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Trading strategies in a combined framework between technical analysis and time series forecasts

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Chapter 1

Introduction

Algorithmic trading has undoubtedly become the most used method by which money is invested in 21st century. Usually, in fact, professional traders do not follow passive strategies in which they buy an asset and hold it until a predefined point in time but, rather, they continuously rebalance their investment by relying on signals that trading rules emit according to the market conditions.

The main purpose of this work is to evaluate, on empirical basis, the profitability of different trading algorithms: the first class of strategies is based on technical analysis techniques (double moving averages crossovers), the second one relies on forecasts generated by some time series models (AR, AR-GARCH, AR-EGARCH) and, finally, the third one represents an integrated approach that combines information of both previous methods. In particular way, the focus is posed on evaluating whether, through the integration between predictive tools with different theoretical foundations, one could overperform the trading results obtained with the individual strategies.

Traders' behavior, in fact, is based on the idea that, by exploiting the timing of active strategies, it is possible to gain from financial investments.

This decisive point triggered the interest and the study of scholars and academics. A deep literature was based especially on proving that financial market movements are unpredictable on the basis of past information and, for this reason, it is impossible to systematically gain in financial markets. This theory took the name of Efficient Market Hypothesis and Chapter 2 is devoted to describe and deepen its assumptions, implications and to cite some methods proposed in literature to test financial market efficiency.

On the basis of empirical evidences, in contrast with this theory, another branch of literature focused on testing whether, at least in some periods and for some markets, it was possible to identify some patterns and predictability degrees present in dynamics of financial assets.

On this basis, several trading methods have been proposed and, among these, the class of technical analysis techniques have gained a considerable reputation among practitioners, because of the intuitive meaning and the simple computations of the market indicators implemented.

Chapter 3 deepens the philosophical and theoretical assumptions underlying technical analysis, with a review of literature about this topic differentiating among early and more recent studies, and provides empirical and theoretical explanations for their profitability. From the other side, academics have usually preferred analyzing financial markets through the implementations of time series and econometric models that could, in principle, catch the several statistical features exhibited in financial markets.

Chapter 4, starting from the stylized facts about financial returns, describes properties of some traditional (and relatively new) time series models commonly used in literature also in order to produce market forecasts.

Despite their different nature, technical techniques and time series models share the basic idea that asset returns can be predicted.

By exploiting this aspect, we founded our empirical case study, first, through the construction of trading systems based on each individual approach and, then, combining both methods of signals generation in the same trading rules. Chapter 5 will be devoted to: provide an exploratory analysis of the data under study, illustrate the adopted methodologies but, particularly, present and comment the empirical results of the individual and combined trading strategies.

Finally, Chapter 6 concludes the thesis by exposing the main conclusions about the work.

Chapter 2

Asset prices predictability

As already pointed out, security prices predictability has been a main issue of discussion among academics, scholars and pratictioners. This debate has been based essentially on understanding whether capital markets are informationally efficient and how portfolio management decisions are affected. The school of thought, which sustains that actual prices contain all public available information and that, future's price changes cannot be predicted basing only on past prices, relates to the theory of Efficient Market Hypothesis (EHM). In contrast with this point of view, mainly on recent decades, many empirical studies have documented significant evidences on some degree of asset returns predictability. In this chapter we present and discuss these two lines of studying financial markets behavior.

2.1 Efficient Market Hypothesis

Efficient Market Hypothesis appeared in its earliest form as Random Walk Theory more than 150 years ago. One of the first formal expressions of market efficiency is a book written in 1863 by Jules Regnault (Regnault, 1863), a broker and amateur mathematician. He argued that market price at any time reflects the wisdom of the crowd and that the only way to profit is to trade on private information that no one had. Moreover, in his work, he was the first to state that market efficiency implied that asset prices should follow a random walk and tested this theory on historical French and British bond data. In 1901, Louis Bachelier (Bachelier, 1901) in his doctoral thesis on option pricing assumed that stock prices movements were modeled by Brownian Motion process, implying the stock price changes unpredictability assumption. Thanks to his studies, Bachelier laid the foundations for modern Black-Scholes formula by which options are priced nowadays. After Second World War, the renewed interest for the study of financial markets boosted the publication of many researching works on EMH and its properties. Especially since 1960s, the concept of efficient markets has assumed a substantial theoretical framework particularly through the studies of Samuelson and Fama. In 1965, the Nobel laureate Paul Samuelson published a popular paper called "A Proof that Properly Anticipated Prices Fluctuate Randomly" (Samuelson, 1965) in which he argued that *"[...] there is no way of making an expected profit by extrapolating past changes in the futures price, by chart or any other esoteric devices of magic or mathematics. The market quotation already contains in itself all that can be known about the future and in that sense has discounted future contingencies as much as is humanly possible"*. In the same year Fama (Fama, 1965) discussed in detail the theory underlying the random walk model and tested the empirical validity of this model actually denying the significance of chart reading technique: *"We suggest, however, that, since the empirical evidence produced by this and other studies in support of the random-walk model is now so voluminous, the counterarguments of the chart reader will be completely lacking in force if they are not equally well supported by empirical work."*.

2.1.1 Theoretical background

In his review, (Fama, 1970) presents a theoretical framework of the works on EMH. By analyzing the concept of market efficiency under four different points of view. A financial environment is considered an efficient market if: returns obey to expected results of a "Fair game" model, the information set is a Submartingale, stock prices follow random walk model and market conditions are consistent with efficiency.

- **"Fair game" property.** In an expected return theory, the forecast of stock prices at time $t+1$ given the information set Φ_t is given by

  $$\mathbb{E}\left(X_{j,t+1}|\Phi_t\right) = [1 + \mathbb{E}\left(r_{j,t+1}|\Phi_t\right)]X_{j,t},$$

  where $X_{j,t}$ is the price of stock j at time t and $r_{j,t+1}$ is the one-step ahead percentage return. The conditional expectation is meant to imply that the information Φ_t is fully employed in the formation of the price $X_{j,t+1}$. The assumption that market efficiency can be expressed in terms of expected returns and that expectations are formed on the basis of the full information Φ_t leads to the following statements. Let

  $$\epsilon_{j,t+1} \equiv X_{j,t+1} - \mathbb{E}\left(X_{j,t+1}|\Phi_t\right)$$

  the difference between actual returns and predicted ones at time $t+1$ on the basis of Φ_t. So if

  $$\mathbb{E}\left(\epsilon_{j,t+1}\right) = 0$$

  it means that the sequence $\{\epsilon_{j,t}\}$ is a fair game with respect to the information set Φ_t.

If

$$\alpha(\Phi_t) = [\alpha_1(\Phi_t), \alpha_2(\Phi_t), ..., \alpha_n(\Phi_t)]$$

is any trading system based on Φ_t which informs the investor the quantity $\alpha_j(\Phi_t)$ of funds that are to be invested in each of the n available assets and

$$V_{t+1} = \sum_{j=1}^{n} \alpha_j(\Phi_t)[r_{j,t+1} - \mathbb{E}\left(r_{j,t+1}|\Phi_t\right)]$$

is the total excess returns amount on the portfolio formed by the n assets, the condition that satisfies the "fair game" property is

$$\mathbb{E}\left(V_{t+1}|\Phi_t\right) = 0.$$

- **Submartingale property** The price sequence $X_{j,t}$ follows a submartingale with respect to Φ_t if $\mathbb{E}\left(X_{j,t+1}|\Phi_t\right) \geq X_{j,t}$ which means that, on the basis of information Φ_t, the projection of security price at $t+1$ is at least equal to current stock price. Fama argues that this property is essential on comparing buy-and-hold strategies with "one security and cash" trading rules. If Submartingale assumption holds, the second strategy cannot dominate the other in expected returns.

