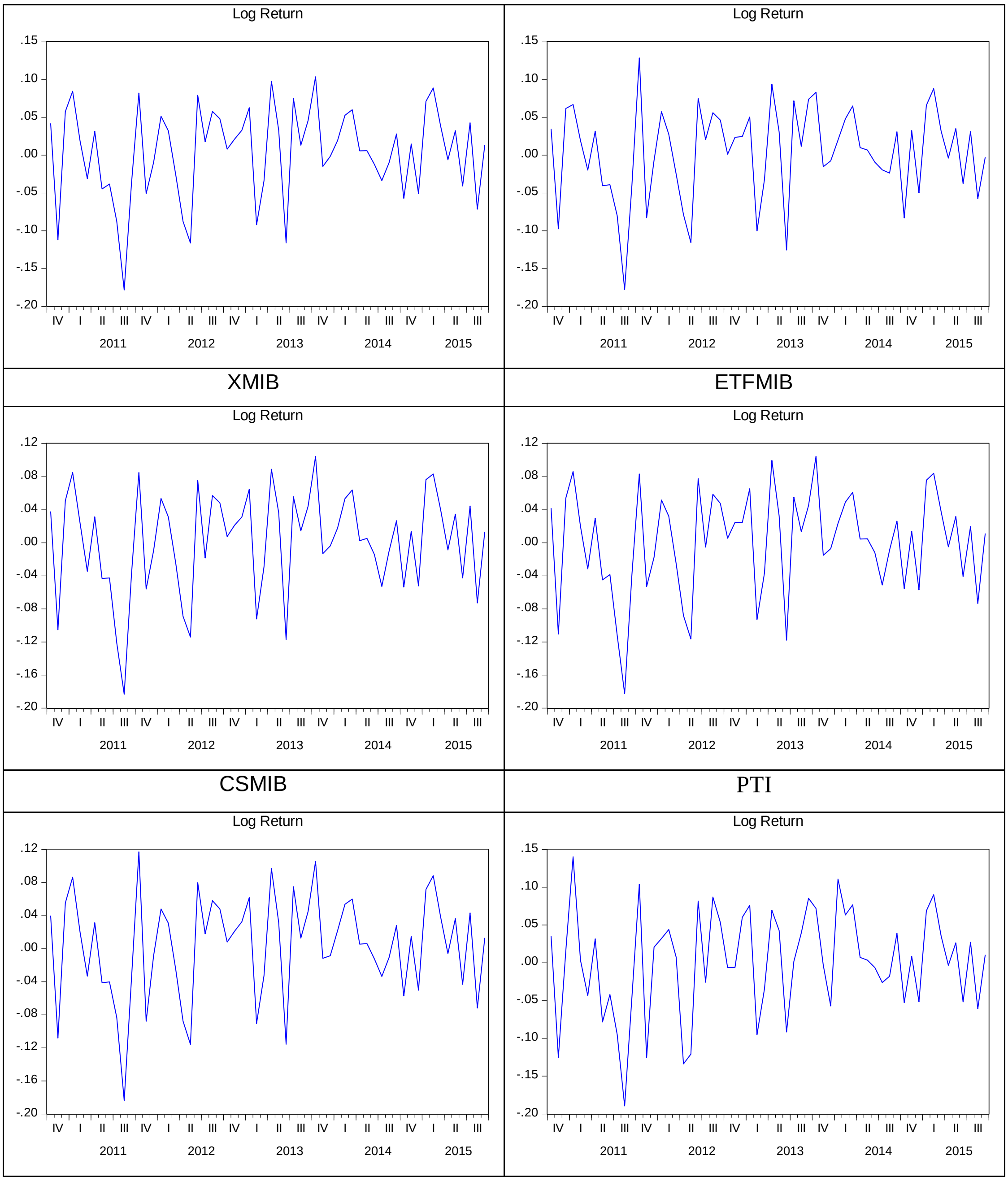


Table 5.9 Time Series Plots of Monthly Log Returns (ETFs)

As expected, Log Returns plots show high volatility of data.

<u>Daily analysis</u>

Descriptive Analysis

Symbol	Mean	Median	St.Dev.	Min	Max	Kurtosis	Skewness
FMI	30.10387	30.65750	5.382371	19.87270	41.45000	2.041567	0.148740
CI1	82.86021	84.52000	13.79790	56.78600	111.1200	1.946983	0.057908
XMIB	18.89311	19.22500	3.075260	12.49400	24.62000	1.724829	-0.026387

ETFMIB	18.69343	19.02950	2.968080	12.42000	24.17400	1.749224	-0.060236
CSMIB	59.65849	60.76500	10.66936	39.47270	81.98000	2.033558	0.169626
PTI	4.955149	5.205650	0.825061	2.896000	6.220000	2.469477	-0.695217

Table 5.1.0 Daily Descriptive Analysis (ETFs)

Unit Root test

In order to apply the analysis for unit roots, it has been used log prices.

Augmented Dickey-Fuller Test

The ADF test comes again to help assessing the existence of a unit root in the log prices time series of the six Italian ETFs, or to assess whether the price series are stationary or not. The second case represents inefficiency. These unit root test are carried out with a constant.

The hypothesis that ETFs' prices follow a RW would prove the weak efficiency. The idea is to verify the null hypothesis of the presence of a unit root:

Hence,

$$\begin{cases} H_0 : \varphi = 1 \\ H_1 : |\varphi| < 1 \end{cases}$$

under the null hypothesis $x_t \sim I(1)$, while the alternative is represented by an autoregressive stationary process $(x_t \sim I(0))$.

LEVEL						
	FMI	CI1	XMIB	ETFMIB	CSMIB	PTI
t-Statistic	-1.249632	-1.409246	-1.539639	-1.661770	-1.257970	-1.446427
Prob.*	0.6546	0.5789	0.5133	0.4506	0.6508	0.5602
TEST CRITICAL VALUE						
1% level	-3.435484	-3.437175	-3.435394	-3.435365	-3.435654	-3.440788
5% level	-2.863695	-2.864442	-2.863655	-2.863642	-2.863770	-2.866037
10% level	-2.567967	-2.568368	-2.567946	-2.567939	-2.568008	-2.569223

*MacKinnon (1996) one-sided p-values.