- **Random walk model** As EMH describes the fact that current price of a security "fully reflects" available information, it is assumed that successive prince changes are independent each other. Moreover, an other assumption included constitutes the fact that future returns are identically distributed. Given this conditions, the natural stochastic process used to model stock price quotation is the Random Walk process. The main property of Random Walk model says that

$$f(r_{j,t+1}|\Phi_t) = f(r_{j,t+1})$$

where $f(\cdot)$ is a density function and, moreover, it is assumed to be the same for all t. A specification of this general Random Walk's feature occurs when we indicate that $\mathbb{E}\left(r_{j,t+1}|\Phi_t\right) = \mathbb{E}\left(r_{j,t+1}\right)$ meaning that expected value of price changes is independent of Φ_t. Fama adds also that *"a random walk arises within the context of fair game models when the environment is (fortuitously) such that the evolution of investor tastes and the process generating new information combine to produce equilibria in which return distributions repeat themselves through time".*

- **Market conditions consistent with efficiency** Fama identifies three sufficient conditions for capital market efficiency. He considers a financial environment in which:

  1. there are no transaction costs in trading stocks;
  2. information is costlessly available to all market participants;
  3. all traders agree on implications of current information for the current price and distributions of future prices of each stock.

  In such a market, the actual price of a security "fully reflects "all available information. According to Fama, these ones represent sufficient but (fortunately) not necessary conditions. In fact, the presence of transaction costs, costly information for some investors and disagreement about the implication of given information are not necessary sources of market inefficiency but they represent potential inefficiencies.

In the same work, Fama distinguishes between three different forms of the EMH:

- *weak form* states that all price information is fully reflected in asset prices in the sense that current price changes cannot be predicted from past prices;
- *semi-strong form* that postulates that asset price changes need to fully reflect all publicly available information and not only past prices;
- *strong form* requires that although some traders or group of investors have privileged access to information, this is fully reflected by prices.

The main purpose of this distinction is to spot the level of information at which the hypotheses that security prices at any point in time fully reflect all available information breaks down.

2.2 Testing Market efficiency

Although Jensen (1978) stated that *""there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Markets Hypothesis."*, since 80s many studies have documented substantial evidence on some degrees of assets returns predictability. In this section we will consider the problem of forecasting future price changes using only past prices: in particular we will focus on several tests proposed to verify Random Walk Hypothesis.

As already highlighted, Random Walk is a particular stochastic process used to model stock prices. We can think of three different versions of this process according to the assumptions made on distribution of the error terms $\{\epsilon_t\}$.

- Called X_t the random variable that represents the stock price at a specific time t, the first and simplest version of this model can be represented as follows:

$$X_t = \mu + X_{t-1} + \epsilon_t, \quad \epsilon_t \sim IID(0, \sigma^2) \tag{2.1}$$

  where μ is a drift parameter and the sequence $\{\epsilon_t\}$ is assumed to be identically and independently distributed with 0 mean and fixed variance. In this model, increments are not only uncorrelated but also any nonlinear functions of the increments are uncorrelated.

- The assumptions of the previous model are considered too restrictive for being applied to real financial assets since returns distributions cannot be considered unchanged over time. For this reason, the second version of the model assumes that $\{\epsilon_t\}$ are independently but not identically distributed (INID). This model's assumption keep the unforecastability of future price changes but allows for unconditional heteroskedasticity of $\epsilon_t's$, a useful feature given time-variation of assets volatility.

- The third version consists on assuming $\{\epsilon_t\}$ as a sequence of uncorrelated but not independent increments. For example, a process in which $Cov(\epsilon_t, \epsilon_{t-k}) = 0$ with $k \neq 0$ but where $Cov(\epsilon_t^2, \epsilon_{t-k}^2) \neq 0$ for $k \neq 0$.

2.2.1 Tests for Random Walk, first version

Despite the assumptions about first version of random walk are quite restrictive, it is interesting to review one of the tests used to detect the IID feature of price changes, introduced by Cowles and Jones (1937). Denoted with r_t the daily log-return of the stock price process, X_t, expressed in Equation 2.1, consider the following indicator function

$$I_t = \begin{cases} 1, & \text{if } r_t > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2.2}$$

The number of sequences N_s for a time-series formed by $n+1$ observations can be obtained as

$$N_s = \sum_{t=1}^{n} S_t \quad \text{with} \quad S_t = I_t I_{t+1} + (1 - I_t)(1 + I_{t+1}) \tag{2.3}$$

then

$$S_t = \begin{cases} 1, & I_t = I_{t+1} = 1 \quad \text{or} \quad I_t = I_{t+1} = 0 \quad \text{(sequence)} \\ 0, & I_t = 1, I_{t+1} = 0 \quad \text{or} \quad I_t = 0, I_{t+1} = 1 \quad \text{(reversal)} \end{cases} \tag{2.4}$$

We can note that S_t is a Bernoulli random variable with

$$\pi_s \equiv P(S_t = 1) = P(I_{t+1} = 1, I_t = 1) + P(I_{t+1} = 0, I_t = 0)$$

If increments of S_t are IID, we can write:

$$\begin{aligned} \pi_s &= P(I_{t+1} = 1) \cdot P(Y_t = 1) + P(I_{t+1}) \cdot P(I_t = 0) \\ &= \pi^2 + (1 - \pi)^2 \end{aligned} \tag{2.5}$$

The test statistic used to evaluate the IID hypothesis is called CJ-statistic and is defined as:

$$\frac{\#\text{sequences}}{\#\text{reversals}} = \frac{N_s}{n - N_s} = \frac{\frac{1}{n}\sum_{t=1}^{n} S_t}{1 - \frac{1}{n}\sum_{t=1}^{n} S_t}$$

If the IID hypothesis holds, according to the weak law of large numbers, the probability limit for $n \to \infty$ of $\frac{1}{n}\sum_{t=1}^{n} S_t$ is equal to the theoretical expected value

$\mathbb{E}(S_t) \equiv \pi^2 + (1-\pi)^2$. Hence:

$$\text{plim}(\widehat{CJ}) = \frac{\pi^2 + (1-\pi)^2}{2\pi(1-\pi)} \tag{2.6}$$

which implies that $\widehat{CJ} \approx 1$ since $\pi_s = 0.5$.

2.2.2 Tests for Random Walk, second version

In order to test the hypothesis of a second version of the Random Walk, some authors proposed two types of test: filter rules and technical analysis.

Filter rules

Alexander (1961, 1964) applied filter rules explaining that their rationale consists on filtering out all movements of price smaller than a specific size (considered noise) and analyzing the remaining changes. At the basis of these tools it is assumed the existence of trends in stock market. Later, Fama's studies (Fama, 1965; Fama and Blume, 1966) analyzed filter rules including dividends and trading costs, their empirical results highlighted that such rules do not perform better than a simple buy and hold strategy.

Technical analysis

Technical analysis includes a series of tools used to extract information by past prices in order to predict future price movements. This is an approach based on the assumption that stock markets tends to repeat themselves in patterns that can be profitably exploited. Moving Average Convergence Divergence, Relative Strength Index, On Balance Volume, Simple Moving Average represent just some of the indicators used by technical analysts. In later section we will discuss in more detail technical analysis and its relationship with statistical time series forecasts.

2.2.3 Tests for Random Walk, third version

Since the third version of of Random Walk makes only assumption about serial uncorrelation of price increments, it is interesting to test the null hypothesis that autocorrelation coefficients at various lags are zero.

Q statistic

The departures from null autocorrelations can be detected, for example, with Q-statistic of Box and Pierce (1970) which is given by $Q_m \equiv T \sum_{k=1}^{m} \rho^2(k)$ where $\rho(k)$ denotes the autocorrelation function at the k-th lag, T is the sample size and m is the number of autocorrelations considered. For IID data, the test statistic is approximately distributed according to a χ^2 distribution with m degrees of freedom. A correction of Q-statistic for small sample size has been offered by Ljung and Box (1978):

$$Q_m^* \equiv T(T+2) \sum_{k=1}^{m} \frac{\rho^2(k)}{T-k}. \tag{2.7}$$

Despite the usefulness of these measures, another type of tests has been proposed.

Variance ratio tests

A particular area of study focused the attention on testing Random Walk Hypothesis by means of variance ratio (VR) test statistics (Lo and MacKinlay, 1988; Poterba and Summers, 1988). The following autoregressive process for the stock price series is defined

$$X_t = \mu + \phi X_{t-1} + \epsilon_t, \quad t\text{=1,2,...,}T \tag{2.8}$$

where μ is an unknown drift term, ϕ is an estimated coefficient and $\{\epsilon_t\}_{t=1}^{T}$ are neither independent nor identically distributed. Then, the VR method consists on testing the null hypothesis that the process is Random Walk against the stationarity alternative. Since the first difference of the (third version) Random Walk process is assumed to be serially uncorrelated with respect to previous values, defined $d_t = X_t - X_{t-1}$ as a proxy of the returns series, the VR statistic for the $k-th$ order lag is defined as

$$V(k) = \frac{Var(d_t + d_{t-1} + ..., d_{t-k+1})/k}{Var(d_t)} = \frac{Var(X_t - X_{t-k})/k}{Var(X_t - X_{t-1})} \tag{2.9}$$

The idea behind Variance Ratio test is that, if $Cov(X_t, X_{t-k}) = 0$, then $Var(X_t - X_{t-k}) = kVar(X_t - X_{t-1})$ and $V(k) = 1$. An unbiased estimate for $V(k)$ is provided by the test statistic $VR(k)$, defined as

$$VR(k) = \frac{\hat{\sigma}^2(k)}{\hat{\sigma}^2(1)}, \quad \text{for } k\text{=2,3,...,}T \tag{2.10}$$

where $\hat{\sigma}^2(1) = (T-1)^{-1}\sum_{t=1}^{T}(d_t - \hat{\mu})^2$ is the unbiased estimator of the one-period proxy returns variance and $\hat{\mu} = T^{-1}\sum_{t=1}^{T} d_t$ is the estimated mean of d_t. On the other hand, its k-period unbiased variance estimator is given by

$$\begin{aligned} \hat{\sigma}^2(k) &= m^{-1}\sum_{t=k}^{T}(d_t + d_{t-1} + ... + d_{t-k+1} - k\hat{\mu}) \\ &= m^{-1}\sum_{t=k}^{T}(X_t - X_{t-k} - k\hat{\mu}) \end{aligned} \tag{2.11}$$

where $m = k(T-k+1)(1-kT^{-1})$.

By means of Variance Ratio tests, Lo and MacKinlay (1988) reject random walk hypothesis for weekly stock market returns. Empirical results obtained by Poterba and Summers (1988), using American and other countries' monthly returns from the period bounded between 1919 and 1985, suggest that stock returns exhibited positive serial correlation in the short term and negative correlation over longer intervals. Both works highlight that, as stated by Fama (1970), rejecting random walk model does not necessarily exclude inefficiency of stock price formations.

More recently, Deo and Richardson (2003) showed that this type of test is weak and potentially biased.

2.2.4 Alternative tests

Despite Random Walk model plays an important role, financial literature offers also a vast field of researches which are not directly related with tests of Random Walk Hypothesis. Some of them are summarized as follows:

- **Runs tests.** An alternative way to investigate how past returns can influence actual observations consists on examining the sign of the price change (+ for price increase, - for decrease). If price changes are positively related, it is plausible that they exhibit long sequences of the same sign, these are called runs. Since correlation coefficient estimation can be influenced by outliers, some authors tested market efficiency referring to runs analysis.

  In particular, Fama (1965) showed that the number of runs for some stocks was smaller than expectations, which means that price changes showed positive relations over time.

- **Testing size effects.** In the same paper of Lo and MacKinlay (1988) and in another study of Conrad and Kaul (1988) we can find empirical evidences that portfolios of stock shares with the same size (number of shares times price per shares) tend to behave similarly, especially for the case of small caps. One of the earliest and quoted work on this field can be endowed to Banz (1981). The author documented that the firm size was a statistically significant factor which helped to explain stock's returns. In particular, he discovered a differential return, from buying small NYSE firms rather than larger ones, of 19.8% per year. This was not always the case since there were periods in which large firms outperformed small ones. Chan and Chen (1988) argued that 'size effect' could be explained by the fact that small firms bear more risk as they have low production efficiency and high leverage and in hard times they have lower survival probability than larger caps. Other authors suggested that lower transaction costs could attract investors to trade small firms' stocks.

- **Testing stocks seasonality.** Scholars and pratictioners studied also stock prices seasonality (Gultekin and Gultekin, 1983; Kato and Shallheim, 1985; Keim, 1983). In particular, the January effect became popular in financial literature as much higher returns were discovered in this month for several countries including the United States. Furthermore Kato and Shallheim (1985) discovered particular relationships between size and excess returns in January for Tokyo Stock Exchange. Keim (1983) offered a partial explanation for this effect arguing that it involves the way in which returns are computed: when stocks are not traded, in fact, returns are calculated as the average of the bid and ask price. The tendency of the last trade of December was to be at the bid and this raised the returns of the respective stock. A second explanation was found on taxation mechanism that makes profitable to sell a stock at the end of December and to buy it in the first days of January. Finally, the January effect and, in general, seasonal patterns are difficult to combine with efficient markets. In general, however, many researches have documented that stock seasonalities or size effects vanish rapidly after they become popular and this could represent a point in favor of market efficiency.

2.3 Technical analysis and time series approach

Generally, besides the specific tests described above, prediction of future market direction has been a main issue of interest among academics and professionals. In this context, the most relevant approaches were referred to technical analysis indicators and the use of time series forecasting. However, more specifically, the purpose of technical analysis does not perfectly match with forecasting generation of profit trends but, instead, it aims to study financial markets in order to detect their turning points. Technical trading strategies prove their advantages when structure of asset prices or returns is not well known. Moreover, they simply rely on price series without accounting for other information derivable from returns distribution.
Despite these techniques lack of a sophisticated theoretical framework, many empirical applications, based on this approach, led to profitable trading rules.
Time series analysis, on the other hand, is more appropriate to model some features of stock returns such as volatility clusters, heavy tails and nonlinear dependence but this approach does not always show a superior forecasting power.
Another issue is related to the generation of trading signals. While basing a trading strategy on technical analysis indicators is quite straightforward as long as they are essentially the results of an operative framework, producing trading signals according to time series forecasts is not so intuitive mainly because they are subject to

prediction errors of point estimates. On the other hand, technical analysis lacks to define such scientific forecasting tools based on probabilistic laws showed by data in the past. As a consequence, a solution proposed in the empirical literature (and also in this work), in order to overcome weaknesses and merge positive aspects of both fields, consisted on building trading strategies able to combine the two approaches.