Table 5.1.1 ADF Test for Daily log prices - ETFs (level)

All the results of the ETFs underline values smaller than the critical ones. This means that all the ETFs show the presence of a unit root, so the null hypothesis cannot be rejected. P-values confirm results at all significance levels. Hence, it is possible to affirm that the market has been proved to be weak form efficient.

Philip-Perron Test

LEVEL						
	FMI	CI1	XMIB	ETFMIB	CSMIB	PTI
t-Statistic	-1.174297	-1.275307	-1.499431	-1.613559	-1.136033	-1.497694
Prob.*	0.6875	0.6428	0.5338	0.4753	0.7034	0.5343
TEST CRITICAL VALUE						
1% level	-3.435484	-3.437175	-3.435394	-3.435365	-3.435654	-3.440788
5% level	-2.863695	-2.864442	-2.863655	-2.863642	-2.863770	-2.866037
10% level	-2.567967	-2.568368	-2.567946	-2.567939	-2.568008	-2.569223

*MacKinnon (1996) one-sided p-values.

Table 5.1.2 PP Test for Daily log prices - ETFs (level)

The PP test, examining the long run effects into the short run dynamic by means of long run variance, confirm the ADF conclusions. Indeed, all the ETFs considered appear to have a unit root, and all p-values affirm that results are significant at 1%, 5% and 10% level.

Serial Correlation Test

$$\begin{cases} H_0: Data\ are\ independently\ distributed\ (the\ correlations\ are\ equal\ to\ zero, so\ any\ observed\ correlations\ resilt\ from\ randomness) \\ H_1: The\ data\ are\ not\ independently\ distributed\ (serial\ correlation) \end{cases}$$

FMI	CI1

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.015	-0.015	0.2722	0.602
		2	-0.027	-0.027	1.1471	0.564
		3	-0.027	-0.028	2.0305	0.566
		4	-0.021	-0.023	2.5850	0.629
		5	-0.048	-0.050	5.4210	0.367
		6	0.054	0.051	9.0539	0.171
		7	-0.002	-0.004	9.0577	0.249
		8	-0.008	-0.008	9.1321	0.331
		9	-0.003	-0.003	9.1424	0.424
		10	-0.036	-0.037	10.718	0.380
		11	0.025	0.028	11.487	0.403
		12	0.006	0.001	11.532	0.484
		13	0.017	0.016	11.898	0.536
		14	-0.029	-0.028	12.928	0.532
		15	0.024	0.022	13.636	0.553
		16	0.037	0.044	15.328	0.501
		17	0.047	0.046	18.075	0.384
		18	-0.030	-0.025	19.177	0.381
		19	-0.009	-0.009	19.282	0.439
		20	0.015	0.023	19.580	0.484
		21	0.004	0.009	19.601	0.547
		22	0.041	0.041	21.649	0.481
		23	-0.018	-0.022	22.043	0.518
		24	-0.062	-0.060	26.796	0.314
		25	-0.041	-0.036	28.943	0.266
		26	0.024	0.021	29.674	0.281
		27	0.031	0.032	30.880	0.276
		28	-0.042	-0.058	33.050	0.234
		29	0.025	0.021	33.865	0.244
		30	-0.002	0.004	33.869	0.286
		31	-0.036	-0.029	35.516	0.264
		32	-0.046	-0.052	38.198	0.208
		33	0.020	0.001	38.693	0.228
		34	0.003	0.004	38.702	0.266
		35	0.003	-0.000	38.716	0.306
		36	-0.030	-0.030	39.850	0.303

XMIB

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.033	-0.033	0.9963	0.318
		2	-0.066	-0.067	5.0091	0.082
		3	0.026	0.022	5.6611	0.129
		4	-0.038	-0.041	7.0205	0.135
		5	0.018	0.019	7.3177	0.198
		6	-0.025	-0.030	7.8974	0.246
		7	0.017	0.020	8.1694	0.318
		8	0.019	0.014	8.4956	0.387
		9	-0.041	-0.035	10.057	0.346
		10	-0.014	-0.018	10.250	0.419
		11	0.043	0.039	11.977	0.365
		12	0.005	0.007	12.000	0.446
		13	-0.004	-0.000	12.017	0.526
		14	-0.070	-0.071	16.593	0.278
		15	-0.025	-0.029	17.188	0.308
		16	0.071	0.061	21.978	0.144
		17	-0.065	-0.058	25.926	0.076
		18	-0.052	-0.055	28.510	0.055
		19	0.038	0.022	29.902	0.053
		20	0.009	0.013	29.972	0.070
		21	-0.007	-0.004	30.020	0.092
		22	0.023	0.024	30.513	0.107
		23	0.036	0.030	31.719	0.106
		24	0.032	0.033	32.678	0.111
		25	-0.018	0.000	32.996	0.131
		26	-0.010	-0.005	33.089	0.160
		27	0.023	0.010	33.610	0.178
		28	-0.037	-0.035	34.906	0.173
		29	0.018	0.020	35.201	0.198
		30	-0.011	-0.011	35.325	0.231
		31	-0.037	-0.042	36.665	0.223
		32	0.050	0.032	39.090	0.181
		33	-0.042	-0.030	40.768	0.166
		34	-0.050	-0.048	43.160	0.135
		35	0.005	-0.019	43.185	0.161
		36	-0.029	-0.026	44.014	0.169

ETFMIB

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.008	-0.008	0.0886	0.766
		2	-0.029	-0.029	1.1212	0.571
		3	-0.019	-0.019	1.5670	0.667
		4	-0.015	-0.016	1.8401	0.765
		5	-0.038	-0.039	3.6458	0.601
		6	0.021	0.019	4.2175	0.647
		7	0.018	0.016	4.6297	0.705
		8	-0.019	-0.019	5.0771	0.749
		9	0.034	0.034	6.4911	0.690
		10	-0.003	-0.004	6.5060	0.771
		11	0.009	0.012	6.6077	0.830
		12	-0.015	-0.013	6.8817	0.865
		13	0.013	0.012	7.0996	0.897
		14	0.011	0.013	7.2406	0.925
		15	-0.006	-0.006	7.2814	0.949
		16	0.027	0.027	8.1843	0.943
		17	0.067	0.068	13.875	0.676
		18	-0.041	-0.038	15.954	0.596
		19	-0.024	-0.019	16.709	0.610
		20	0.032	0.031	17.999	0.587
		21	0.001	0.004	18.000	0.649
		22	0.027	0.031	18.941	0.649
		23	-0.016	-0.022	19.247	0.687
		24	-0.022	-0.021	19.844	0.706
		25	-0.057	-0.052	23.981	0.520
		26	0.011	0.003	24.145	0.568
		27	0.031	0.029	25.335	0.556
		28	-0.008	-0.012	25.423	0.605
		29	-0.028	-0.030	26.394	0.604
		30	0.004	-0.000	26.413	0.654
		31	0.019	0.018	26.888	0.678
		32	-0.029	-0.024	27.971	0.671
		33	-0.012	-0.020	28.153	0.707
		34	0.000	-0.002	28.153	0.749
		35	-0.009	-0.003	28.249	0.784
		36	-0.018	-0.020	28.677	0.802