Chapter 3

Technical analysis

3.1 Introduction

Technical analysis is a methodological approach to investment, essentially based on the idea that prices move in trend. *"The art of technical analysis, for it is an art, is to identify at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed."* (Pring, 2014). Practically, in order to generate trading signals, technical analysts employ several indicators such as moving averages, strength indices, channels and momentum oscillators.

Many researches and surveys on this field have witnessed that most of pratictioners rely heavily on technical analysis approach and techniques. In the earliest survey of this type, Smidt (1965) discovered that over 50% of interviewees used charts to identify trends, Billingsley and Chance (1996) estimated that about 60% of commodity trading advisors trusted on technical analysis algorithms in order to generate trading signals, finally Fung and Hsieh (1997) concluded that trend following strategies were the most implemented by professional traders.

In their systematic and comprehensive study, Park and Irwin (2007) surveyed financial literature devoted to this topic and identified two order of reasons for which academics were so skeptical about technical analysis methods. The first is linked to the efficient market hypothesis acceptance for which, as we already described, past trends cannot have prediction power on future prices. As second motivation, they enclosed the negative empirical findings obtained by first and widely cited works. However the usefulness and the profitability of technical trading rules, still nowadays, represent open questions and important topics of debates between academics and praticitioners.

3.2 Foundations and assumptions of technical analysis

An influential technical analyst, Murphy (1991), gathered the main philosophical premises underlying this financial markets approach and described some important applications in his book.
The most relevant foundations for technical analysts are the following:

1. **Market action discounts everything.**

   With this claim, described by Murphy (1991) as the "*cornerstone of technical analysis*", the author wants to emphasize that price behavior is the only indicator the technician is interested in. From this premise he argues that only by studying price movements one can get the insight to understand behaviors of demand and supply for a specific asset. "*[...] if prices are rising, for whatever the specific reasons, demand must exceed supply and the fundamentals must be bullish. If prices fall, the fundamentals must be bearish*". Apparently, this is the same line of reasoning followed by authors who sustain Efficient Market Hypothesis according to which prices discount everything. Actually, while academics believe there is no way to profit from stock prices actions since markets discount information quickly, technical analysis forecasts are based on the idea that important information are discounted in stock prices before to be known. In this way, technicians assign to asset prices a degree of predictability that could be exploited to generate profits.

2. **Prices move in trends.** Murphy identifies the essence of technical analysis with the concept of trend. When a stock price is increasing (decreasing) it means that, on average, the market actors have positive (negative) expectations about the future state of that firm or, in other terms, they think that the real value of that security is higher (lower) than its current price. When stock price dynamics exhibit the predominance of the market sentiment for a specific expectation over relatively long periods of time, a trend is generated. However, technical analysis suggests that future cannot be anticipated but, instead, the most a trader can do consists on following the current sentiment of the market and adapting to it. Generally, in fact, technicians aim to spot trends in early stages in order to take a position coherent with the direction of them. The corollary at the basis of this line of reasoning says that *" a trend in motion is more likely to continue than to reverse"* which is a derivation of Newton's first law of motion. Moreover, study of trends and their characterization have been developed over time. Most of definitions were described in a series of editorials written for the *Wall Street Journal* by Charles Dow, founder of the modern technical analysis. The ideas there contained took the name of *Dow Theory* and produced the following definitions.

The Market Has Three Trends

According to Dow, a market can have three type of trends: primary, secondary and minor movements.

- The features of the primary trend characterize a bullish or a bearish market: in particular Dow defined an uptrend as the situation in which successive peaks and troughs are increasing. The downtrend, instead, is defined in the opposite way (decreasing peaks and troughs). The primary trend can last for one year or more.
- The secondary movement represents intermediate correction to the first one and, generally, lasts half of the previous move.
- Finally, the minor trend lasts from hours to few weeks and provides corrections to the intermediate movement.

The Major Trends Have Three Phases.

Dow studied in more detail the primary (or major) trends. They usually take place in three different phases:

- The first is called *accumulation phase* and consists in that period in which only the most astute (or informed) investors assume a position in the asset. In this phase the stock price does not change since these investors represent the minority of the demand.
- The *public partecipation* phase takes place when most of trend-following investors begin to participate. At this point, a rapid change of the price occurs, business information spreads.

- Finally, during the *distribution phase* economic news further improves and speculative volume and public participation increase. Moreover, in this phase, better informed investors who assumed a position during the accumulation period, begin to "distribute" (e.g. selling the stock) before anyone else.

Volume Must Confirm the Trend.

Dow identified volume as an important indicator to confirm signals deriving by prices. According to his ideas *"volume should expand or increase in the direction of the major trend"*. For instance, when price movements are confirmed by high trading volumes, it is likely that the actual trend represents the true market opinion about that specific asset. In this way, Dow considers volume as confirmation indicator of the developing trend.

3. **History repeats itself.** This claim is more linked to the study of human psychology. The humans, in fact, on equal terms will tend to take the same decisions. And besides, financial markets are heavily based on human decisions so that they inevitably reflect behavior of their agents. This line of reasoning leads technicians to conclude that, since past patterns have worked well in the past, they will continue to do so, even in the future. Murphy added that *"Another way of saying this last premise[...]is that the key to understanding the future lies in a study of the past, or that the future is just a repetition of the past"*. In fact, once a technician spots a pattern exhibited by the historical prices of stocks or indices, usually he validates it through the past process. Actually, this assumption is not typical of technical analysis but is common in any method that analyzes the past in order to get useful information for

inferring about the future.

3.2.1 Some considerations about technical analysis framework

Foundations of technical analysis need to be contextualized within its historical duality with the fundamental approach. While, in fact, technicians focus on the study of market actions, the fundamentalists start from the dynamics of economic forces like demand and supply for determining the fair value of the stock price. In light of their analysis, which involves also the study of firms' balance sheets, they buy the asset if company's share value is undervalued or sell it in the opposite case. Technical analysis, then, was introduced to overcome the limitations of this approach, linked to the difficulty on: computing the fair value of a company, analyzing and interpreting the mass of information present in the balance sheets and dealing with the problem of data delay since, usually, when new statements are released, they refer to several months before. In this context, then, technical methods provide more quickly the operative signals needed for adjusting the investment strategy according to the market events. As regards the theoretical assumptions underlying technical analysis, the one that separates it more clearly from other financial markets approach consists on the idea that stock prices move in trends and, in order to profit from it, traders need to follow the predominant market behavior. In particular, this view is important as long as it introduces the concept that, in the real world, market efficiency is not always achievable and the consequent generation of trends in stock prices might provide traders the chances to open profitable positions. In general, however, the nature of technical analysis prevents the trader to keep a constant degree of reliability because it does not aim to forecast the future direction of prices (such as, for instance, time series forecasts) but, instead, it provides operative guidelines for the trading activity.

Finally, one of the main issues that, still nowadays, contribute to the success and popularity of technical analysis consists on the intuitiveness of its indicators and also of the terminology used. The study of financial markets through technical analysis and the definitions that result from it (e.g. the concepts of *supports and resistances* or *bearish and bullish periods*) should be interpreted in relation to the operative context in which they have been using.
If under a methodological point of view, this type of financial markets analysis cannot be completely classified as scientific, on the other hand, the unquestionable intensive use of technical analysis, among practitioners, demonstrated the popularity reached by this operative discipline.

3.3 Literature review of technical trading strategies

Implementation of technical analysis techniques is basically divided into two main categories:

- Graphical technical analysis which consists on drawing, on a graph of the past asset prices, specific lines of *support* and *resistance* that should give a representation of developing trends. *Support* is defined as an effective or potential flow of purchases large enough to stop, for a large amount of time, a descending trend. On the other hand, *resistance* is as an effective or potential flow of sells large enough to stop, for a large amount of time, an ascending trend. Essentially, the purpose of these techniques is to spot (through an immediate graphical way) potential ascending/descending market movements and to warn the analysts when a trend inversion occurs.

- Quantitative technical analysis, instead, deals with statistical or heuristic methods applied to financial time series data. Essentially, they take form of filter rules, moving averages, channels, momentum and strength index indicators that contribute to build trading systems. Since these techniques can be expressed in mathematical form, academic research on this field (and then this work) is generally related to study and implementation of these kind of methods.

Park and Irwin (2007) proposed to differentiate empirical literature on technical strategies between *early* and *modern* studies.

3.3.1 Early studies

Among popular *early* studies we can cite: Alexander (1961), Fama and Blume (1966) and Smidt (1965). In particular, the most influential work is represented by Fama and Blume (1966). They tested filter rules based strategies on daily closing prices of 30 specific individual stocks in the Dow Jones Industrial Average (DIJA) between 1956 and 1962. In terms of excess returns, an inconsistent dominance of technical trading systems over benchmark Buy & Hold strategy, was found. Moreover, they argued that accounting for commission fees heavily contributed to the generation of technical strategies which did not improve benchmark results.
Moreover, while *early* studies on stock markets did not discover profitable strategies, the majority of empirical researches on extra U.S. exchange and future markets proved their profitability also in presence of operational costs (Smidt, 1965; Stevenson and Bear, 1970; Leuthold, 1972; Sweeney, 1986). Despite results may suggest that stock markets were more efficient than other markets considered before the mid-1980s, Park and Irwin argued that these conclusions are not fully reliable since early studies suffered from the following methodological flaws.

1. The first aspect discussed was referred to the number of trading rules considered

by the works' authors which, according to Park and Irwin, was small: often just one or two trading systems were tested.

2. Most studies above described did not perform statistical significance tests on trading results. Moreover, as Lukac and Brorsen (1990) showed, technical trading returns do not follow a Normal distribution, then implementation of Z- or t-tests, might lead to spurious results since their underlying assumptions do not hold.

3. Only a few studies included measures of risk when evaluating performances of technical strategies. In light of investor risk-aversion, in fact, investment returns should be weighted also in terms of their bearing risk and consideration of measures for gauging it could help in strategy selection process.

4. Early studies results are often products of average performances across all trading rules or assets. Averaging has its pros and cons: if, on one hand, it reduces weight of trading rules that could work perfectly for some stocks by pure chance, on the other side it can shadow results of models that possesses effective forecasting power.

5. Given the parametric nature of technical analysis systems, most studies searched best strategies over a large number of parameters. The risk of this choice is represented by the overfitting problem which emerges when a filtering model gets extraordinary in-sample results but fails the out-of-sample test. In practice, when we implement several trading systems and get that some of these ones perform better than buy-and-hold rule, we cannot simply infer that they will produce profitable results even in practice. In order to solve data snooping problems, Jensen (1967), for instance, suggested a validation procedure

which consists on selecting the best trading strategies in the first half of the sample and then validating it using the rest of sample data. In general, however, trading rules optimization was often ignored by early studies and some authors reported that presence of data snooping selection biases should not be underestimated.

3.3.2 More recent studies

Since the end of 1980s and start of 1990s, empirical research on technical analysis literature produced what Park and Irwin (2007) called *modern* studies. These works contributed to overcome the above described limitations of the previous ones and according to the different methods and aspects of analysis, they were subdivided into seven categories. We will report only five of them by not including *chart pattern* and *other* studies. The former because we are not really interested into trading strategies that cannot be expressed in mathematical form, the latter because they are similar to early studies since they ignore trading rules optimization, out-of-sample verification and data snooping issues.

Standard studies The main improvements of standard studies with respect to previous works consisted on the introduction of parameter optimization and out-of-sample validation. Moreover, the incorporation of commission costs and measures of risk represented an important achievement into empirical literature of trading strategies verification. In Lukac et al. (1988), the authors test 12 technical trading systems on 12 firms' stocks from agricultural, metal and financial future markets between 1975 and 1984. Parameters adaptivity and out-of-sample verification are assured by the recursive technique chosen by authors that provides for a 3-year validation period, after that, only parameters of optimal strategies are selected and used for the next year's period.

Furthermore, in this work two tailed and one-tailed t-tests were performed to verify, respectively, if null hypotheses of zero gross and net returns were not refused. Since Lukac et al. found statistically significant positive net returns, their main conclusion was that future markets during that sample period showed signs of inefficiency.

Model-based bootstrap studies With regard to different methods proposed to test statistical significance of trading returns and in order to overcome above described limitations of t-tests, Brock et al. (1992) implemented bootstrap simulation techniques. In particular, the approach there followed was to generate samples of price series using model-based bootstrap methods and apply technical strategies systems (moving average oscillators and trading range break-out) on each simulated price series. Model based bootstrap method consists on fitting time series models to data sample and resampling with replacement their residuals in order to generate bootstrap samples of price sequences.

Brock et al. adopted a random walk with drift, an autoregressive process of order one (AR(1)), a generalized autoregressive conditional heteroskedasticity in mean (GARCH-M)and an exponential GARCH (EGARCH) on DIJA stock index from a period ranging from 1897 to 1986. For each model, then, was generated a specified number of bootstrap samples containing price series. The procedure used for random walk model was different since log-returns of original price series were taken and sampled with replacement.

Beside the methodological aspect, Brock et al.'s work gained importance among financial community for their findings. Analyzing returns during days when buy (sell) signals were generated, they discovered that all technical trading systems considered generate positive (negative) returns and, in general, these results dominated performances of Buy & Hold strategy. Moreover, returns during buy signals have also a lower standard deviation if compared with those of sell days. In this way, Brock et al. argued that technical trading returns cannot be explained by risk then *"[...] the returns generating process of stocks is probably more complicated than suggested by the various studies using linear models. It is quite possible that technical rules pick up some of the hidden patterns"*.

Then, this work assigned to technical analysis a validity that it did not have before. For the first time, its usefulness in catching some of the non linear aspects present in financial markets was recognised also by academics. Despite results did not include transaction costs, other authors considered Brock et al.'s trading rules and findings as guidelines for their researches: Bessembinder and Chan (1995, 1998), Raj and Thurston (1996) and Fang and Xu (2003) just to cite someone. In general, despite results of these works vary across markets, technical trading rules seem more profitable for stock indices of emerging countries while developed markets show more efficiency.

Reality check studies Other considerable works on technical strategies analysis consist on reality check studies. In order to quantify data snooping bias that occurs when profitable trading rules are searched 'in-sample', they adopt White (2000) bootstrap reality check method. This consists on building a testing framework where the null hypothesis is:

$$H_0 : \mathrm{E}(f^*) \leq 0$$

where f^* is $l \,\mathrm{x}\, 1$ vector of mean excess returns over a predetermined benchmark where l is the number of trading strategies considered.