CSMIB

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.009	0.009	0.1024	0.749
		2	-0.046	-0.046	2.8048	0.246
		3	-0.013	-0.013	3.0289	0.387
		4	-0.025	-0.027	3.8130	0.432
		5	-0.039	-0.040	5.7036	0.336
		6	0.022	0.020	6.2880	0.392
		7	0.019	0.015	6.7514	0.455
		8	-0.039	-0.039	8.6772	0.370
		9	0.035	0.036	10.185	0.336
		10	-0.026	-0.031	11.053	0.353
		11	0.007	0.012	11.115	0.434
		12	-0.019	-0.022	11.568	0.481
		13	0.027	0.026	12.501	0.487
		14	-0.009	-0.009	12.612	0.557
		15	0.011	0.012	12.773	0.620
		16	0.044	0.042	15.224	0.508
		17	0.058	0.062	19.490	0.301
		18	-0.030	-0.029	20.631	0.298
		19	-0.039	-0.029	22.569	0.257
		20	0.024	0.023	23.300	0.274
		21	0.019	0.026	23.779	0.304
		22	0.027	0.025	24.704	0.311
		23	-0.020	-0.023	25.225	0.339
		24	-0.020	-0.018	25.745	0.366
		25	-0.049	-0.042	28.863	0.270
		26	0.006	0.003	28.908	0.315
		27	0.042	0.040	31.168	0.264
		28	-0.010	-0.013	31.284	0.305
		29	-0.021	-0.023	31.851	0.326
		30	0.010	0.007	31.982	0.368
		31	0.010	0.010	32.110	0.411
		32	-0.034	-0.031	33.626	0.389
		33	0.003	-0.009	33.637	0.436
		34	-0.017	-0.019	34.001	0.468
		35	-0.034	-0.028	35.481	0.446
		36	0.003	0.000	35.492	0.493

PTI

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.016	-0.016	0.3164	0.574
		2	-0.026	-0.026	1.1315	0.568
		3	-0.024	-0.025	1.8059	0.614
		4	-0.027	-0.028	2.6587	0.616
		5	-0.050	-0.053	5.6815	0.338
		6	0.013	0.009	5.8816	0.437
		7	0.038	0.035	7.6505	0.364
		8	-0.024	-0.025	8.3270	0.402
		9	0.035	0.034	9.8322	0.364
		10	0.038	0.038	11.523	0.318
		11	-0.037	-0.032	13.170	0.282
		12	0.021	0.026	13.700	0.320
		13	-0.020	-0.020	14.164	0.362
		14	0.028	0.032	15.116	0.370
		15	0.011	0.015	15.258	0.433
		16	0.013	0.008	15.465	0.491
		17	0.037	0.041	17.087	0.449
		18	-0.070	-0.067	23.029	0.189
		19	-0.011	-0.013	23.176	0.230
		20	0.038	0.042	24.939	0.204
		21	-0.016	-0.019	25.238	0.237
		22	0.033	0.035	26.590	0.227
		23	-0.013	-0.018	26.784	0.265
		24	-0.067	-0.074	32.269	0.120
		25	0.007	0.018	32.321	0.149
		26	0.044	0.032	34.707	0.118
		27	-0.003	-0.002	34.716	0.146
		28	-0.045	-0.038	37.159	0.115
		29	0.012	-0.007	37.324	0.138
		30	0.017	0.025	37.670	0.158
		31	0.002	0.005	37.676	0.190
		32	-0.016	-0.025	37.993	0.215
		33	0.012	0.021	38.175	0.246
		34	-0.012	-0.010	38.338	0.279
		35	0.010	0.014	38.453	0.316
		36	-0.015	-0.023	38.745	0.347

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.028	-0.028	0.4869	0.485
		2	-0.027	-0.028	0.9304	0.628
		3	0.057	0.056	2.9463	0.400
		4	0.068	0.070	5.7918	0.215
		5	0.040	0.047	6.7612	0.239
		6	-0.076	-0.074	10.373	0.110
		7	-0.070	-0.082	13.417	0.063
		8	0.082	0.065	17.617	0.024
		9	-0.024	-0.019	17.978	0.035
		10	-0.046	-0.027	19.301	0.037
		11	-0.020	-0.016	19.541	0.052
		12	0.069	0.062	22.571	0.032
		13	-0.027	-0.034	23.028	0.041
		14	-0.009	0.005	23.078	0.059
		15	-0.092	-0.091	28.436	0.019
		16	-0.015	-0.039	28.587	0.027
		17	0.020	0.010	28.828	0.036
		18	-0.036	-0.010	29.629	0.041
		19	0.065	0.089	32.326	0.029
		20	-0.010	-0.014	32.395	0.039
		21	0.013	0.011	32.499	0.052
		22	0.007	-0.017	32.527	0.069
		23	0.049	0.056	34.072	0.064
		24	0.071	0.064	37.334	0.041
		25	-0.084	-0.081	41.813	0.019
		26	0.017	0.016	41.996	0.025
		27	0.037	0.021	42.880	0.027
		28	0.054	0.065	44.772	0.023
		29	-0.042	-0.034	45.937	0.024
		30	-0.093	-0.085	51.505	0.009
		31	0.041	-0.003	52.601	0.009
		32	0.045	0.035	53.903	0.009
		33	-0.053	-0.017	55.724	0.008
		34	-0.080	-0.053	59.948	0.004
		35	0.004	-0.012	59.956	0.005
		36	-0.077	-0.122	63.862	0.003

Table 5.1.3 Serial Correlation of Daily log prices - ETFs

Even for ETFs, results show tendency to be equal to zero, with reliable p-values over many lags. This leads not to reject the null hypothesis, so the weak form efficiency could be confirmed.