White's method involves to consider results of all trading rules and, by simulating the asymptotic distributions of their performance values (through specific bootstrap simulations), we can compute their test p-values. If, at the end of this process, a relatively low p-value is returned, we can infer, with a specific significance level, that at least one trading strategy dominates the benchmark. If we repeat the same process, considering just a specific rule, we can claim whether their returns are results of data snooping or not.

Sullivan et al. (1999) implemented White's methodology using the same data sample considered by Brock et al. (1992) adding the last decade for out-of-sample validation. Reality check verification confirmed robustness of Brock et al. findings but p-value of their best strategy disproved its out-of-sample forecasting power.

Genetic programming based studies Some authors, then, proposed to implement generic programming methodologies for strategy selection. It involves the use of numerical optimization procedures based on Darwinian principle of survival of the fittest. In application to trading strategies, several functions of past prices, both numerical and logical, are composed and constitute the starting population. According to a fitness criterion some trading rules will survive and others will be replaced. The difference with traditional testing procedure consists on the fact that, here, the parameter space of the rules is not predetermined and fixed ex ante, which is a main step forward in order to avoid data snooping risks. Allen and Karjalainen (1999) applied this procedure to daily S&P 500 stock index from 1928 to 1995 using excess returns over a Buy & Hold strategy as fitness measure and including also transaction costs and out of sample validations. Despite its methodological elegance, results showed that genetic programming did not produce substantial excess returns and market efficiency seemed preserved.

Like other above described studies, those who implemented genetic programming algorithms generate mixed results but in general they conclude that technical rules are not profitable in developed stock markets, above all in relatively recent years, while future and exchange markets show more signs of inefficiency. A general evaluation of genetic programming methodology is given in Park and Irwin (2007) in which they highlight it reduces data snooping risks but does not eliminate them definitely. Moreover, technical strategies resulting from the procedures are too cumbersome and are not easily applicable in practice.

Non linear models based studies Non linear methods to evaluate trading strategies performances encompass application of feed-forward neural network or nearest neighbour regression. While classical application of these models provides for the inclusion only of raw returns, these studies add past trading signals as regressors. Main findings of Gençay (1999), whose works are the most famous among non linear studies, were that application of those models based on past buy and sell signals to a sample period ranging from 1973 to 1992 produced more accurate forecasts than those based on past raw returns. Other studies of these category include: (Gençay, 1999) who encompassed 10-day volume indicator to neural network model, (Fernandez Rodriguez et al., 2000) who fitted a feed forward neural network to the Madrid stock exchange, (Sosvilla Rivero et al., 2002) who used nearest neighbour regression for the Mark and Yen historical values. Generally, incorporation of technical trading indicators on non linear models proved to produce good results and, in light of this Brock et al.'s words, according to which technical analysis reveals some of the patters hidden when analysis is performed with linear models, find a basis. However, as Timmermann and Granger (2004) suggested, application of non-linear approaches developed in the recent years on 1970s' or 1980s' prices can be inappropriate.

3.4 Explanations for technical trading profits

As we have seen, although a vast literature is devoted to verify performances of technical trading strategies, their profitability still remains an open question. However, if we concentrate on modern studies it is worth noting that most of them reported positive results. Some financial academics, then, developed theoretical models while others proposed empirical reasons for attempting to explain technical trading profits generation.

3.4.1 Theoretical explanations

Theoretical motivations can be found in economic models of Grossman and Stiglitz (1980), Brown and Jennings (1989) and Blume et al. (1994). All of these works consider Grossman and Stiglitz's noisy rational expectations equilibrium models, in which noise prevents prices to reflect all available information present in the markets. The process of adjustment to the hypothetical equilibrium price then, is slower and patterns of prices can be exploited by traders. Main conclusion of Brown and Jennings (1989)'s work is that: if current price does not represent all available information because of noise, a combination with past prices might improve investor's information levels. Blume et al. consider the same framework and, as source of information, substituted current and past price levels with volume. Other forms of theoretical framework regard the field of behavioral finance which was firstly developed by financial economists at the start of 1990s. Unlike traditional economic models, in which dominates the figure of rational agents, behavioral studies assume that financial markets are dominated by arbitrageurs (smart investors) and noise traders (agents affected by irrational beliefs and sentiments who trade on noise). Former ones operate on the basis of rational expectations while the latter ones follow the trend and represent technical analysis principle. For example, they buy when prices rise and sell when these fall. Long et al. (1990)'s study, which was one of the main influent in this field, suggested that presence of price patterns, which justify technical strategies profitability, might be due to irrational actions of noise traders whose effects are amplified by arbitrageurs, in the short run.

Some other scholars proposed to analyze technical strategies profitability from the herding models' point of view. What they argue is that popularity of some trading methods causes a herding effect that leads to a self-fulfilling prophecy. In practice, Schmidt (2002) reported that concerted actions of technical traders are able to affect price directions provoking ripple effects that force also regular (non-technical) traders to deal with these movements.

Additional theoretical explanations were referred to the relations between technical analysis and chaotic (non linear) systems. Some tests were performed by (Clyde and Osler, 1997) who applied technical techniques to non-linear data and, indeed, results were promising since these techniques performed better on these data than on random data and profits were generally better than those produced by a random strategy. Another study (Stengos, 1996) emphasized how much these performances are affected by the assumptions and the specification of the non-linear data generating process.

3.4.2 Empirical explanations

As regards the empirical explanations, the first one in terms of consensus generated among academics (Sweeney, 1986; Lukac et al., 1988; Davutyan and Pippenger, 1989; Levich and Thomas, 1993; Silber, 1994) refers to the correlation between central bank interventions and technical trading profits in the exchange markets. In particular, the rationale is that, when central bank interventions are announced, but postponed, this situation generates a trend towards a new equilibrium level that can be exploited by technical traders. This idea was tested by some authors (Szakmary and Mathur, 1997; LeBaron, 1999) and results confirm that some relation between central bank actions and technical trading returns is present. Some other studies (Neely and Weller, 2001; Neely, 2002) inverted the above described relation sustaining that interventions appear when these trends are in place. Finally, a more recent paper of Sapp (2004) claimed that this link is less direct than what it was before the mid 1990s.

Order flows analysis was used to investigate its relations with technical strategies profitability. Main findings of Kavajecz and Odders-White (2004) uncovered the fact that sell (buy) signals generated by moving average rules correspond to a shift in order books toward sellers (buyers). In practice, technical strategies signals seem to anticipate information about liquidity state of a specific security.

Others identified success of technical strategies before 1990s with temporal market inefficiencies. In particular, when new financial forecasting methods appear and are used in practice, they are likely to produce profits for a short limited periods of time since markets will tend to incorporate these new information into prices, preventing them to be successful even in the future. Other reasons for limited gains of technical strategies have been related to structural changes present in market. Predictive methodologies, of this type, in fact cannot be successful forever since technological changes will change economic and financial environment and, as a consequence, the way of trading.

Some researches tried to inspect whether technical trading returns could be explained by risk premiums. The measures of risk chosen to quantify it were Sharpe ratio (Lukac and Brorsen, 1990; Chang and Osler, 1999; LeBaron, 1999) and that one provided by Capital Asset Pricing Model (CAPM) with constant risk premium over time (Sweeney, 1986; Lukac et al., 1988; Levich and Thomas, 1993). In general, however, results were not so promising partly also because of some limitations of the considered risk indicators. For instance, the fact that positive and negative deviations of the asset value from its mean have the same weight is not recommended for a trader who would expect, from a risk measure, that it gauges only negative ones. Market microstructure deficiencies could also lead to overestimate profits of technical strategies. For example, inclusion of too low transaction costs or total ignorance of bid-ask spreads (a measure that reflects liquidity level of a security) which could hamper buy or sell activities, might lead to biased results. In particular, the second point is still an open issue as long as bid-ask spread estimators proposed in literature have not proven to work successfully yet if assumptions about market microstructure are not well specified (Locke and Venkatesh, 1997). In order to overcome this limitation, one way consisted in considering greater than actual commission costs (Schwager, 1996). As final, but not least important, explanation for technical analysis profitability, literature includes data snooping which, as we have described in previous section, has hit some research studies in different forms.

Chapter 4

Time series models

4.1 Introduction

Study of financial time series led scholars and academics to propose statistical and econometric models with the purpose of mimicking their principal features and improving forecast accuracy. The fact that research on financial time series is still an active field for discussions and new proposals proves how difficult these tasks are and how much work still needs to be done. Extensive researches of exploratory data analysis, in fact, suggest that simple linear autoregressive processes are not always enough to catch all the statistical aspects that characterize stock returns. Aim of this chapter, then, is to describe the main stylized facts about financial returns and present some popular models used to tackle them, with a particular focus on (G)ARCH framework and some of its extensions since this class of time series tools will be used in the empirical part of our work. A disclaimer is needed before presenting this section: if technicians base their studies on analysis of prices in order to discover and exploit trends, usually, for time series forecasts, the focus is posed on structure of assets returns. One of the justifications lies on the fact that assumption of stationarity is more suitable for returns than for asset prices. The main consequence of stationary processes is related to the immutability of the probability laws that rule them. Given a weakly stationary process $\{Y_t\}$ the joint distribution of $Y_t, Y_{t+1}, Y_{t+2}, ...$ corresponds to the joint distribution of $Y_{t+k}, Y_{t+1+k}, Y_{t+2+k}, ...$ for a given time lag k. Although exist models that are able to address so called *integrated time series* (and the last section of this chapter will be focused on describing some of them) the assumption of (weak) stationarity makes the results of the statistical inference more reliable. For this reason, the interest will be especially focused on the statistical properties showed by financial returns.

4.2 Statistical properties of financial returns

Purpose of time series analysis consists on making inference about the structure of a stochastic process on the basis of an observed record of that process. Hence, it needs a preliminary analysis of the properties that a series of data indexed by time have shown in the past. These aspects of analysis have not only a statistical importance (*e.g.* accuracy and significance of estimated parameters) but also an economic impact on investors choices. Over time, then, many interesting properties of financial asset returns series were discovered. Some of these proved to be present only for limited periods of time and for specific securities while others have recurred more frequently regardless of sampling frequency, type of security and observation period or market. For purposes of this work (*i.e.* we will not concentrate on the multivariate properties that financial series usually exhibit) we will concentrate on the following stylized facts showed by financial returns:

1. Non linear dependence and volatility clustering.

2. Nonnormality or heavy tails.

3. Leverage effect.

4.2.1 Non linear dependence and volatility clustering

A typical feature of price movements is the absence of significant linear autocorrelation, except for very short intervals of time. This property is widely recognized and constitutes the empirical foundation of the general market efficiency hypothesis. Despite this, absence of linear correlation over time does not rule out possibilities for other forms of dependence such as the nonlinear one (Hsieh, 1993). Indeed, when nonlinear transformations are performed (such as taking absolute or squared returns) we can note that they are not independent but rather exhibit positive and persistent (slowly decaying) serial correlation patterns. In some way, then, returns show a degree of predictability not immediately detectable with traditional linear tools (autocovariance analysis or ARMA models) and that deserves to be analyzed with other measures. Particular attention was devoted to the so called 'volatility clustering' phenomenon (or also *Garch effect*) that gained popularity after Engle (1982) publication. It refers to the tendency of financial returns to group together into periods of high and low volatility. In particular, high (low) squared or absolute returns are followed by high (low) squared or absolute returns. Hence, this fact shows a dependence in conditional variance of financial time series that needs to be modeled as we will later see. Detection of this feature can be carried out through the estimation of the empirical autocorrelation and partial autocorrelation functions of the squared or absolute series returns. Once is noted that their values are statistically significant even at high orders of lags, null hypothesis of presence of volatility clusters might not be refused. Furthermore, a Ljung-Box test can be used to test the joint significance of autocorrelation coefficients at several lags. In fact, under the null hypothesis (no Garch effect) the Ljung Box statistics should be χ^2 distributed with m degrees of freedom, where m is the order of lags considered.

4.2.2 Nonnormality and heavy tails

In contrast to efficient market hypothesis which sustains that important aspects of returns distributions rely only on their first and second moments, increasingly greater attention was devoted in literature to the analysis of other market measures more linked to concept of risk. From empirical studies, in fact, emerges that financial returns exhibit heavy tails which implies that market generates more extreme values than one would expect from a Normal distribution with the same mean and variance. This property was firstly described long time ago by Mandelbrot (1963) and Fama (1965) and, referred to empirical returns distribution, leads often to refuse hypothesis of normality. This property is usually measured by kurtosis which is a shape parameter (fourth central moment divided by the standard deviation to the fourth) that represents how much of the distribution is concentrated in the center and in the tails. Values higher than 3 (which is the kurtosis of the standard Normal) indicate leptokurtic proability density functions where extreme values are more frequent, which is the case of financial returns. If leptokurtosis is a fact documented by many empirical works, for what concerns symmetry of returns distributions, the state of the art is not so clear: Peiro (1999) reported that studies based on skewness indicator (third central moment divided by the cube of standard deviation) of returns distributions generally tend not to reject null hypothesis of symmetry since no statistically significant values are discovered. On the other hand, other works showed opposite examples in which kurtosis is more pronounced: Simkowitz and Beedles (1978), Kon (1984) and So (1987). Besides empirical estimation of kurtosis and skewness, normality of distribution can be tested both through graphical way and using statistical tests. As regards the former method, Gaussian quantile-quantile (QQ) plots are usually drawn in order to graphically analyze whether some departures from the Normal distribution appear. For what concerns the other approach, many tests can be performed, two of them are worth to be cited: Jarque-Bera and Kolmogorov-Smirnov tests. The former, jointly considering sample skewness and kurtosis values, assumes independently and identically distributed sequence $\{Y_i\}_{i=1,\ldots,n}$ and defines the test statistics as

$$JB = \frac{ng_1^2}{6} + \frac{ng_2^2}{24}$$

where g_1 and g_2 are respectively empirical skewness and kurtosis. Under the null hypothesis of data Normality JB statistics is χ^2 distributed with two degrees of freedom. In particular, if the statistics is too large, the normality assumption is rejected.

Kolmogorov-Smirnov (KS) test, instead, is considered more powerful since it does not make any assumption about data distribution and it can be used also to test whether sample comes from a given distribution different from the Normal. This flexibility comes from the fact that KS is a non-parametric test as it is based on the maximum distance between cumulative density functions (CDFs): in case of a Gaussianity test, sample CDF is compared with a Normal CDF with mean and variance respectively represented by their sample point estimates ($\overline{Y}$ and s_Y^2).

KS statistics, then, is given by:

$$KS = \sup_{x} |F_n(x) - F(x)|$$

where $F_n(x)$ and $F(x)$ are the respective empirical and given CDFs.