Weekly analysis

Descriptive Analysis

Symbol	Average	Median	St.Dev.	Min	Max	Kurtosis	Skewness
FMI	30.21355	30.86250	5.375319	20.21000	41.08000	2.036904	0.122903
CI1	82.75414	82.75414	13.74313	57.58000	109.8900	1.951775	0.132985
XMIB	18.93727	19.29000	3.079632	13.11500	24.45500	1.729187	-0.043066
ETFMIB	18.73949	19.08000	2.972988	12.95300	24.17400	1.751527	-0.074414
CSMIB	59.94001	61.22000	10.60562	40.13000	81.42000	2.028026	0.119471
PTI	4.839880	5.092700	0.891918	2.925300	6.205000	2.078797	-0.508082

Table 5.1.4 Descriptive Analysis of Weekly log prices - ETFs

Unit Root test

Augmented Dickey-Fuller Test

LEVEL						
	FMI	CI1	XMIB	ETFMIB	CSMIB	PTI
t-Statistic	-1.137939	-1.341879	-1.444952	-1.581016	-1.140459	-1.277937
Prob.*	0.7012	0.6102	0.5600	0.4909	0.7001	0.6394
TEST CRITICAL VALUE						
1% level	-3.455486	-3.457630	-3.455387	-3.455387	-3.455585	-3.468749
5% level	-2.872499	-2.873440	-2.872455	-2.872455	-2.872542	-2.878311
10% level	-2.572684	-2.573187	-2.572660	-2.572660	-2.572707	-2.575791

*MacKinnon (1996) one-sided p-values.

Table 5.1.5 ADF Test for Weekly log prices - ETFs (level)

The weekly log prices give back same results as before, strongly confirming the null hypothesis at all significance levels. It is possible to see that high significant p-values confirm results both for the above ADF test that for the below PP test as well.

Philip-Perron Test

LEVEL						
	FMI	CI1	XMIB	ETFMIB	CSMIB	PTI
t-Statistic	-1.142268	-1.258622	-1.512727	-1.593731	-1.160811	-1.337988
Prob.*	0.6994	0.6490	0.5258	0.4843	0.6917	0.6113
TEST CRITICAL VALUE						
1% level	-3.455486	-3.457630	-3.455387	-3.455387	-3.455585	-3.468749
5% level	-2.872499	-2.873440	-2.872455	-2.872455	-2.872542	-2.878311
10% level	-2.572684	-2.573187	-2.572660	-2.572660	-2.572707	-2.575791

*MacKinnon (1996) one-sided p-values.

Table 5.1.6 PP Test for Weekly log prices - ETFs (level)

Serial Correlation Test

$$\begin{cases} H_0\text{: Data are independently distributed (the correlations are equal to zero, so any} \\ \text{observed correlations resilt from randomness)} \\ H_1\text{: The data are not independently distributed (serial correlation)} \end{cases}$$

FMI	CI1

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.066	-0.066	1.1530	0.283
		2	0.026	0.022	1.3299	0.514
		3	0.045	0.048	1.8644	0.601
		4	0.020	0.026	1.9731	0.741
		5	-0.016	-0.016	2.0441	0.843
		6	-0.025	-0.031	2.2148	0.899
		7	-0.094	-0.100	4.5718	0.712
		8	0.015	0.005	4.6365	0.796
		9	0.017	0.027	4.7108	0.859
		10	-0.119	-0.108	8.5645	0.574
		11	0.055	0.042	9.3778	0.587
		12	-0.015	-0.009	9.4359	0.665
		13	0.047	0.048	10.035	0.691
		14	0.035	0.036	10.369	0.735
		15	0.022	0.022	10.500	0.787
		16	-0.005	-0.010	10.508	0.839
		17	-0.000	-0.028	10.508	0.881
		18	-0.077	-0.073	12.166	0.839
		19	-0.039	-0.045	12.592	0.859
		20	0.076	0.077	14.226	0.819
		21	-0.040	-0.003	14.681	0.839
		22	0.093	0.095	17.133	0.756
		23	0.050	0.068	17.840	0.766
		24	-0.174	-0.191	26.603	0.323
		25	0.032	-0.013	26.899	0.361
		26	-0.054	-0.068	27.755	0.371
		27	-0.051	-0.038	28.509	0.385
		28	-0.051	-0.058	29.279	0.398
		29	-0.020	-0.009	29.399	0.444
		30	-0.032	-0.002	29.695	0.481
		31	-0.064	-0.105	30.902	0.471
		32	-0.038	-0.008	31.341	0.500
		33	-0.009	-0.018	31.366	0.549
		34	0.076	0.035	33.126	0.510
		35	0.017	0.028	33.212	0.555
		36	0.100	0.071	36.268	0.456

XMIB

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.097	-0.097	2.3082	0.129
		2	0.063	0.054	3.2766	0.194
		3	-0.007	0.004	3.2900	0.349
		4	-0.024	-0.028	3.4264	0.489
		5	-0.016	-0.020	3.4861	0.625
		6	0.017	0.017	3.5616	0.736
		7	-0.079	-0.075	5.1348	0.644
		8	0.067	0.051	6.2620	0.618
		9	-0.035	-0.017	6.5761	0.681
		10	-0.079	-0.092	8.1436	0.615
		11	0.040	0.026	8.5490	0.663
		12	-0.052	-0.037	9.2481	0.682
		13	0.004	-0.007	9.2525	0.754
		14	0.069	0.064	10.465	0.727
		15	-0.034	-0.016	10.771	0.769
		16	-0.024	-0.045	10.919	0.814
		17	0.071	0.062	12.242	0.785
		18	-0.105	-0.076	15.116	0.654
		19	0.048	0.010	15.711	0.676
		20	0.041	0.060	16.160	0.707
		21	0.006	0.021	16.170	0.760
		22	0.024	0.000	16.325	0.799
		23	-0.082	-0.079	18.109	0.752
		24	-0.086	-0.083	20.097	0.691
		25	-0.042	-0.077	20.578	0.716
		26	-0.063	-0.046	21.645	0.708
		27	-0.035	-0.038	21.979	0.738
		28	-0.012	-0.048	22.016	0.781
		29	0.054	0.075	22.820	0.785
		30	-0.137	-0.149	28.017	0.570
		31	-0.022	-0.073	28.150	0.613
		32	-0.069	-0.050	29.462	0.596
		33	0.171	0.152	37.713	0.262
		34	0.084	0.104	39.704	0.231
		35	0.063	0.065	40.846	0.229
		36	-0.031	-0.050	41.122	0.256

ETFMIB

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.049	-0.049	0.6386	0.424
		2	0.046	0.044	1.2084	0.547
		3	0.028	0.032	1.4127	0.703
		4	0.046	0.047	1.9693	0.741
		5	-0.017	-0.015	2.0424	0.843
		6	-0.033	-0.040	2.3292	0.887
		7	-0.088	-0.094	4.4146	0.731
		8	-0.005	-0.012	4.4204	0.817
		9	0.031	0.043	4.6869	0.861
		10	-0.107	-0.095	7.8438	0.644
		11	0.039	0.035	8.2699	0.689
		12	-0.027	-0.021	8.4762	0.747
		13	0.055	0.047	9.3176	0.749
		14	0.027	0.035	9.5271	0.796
		15	0.042	0.038	10.016	0.819
		16	0.000	-0.000	10.016	0.866
		17	-0.011	-0.039	10.049	0.902
		18	-0.036	-0.041	10.412	0.918
		19	-0.052	-0.052	11.173	0.918
		20	0.080	0.083	13.003	0.877
		21	-0.035	-0.000	13.355	0.896
		22	0.091	0.092	15.746	0.828
		23	0.020	0.038	15.857	0.861
		24	-0.160	-0.191	23.291	0.503
		25	0.007	-0.018	23.306	0.560
		26	-0.063	-0.074	24.479	0.549
		27	-0.059	-0.046	25.511	0.546
		28	-0.068	-0.054	26.889	0.524
		29	-0.027	-0.027	27.098	0.566
		30	-0.029	-0.001	27.340	0.605
		31	-0.072	-0.116	28.885	0.575
		32	-0.035	-0.010	29.255	0.606
		33	0.006	0.002	29.266	0.654
		34	0.053	0.022	30.122	0.658
		35	0.047	0.050	30.783	0.672
		36	0.119	0.094	35.109	0.511

CSMIB

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.074	-0.074	1.4359	0.231
		2	0.013	0.008	1.4825	0.477
		3	0.045	0.046	2.0129	0.570
		4	0.044	0.051	2.5352	0.638
		5	-0.022	-0.016	2.6657	0.751
		6	-0.015	-0.021	2.7231	0.843
		7	-0.090	-0.098	4.9132	0.671
		8	0.009	-0.006	4.9337	0.765
		9	0.011	0.018	4.9653	0.837
		10	-0.107	-0.096	8.1089	0.618
		11	0.055	0.049	8.9499	0.627
		12	-0.024	-0.020	9.1118	0.693
		13	0.057	0.059	10.004	0.694
		14	0.015	0.022	10.069	0.757
		15	0.024	0.019	10.226	0.805
		16	-0.003	-0.003	10.228	0.854
		17	0.005	-0.022	10.235	0.893
		18	-0.056	-0.052	11.134	0.889
		19	-0.034	-0.045	11.468	0.907
		20	0.066	0.066	12.710	0.889
		21	-0.048	-0.018	13.375	0.895
		22	0.109	0.113	16.759	0.777
		23	0.030	0.057	17.023	0.808
		24	-0.171	-0.189	25.462	0.381
		25	0.005	-0.034	25.469	0.436
		26	-0.046	-0.080	26.097	0.458
		27	-0.041	-0.025	26.586	0.486
		28	-0.070	-0.068	28.031	0.463
		29	-0.034	-0.025	28.367	0.498
		30	-0.005	0.024	28.374	0.551
		31	-0.062	-0.102	29.534	0.541
		32	-0.050	-0.021	30.283	0.554
		33	-0.005	-0.033	30.290	0.603
		34	0.066	0.035	31.617	0.585
		35	0.033	0.041	31.956	0.616
		36	0.104	0.087	35.231	0.505

PTI

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.073	-0.073	1.3874	0.239
		2	0.066	0.061	2.5477	0.280
		3	0.022	0.031	2.6704	0.445
		4	0.028	0.028	2.8855	0.577
		5	-0.029	-0.028	3.1031	0.684
		6	-0.036	-0.045	3.4561	0.750
		7	-0.080	-0.084	5.1523	0.641
		8	0.008	0.003	5.1710	0.739
		9	0.021	0.037	5.2897	0.808
		10	-0.107	-0.099	8.3985	0.590
		11	0.052	0.037	9.1364	0.609
		12	-0.034	-0.024	9.4590	0.663
		13	0.066	0.056	10.669	0.639
		14	0.002	0.013	10.670	0.712
		15	0.049	0.041	11.343	0.728
		16	-0.015	-0.015	11.404	0.784
		17	-0.045	-0.074	11.961	0.802
		18	0.008	0.009	11.979	0.848
		19	-0.049	-0.039	12.644	0.856
		20	0.045	0.047	13.218	0.868
		21	0.005	0.033	13.224	0.901
		22	0.070	0.065	14.640	0.877
		23	0.019	0.033	14.739	0.904
		24	-0.173	-0.210	23.359	0.499
		25	0.040	0.022	23.811	0.530
		26	-0.041	-0.034	24.293	0.559
		27	-0.116	-0.117	28.213	0.400
		28	-0.039	-0.028	28.658	0.430
		29	-0.023	-0.027	28.809	0.475
		30	-0.030	-0.011	29.078	0.514
		31	-0.025	-0.058	29.258	0.556
		32	-0.060	-0.032	30.314	0.552
		33	-0.007	-0.025	30.327	0.601
		34	0.156	0.109	37.614	0.307
		35	0.016	0.052	37.689	0.347
		36	0.101	0.066	40.758	0.269

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.073	0.073	0.9282	0.335
		2	-0.056	-0.061	1.4709	0.479
		3	-0.067	-0.059	2.2599	0.520
		4	-0.003	0.003	2.2616	0.688
		5	-0.024	-0.032	2.3690	0.796
		6	0.035	0.035	2.5870	0.859
		7	0.046	0.038	2.9628	0.888
		8	0.063	0.058	3.6901	0.884
		9	-0.032	-0.032	3.8733	0.920
		10	-0.018	-0.002	3.9319	0.950
		11	0.082	0.091	5.1885	0.922
		12	-0.158	-0.180	9.8519	0.629
		13	0.002	0.041	9.8529	0.706
		14	-0.001	-0.021	9.8532	0.773
		15	0.081	0.063	11.117	0.744
		16	0.083	0.084	12.446	0.713
		17	0.045	0.028	12.844	0.747
		18	0.053	0.079	13.385	0.768
		19	-0.048	-0.055	13.837	0.793
		20	-0.045	0.005	14.241	0.818
		21	0.092	0.091	15.914	0.774
		22	0.060	0.012	16.629	0.783
		23	-0.060	-0.040	17.346	0.792
		24	0.070	0.050	18.325	0.787
		25	0.020	0.020	18.402	0.825
		26	0.064	0.055	19.239	0.826
		27	-0.106	-0.098	21.538	0.760
		28	-0.126	-0.102	24.855	0.636
		29	-0.126	-0.138	28.176	0.509
		30	-0.146	-0.150	32.662	0.337
		31	0.032	0.016	32.878	0.375
		32	0.062	-0.032	33.706	0.385
		33	0.042	0.042	34.094	0.415
		34	-0.027	-0.005	34.248	0.456
		35	-0.077	-0.076	35.558	0.442
		36	-0.058	-0.002	36.286	0.455

Table 5.1.7 Serial Correlation of Weekly log prices - ETFs

Each ETF show less tendency to zero AC, and increasing p-values results as lags increase. The AC and PAC appear both negative and positive correlated but close to zero, leading not to reject the null hypothesis. Hence ETFs do appear to be weak form efficient.

<u>Monthly analysis</u>

Descriptive Analysis

Symbol	Average	Median	St.Dev.	Min	Max	Kurtosis	Skewness
FMI	30.41930	31.34750	5.464673	20.31500	40.49000	1.853019	0.079101
CI1	83.17748	85.13000	13.62263	57.81000	108.5000	1.854691	0.093383
XMIB	19.00788	19.42750	3.109806	13.20500	24.13000	1.636921	-0.060405
ETFMIB	18.82170	19.22500	2.992595	13.02700	23.77800	1.649958	-0.099583
CSMIB	60.40863	62.23500	10.74446	40.33000	80.23000	1.861766	0.067873
PTI	4.598062	4.617550	0.916963	2.989700	6.150000	1.557294	0.012218

Table 5.1.8 Descriptive Analysis of Monthly ETFs

Unit Root test

Augmented Dickey-Fuller Test

LEVEL						
	FMI	CI1	XMIB	ETFMIB	CSMIB	PTI
t-Statistic	-0.946420	-1.147735	-1.320984	-1.418300	-1.011838	-1.207373
Prob.*	0.7664	0.6910	0.6142	0.5674	0.7436	0.6657
TEST CRITICAL VALUE						
1% level	-3.546099	-3.546099	-3.546099	-3.546099	-3.546099	-3.546099
5% level	-2.911730	-2.911730	-2.911730	-2.911730	-2.911730	-2.911730
10% level	-2.593551	-2.593551	-2.593551	-2.593551	-2.593551	-2.593551

*MacKinnon (1996) one-sided p-values.

Table 5.1.9 ADF Test for Monthly log prices - ETFs (level)

ADF test over Monthly log prices of the selected ETFs show, again, the impossibility to reject the null hypothesis. Results appear really strong especially for the FMI.MI, that shows a statistic value of -0.946420, on the basis of a p-value of 0.7664.

Philip-Perron Test

LEVEL						
	FMI	CI1	XMIB	ETFMIB	CSMIB	PTI
t-Statistic	-1.033526	-1.147735	-1.425537	-1.524286	-1.075665	-1.207373
Prob.*	0.7357	0.6910	0.5638	0.5145	0.7198	0.6657
TEST CRITICAL VALUE						
1% level	-3.546099	-3.546099	-3.546099	-3.546099	-3.546099	-3.546099
5% level	-2.911730	-2.911730	-2.911730	-2.911730	-2.911730	-2.911730
10% level	-2.593551	-2.593551	-2.593551	-2.593551	-2.593551	-2.593551

*MacKinnon (1996) one-sided p-values.

Table 5.2.0 PP Test for Monthly log prices - ETFs (level)

Here, as before in the ADF test, results show the possibility to be able to approve the weak efficicency of the ETFs considered.

Serial Correlation Test

$$\begin{cases} H_0\text{: } Data\ are\ independently\ distributed\ (the\ correlations\ are\ equal\ to\ zero, so\ any \\ \quad observed\ correlations\ resilt\ from\ randomness) \\ H_1\text{: } The\ data\ are\ not\ independently\ distributed\ (serial\ correlation) \end{cases}$$

FMI	CI1

FMI

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.067	0.067	0.2801	0.597
		2	-0.118	-0.123	1.1710	0.557
		3	0.045	0.064	1.3051	0.728
		4	0.006	-0.018	1.3072	0.860
		5	-0.072	-0.059	1.6588	0.894
		6	-0.016	-0.010	1.6760	0.947
		7	-0.224	-0.245	5.2117	0.634
		8	0.049	0.098	5.3822	0.716
		9	0.190	0.129	8.0039	0.534
		10	0.139	0.164	9.4399	0.491
		11	-0.010	-0.001	9.4482	0.581
		12	-0.094	-0.135	10.133	0.604
		13	0.026	0.031	10.187	0.679
		14	-0.005	-0.075	10.190	0.748
		15	-0.072	0.020	10.620	0.779
		16	-0.029	0.043	10.691	0.828
		17	-0.116	-0.114	11.863	0.808
		18	0.170	0.189	14.415	0.702
		19	0.058	-0.126	14.724	0.740
		20	-0.088	-0.024	15.449	0.750
		21	0.027	0.039	15.520	0.796
		22	-0.008	-0.076	15.527	0.839
		23	-0.142	-0.057	17.568	0.780
		24	0.041	-0.019	17.741	0.815
		25	-0.119	-0.057	19.258	0.785
		26	-0.124	-0.093	20.945	0.745
		27	0.101	0.042	22.095	0.733
		28	-0.030	-0.090	22.196	0.772

CI1

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.020	0.020	0.0262	0.872
		2	-0.126	-0.127	1.0482	0.592
		3	0.023	0.029	1.0841	0.781
		4	-0.003	-0.021	1.0847	0.897
		5	-0.070	-0.064	1.4189	0.922
		6	-0.006	-0.006	1.4214	0.965
		7	-0.277	-0.300	6.8119	0.449
		8	0.072	0.099	7.1877	0.517
		9	0.176	0.102	9.4559	0.396
		10	0.150	0.192	11.139	0.347
		11	-0.033	-0.018	11.224	0.425
		12	-0.073	-0.103	11.635	0.475
		13	-0.006	-0.010	11.638	0.558
		14	0.009	-0.078	11.644	0.635
		15	-0.035	0.068	11.743	0.698
		16	-0.038	0.027	11.867	0.753
		17	-0.148	-0.107	13.762	0.684
		18	0.207	0.183	17.555	0.485
		19	0.107	-0.042	18.603	0.483
		20	-0.103	-0.061	19.595	0.483
		21	0.028	0.048	19.672	0.542
		22	0.013	-0.020	19.688	0.603
		23	-0.139	-0.087	21.636	0.542
		24	0.030	-0.041	21.729	0.595
		25	-0.122	-0.051	23.323	0.559
		26	-0.138	-0.112	25.411	0.496
		27	0.089	0.023	26.312	0.501
		28	-0.030	-0.124	26.417	0.550

XMIB	ETFMIB

XMIB

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.096	0.096	0.5830	0.445
		2	-0.086	-0.096	1.0610	0.588
		3	0.020	0.039	1.0866	0.780
		4	0.027	0.012	1.1336	0.889
		5	-0.076	-0.076	1.5251	0.910
		6	-0.070	-0.052	1.8613	0.932
		7	-0.228	-0.237	5.5237	0.596
		8	0.079	0.127	5.9652	0.651
		9	0.150	0.099	7.6098	0.574
		10	0.137	0.155	9.0152	0.531
		11	0.040	0.036	9.1358	0.609
		12	-0.082	-0.139	9.6515	0.647
		13	0.030	0.033	9.7218	0.717
		14	-0.006	-0.082	9.7250	0.782
		15	-0.081	0.029	10.272	0.802
		16	-0.016	0.069	10.292	0.851
		17	-0.112	-0.114	11.372	0.837
		18	0.122	0.161	12.684	0.810
		19	0.051	-0.125	12.920	0.843
		20	-0.067	-0.029	13.336	0.862
		21	0.005	0.007	13.338	0.896
		22	-0.019	-0.083	13.375	0.922
		23	-0.105	-0.010	14.476	0.912
		24	0.051	0.001	14.741	0.928
		25	-0.113	-0.051	16.104	0.912
		26	-0.109	-0.103	17.410	0.896
		27	0.085	0.052	18.217	0.897
		28	-0.025	-0.072	18.289	0.919

ETFMIB

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.097	0.097	0.5972	0.440
		2	-0.118	-0.129	1.4951	0.474
		3	0.034	0.061	1.5719	0.666
		4	0.017	-0.010	1.5906	0.810
		5	-0.067	-0.057	1.8899	0.864
		6	-0.061	-0.050	2.1497	0.905
		7	-0.234	-0.246	5.9838	0.542
		8	0.069	0.124	6.3286	0.610
		9	0.168	0.099	8.3819	0.496
		10	0.133	0.162	9.6920	0.468
		11	0.009	0.002	9.6976	0.558
		12	-0.087	-0.128	10.279	0.591
		13	0.039	0.040	10.402	0.661
		14	-0.008	-0.091	10.407	0.732
		15	-0.074	0.046	10.864	0.762
		16	-0.024	0.044	10.912	0.815
		17	-0.118	-0.116	12.120	0.793
		18	0.143	0.175	13.935	0.733
		19	0.058	-0.133	14.235	0.770
		20	-0.079	-0.002	14.821	0.787
		21	0.000	-0.011	14.822	0.832
		22	-0.015	-0.072	14.844	0.869
		23	-0.116	-0.038	16.190	0.847
		24	0.044	-0.011	16.388	0.874
		25	-0.101	-0.024	17.471	0.864
		26	-0.128	-0.134	19.251	0.826
		27	0.088	0.074	20.117	0.826
		28	-0.019	-0.107	20.160	0.859

CSMIB	PTI

Lag	AC	PAC	Q-Stat	Prob
1	0.034	0.034	0.0748	0.784
2	-0.144	-0.145	1.4073	0.495
3	0.064	0.076	1.6743	0.643
4	0.021	-0.006	1.7045	0.790
5	-0.058	-0.040	1.9355	0.858
6	0.006	0.009	1.9384	0.925
7	-0.256	-0.280	6.5239	0.480
8	0.061	0.110	6.7929	0.559
9	0.184	0.105	9.2630	0.413
10	0.125	0.183	10.422	0.404
11	-0.032	-0.008	10.500	0.486
12	-0.070	-0.108	10.880	0.539
13	0.018	0.012	10.907	0.619
14	-0.005	-0.103	10.909	0.693
15	-0.047	0.055	11.094	0.746
16	-0.033	0.022	11.188	0.798
17	-0.129	-0.099	12.629	0.761
18	0.167	0.167	15.087	0.656
19	0.082	-0.085	15.692	0.678
20	-0.112	-0.042	16.858	0.662
21	0.033	0.033	16.964	0.713
22	-0.011	-0.076	16.977	0.765
23	-0.150	-0.076	19.245	0.687
24	0.063	0.001	19.652	0.716
25	-0.115	-0.065	21.052	0.690
26	-0.128	-0.075	22.849	0.641
27	0.090	0.015	23.768	0.643
28	-0.026	-0.090	23.849	0.689

Lag	AC	PAC	Q-Stat	Prob
1	0.084	0.084	0.4452	0.505
2	-0.154	-0.162	1.9589	0.376
3	0.046	0.077	2.0989	0.552
4	0.049	0.012	2.2577	0.688
5	0.009	0.023	2.2633	0.812
6	0.013	0.016	2.2746	0.893
7	-0.288	-0.302	8.0828	0.325
8	0.141	0.238	9.5108	0.301
9	0.154	0.005	11.249	0.259
10	0.084	0.185	11.770	0.301
11	-0.004	-0.025	11.771	0.381
12	0.036	0.052	11.874	0.456
13	-0.012	-0.027	11.886	0.537
14	0.071	-0.028	12.299	0.582
15	-0.092	0.001	12.997	0.603
16	-0.108	-0.106	13.980	0.600
17	-0.023	0.047	14.025	0.665
18	0.070	-0.022	14.458	0.699
19	0.100	0.159	15.363	0.699
20	-0.004	-0.098	15.365	0.755
21	-0.103	-0.038	16.368	0.749
22	-0.073	-0.172	16.896	0.769
23	-0.050	-0.089	17.145	0.802
24	0.050	0.118	17.405	0.831
25	-0.067	-0.088	17.880	0.847
26	-0.177	-0.017	21.315	0.726
27	0.107	0.057	22.606	0.706
28	-0.016	-0.158	22.635	0.751

Table 5.2.1 Serial Correlation of Monthly log prices - ETFs

Each ETF, analysed on the basis of Monthly data, show less tendency to zero AC, and increasing p-values results as lags increase. The AC and PAC appear both negative and positive correlated, leading not to reject the null hypothesis. Again, ETFs do appear to be weak form efficient.

Conclusions

The analysis carried out has shown some significance relative to the efficiency of the Italian market. Although there exist proofs of the weak efficiency of the market, few indexes and companies rejected the random walk hypothesis. This leads not to completely confirm the efficiency of the market. The analysis for the semi-strong form has been computed observing the dividend yields impact over returns, showing absence of any influence by dividends announcement (or issues). Hence, it is possible to think at the Italian market as a weak and semi-strong form efficient market. Therefore, as underlined by a long literature, the efficient market hypothesis has been strongly challenged. A part from the evidences emerged by econometrics analysis, that can, or cannot, be proved nowadays, one of the big deal that the EMH has to face. is represented by renowned traders that are in contact with many investors whose ask for advice. I take my personal experience as an example. During a seminar at Giotto SIM in Padua, I listened the trader Giovanni Borsi explaining easily this concept: movements of masses represent a profitable information that some traders could get in advance because investors literally told them what they are going to do. This could represent an information that the trader himself obtains to beat the market. Moreover Borsi, actually focused on Banca Monte dei Paschi di Siena issue, explained that he usually speaks with some professionals of the Bank with whom he compares his forecasting thoughts about future trends over the BMPS.MI. Beyond the fact that during all the seminar I could not avoid to think that Borsi was just showing his skills to scrape together clients, I want to make some considerations on his speech. Indeed, even if a single, or a few groups of traders, really got some information in advice with respect to the market, this would not mean that they are able to exploit them. The investors that ask them for advice would make their own finally move, more or less linked to rational or irrational thoughts. There exist no possibility that all investors gathered could outperform in turn the market on the basis of a well-known anomalies of the market. Borsi himself underlined that investors try to exploit the January effect yet. The consequence is just that everyone tries to buy or sell at the same time, so none becomes able to beat the market. However Borsi stated that knowing these attitude of investors, he beat the market with a move in advance based on investors' information. The problem is that if all traders with "information in advance" think to the same moves, hence there is no information to exploit, they will generate the same flow in the market. Clearly the confuse and twisted speech underlined could be interpreted as a chess game in which investors should know at least three or four moves to do in advice with respect to the market. The existence in past of certain anomalies could not be deny, but as the same Borsi explained, nowadays practically feasibility shows that investors do not be able to exploit them to beat the market. That means the investors themselves, as part of the market, canceled the anomalies. This could lead to agree with Andrew Lo's theory of an Adaptive Market[56] in which the efficiency of the market depends on the environment. However the Adaptive Market theory is none other than an extension of the efficient market hypothesis. Again, Borsi stated that, basically, him could not periodically gain from the market just by carrying out some strategies. He affirmed that this game would be effective just when it is played at full time, but I imagine investors would join at least the seven or eight sleeping hours. A part from jokes, maybe the real potshots of the EMH are represented by financial crisis. In fact an efficient market is supposed to include all the available public information (semi-strong efficiency). The problem occurs when public information do not reflect the real situation of a market because of forgery or other issues. However my opinion is that these kind of troubles are characteristic of a strong form of efficiency, that is not object of the current debate.

After this parenthesis is useful to go back on the current results, aware of the fact that there exist other approaches to assess the EMH, but the econometrics one is the approach assumed to be more reliable under my point of view. As asserted by Edwards Deming, what count are data.

Results obtained suggest that not all the component owned by the Italian Stock Exchange respect the random walk hypothesis, few analysis revealed the presence of serial correlation among prices rather than the absence of unit roots as a proof of the non-efficiency. If we look just at the specific case of the ETFplus market, results suggests a good degree of weak form efficiency on the basis of the represented Italian ETFs.

Many time the truth is somewhere in-between. So, is it possible that the market is efficient but some exogenous events can briefly affect the market leaving it to remain efficient? In other words, is it possible that the inefficiency of the market is so temporary that could not be classified as inefficiency?

My conclusion will not be somewhere in-between. Considering the whole analysis performed the Italian Market results at least weak form efficient. The possibility to outperform the market do not appear so evident to classified the market out of the first two forms defined by Fama. Obviously the present analysis is a drop in the bucket compared with the whole literature generated by the EMH, but it represents a recent proof of the fact that the complexity of any market, especially the Italian one, could not be so easily interpreted. To approach with financial markets means to be aware of the possibility to face markets with a variety of treats and non-physical walls that an inexpert investors could suffer. Beyond the

[56] A theory developed in 2004 by Andrew Lo (MIT) that tries to gather the efficient market hypothesis to the behavioral finance.

trading possibility the market was born to exchange financial instruments and support companies in which someone trust. The starting point to approach any market is to know it. The weak form efficiency of the Italian market, and the awareness that it includes some potshots, supplies the basic knowledge that anyone need to be a conscious investor, or analyst, or any other financial professional going near this interesting field.

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