4.2.3 Volatility-returns correlation and leverage effect

In addition to conditional heteroskedasticity and heavy tails, financial returns distributions are also characterized by a volatility-return correlation also called leverage effect. In particular, empirical analysis of financial time series lead to infer that reaction of volatility to past returns is more pronounced in presence of negative returns in comparison with positive ones, in such a way establishing an asymmetric impact of past returns on actual stock price variability. This phenomenon was firstly reported by Black (1976) in a seminal paper and later confirmed by many authors among which Christie (1982), Cheung and Ng (1992) and Duffee (1995) who tried to explain it involving the degree of leverage in the firms' capital structure, hence its name. For instance, when bad news about a firm with high debt start to spread, the immediate consequence is represented by a stock price falling. As this occurs, firm's debt-to-equity ratio rises together with uncertainty about its financial soundness. Once this process starts, one might expect negative returns today and higher volatility tomorrow and so on. Some authors, however, argued that leverage effect cannot completely explain negative correlation between volatility and returns in financial markets. For example, more recent empirical studies (Bekaert and Wu, 2000; Li et al., 2005; Aydemir et al., 2007) tend to support the idea that these asymmetric effects of volatility can be better explained by time-varying risk premium theory (volatility feedback effect) or *panic-like* effects. In particular, the former motivation, suggests that increases of volatility lead to higher required rates of return that, in turn, need stock price declines to put them in place. Therefore, the impact of volatility reflects directly to prices.

This rationale inverts the above described casualty link because explains how a volatility increase has an impact on returns. In order to detect this type of behavior, usually, structure of cross correlation between volatility and simple returns is analyzed.

Bollerslev et al. (2006), for instance, relying on high-frequency five-minute SP500 future returns, recorded persistent and significant negative correlations between volatility proxies and current and lagged returns (supporting the impact of negative returns on future volatility) lasting several days. On the other side, they discovered also strong contemporaneous cross-correlation between the two quantities, confirming, at least, the volatility feedback effect.

4.3 Some time series models

Over time it has transpired that traditonal ARMA models (and their underlying assumptions) were too restrictive to catch the emerging issues brought up by empirical studies. This gave impulse to the rise of a huge number of time series models with different features.

However, two issues still remain open questions: on the one hand, the increasing level of model refinement have not always corresponded to an improvement in terms of predictive power and, on the other one, despite their attracting theoretical properties often some methodological problems arise.

4.3.1 ARCH models and their generalizations

Class of ARCH (Autoregressive Conditional Hetereskedasticity) models, firstly proposed by Engle (1982), represented one of the most important recognized innovations in economic and financial literature since they possess most of the theoretical features able to mimic the behavior of empirical quantities computed on financial time series. In particular, their formulation has gained popularity in finance because the following assumptions about the erratic component of this class of models actually reflect many of the above described stylized facts detected in financial markets.

1. It is not autocorrelated.
2. Its variance is not constant over time but serially correlated.
3. Its distribution is leptokurtic, just like that of financial returns.

ARCH models describe the dynamic changes in conditional variance as a deterministic quadratic function of past returns in which the number of squared returns involved reflects the order p of the process. In the case of ARCH(1), the following generation of returns series r_t is assumed:

$$r_t = \sigma_{t|t-1}\epsilon_t, \quad \epsilon_t \sim IID(0,1) \tag{4.1}$$

$$\sigma^2_{t|t-1} = \omega + \alpha r^2_{t-1} \tag{4.2}$$

In the former equation, in order to model the process conditional mean, a White Noise model is considered: we will later see that this assumption can be extended to other types of processes. By exploiting the unit variance property of ϵ_t and the independence between ϵ_t and r_t, the conditional variance of r_t is given by $\sigma^2_{t|t-1}$. The model for conditional variance, in fact, is seen as a latent equation that depends from the one-lagged squared return where ω and α are unknown parameters and $0 \leq \alpha < 1$ is a necessary and sufficient condition to ensure (weak) stationarity of the ARCH(1) model. The nonnegativity constrain for the conditional variance, instead, is guaranteed when all ARCH parameters are greater than 0.

Moreover, through simple manipulations, it can be proved that the squared returns series satisfies an AR(p) model if an ARCH(p) model is assumed for the return series. It is worth noting that the class of ARCH models prove, by induction, that concepts of conditional heteroskedasticity and (weakly) stationarity are compatible each other as long as $\{r_t\}$ returns series is a White Noise realization but, in the same time, its conditional variance varies over time.

Another attractive property which makes this type of models feasible for financial applications is that they possess heavy tails even if the innovations $\{\epsilon_t\}$ follow a normal distribution. When, for example, $\alpha < \frac{1}{\sqrt{3}}$, the ARCH(1) model has finite fourth moment and the unconditional kurtosis of r_t is

$$\frac{\mathbb{E}\left(r_t^4\right)}{\mathbb{E}\left(r_t^2\right)^2}$$

where, exploiting normality and independence properties of $\{\epsilon_t\}$, the numerator can be expressed as

$$\begin{aligned}
\mathbb{E}\left(r_t^4\right) &= \mathbb{E}\left(\sigma_{t|t-1}^4 \epsilon_t^4\right) \\
&= \mathbb{E}\left[\mathbb{E}\left(\sigma_{t|t-1}^4 \epsilon_t^4 | r_{t-j}\right), j = 1, 2, 3, ...\right] \\
&= 3\mathbb{E}\left(\sigma_{t|t-1}^4\right) \\
&= 3[\underbrace{\mathrm{Var}(\sigma_{t|t-1}^2)}_{>0} + \mathbb{E}\left(\sigma_{t|t-1}^2\right)^2] \\
&> 3\mathbb{E}\left(\sigma_{t|t-1}^2\right)^2 .
\end{aligned} \tag{4.3}$$

Hence,

$$\text{Kurtosis}(r_t) = \frac{\mathbb{E}\left(r_t^4\right)}{\mathbb{E}\left(r_t^2\right)^2} > 3$$

The principal limitation of ARCH models can be related to the high number of lagged returns to include in order to fit the observed data.

One way to overcome this difficulty was offered by Bollerslev (1986) who proposed to generalize ARCH models introducing the class of GARCH (Generalized Autoregressive Conditional Hetereskedasticity) processes. In order to enhance ARCH models' memory with a more parsimonious structure, GARCH(p,q) processes assume that conditional variance at time t is a deterministic function of fixed p past squared returns and q lagged conditional variances.

Among this class of models, the GARCH(1,1) is the most used in statistical and econometric practice. Its conditional variance equation is a generalization of (4.2) and can be expressed as:

$$\sigma^2_{t|t-1} = \omega + \alpha_1 r^2_{t-1} + \beta_1 \sigma^2_{t-1|t-2} \tag{4.4}$$

where $\alpha_1 + \beta_1 < 1$ is the necessary and sufficient condition for the process stationarity. While ARCH models show analogies with AR framework, GARCH, on the other side, share representation and properties of ARMA models. A GARCH$(1, 1)$, for instance, assumes that an ARMA$(1, 1)$ model drives the generation process of the squared returns.

If the above described assumptions show the reliability of (G)ARCH models' theoretical foundations, another proof of their goodness is given by the high number of empirical studies that applied this framework for characterizing variance and covariance structure of financial returns. Often, in order to further adapt this type of models to the empirical findings emerged in financial markets, some extensions were proposed, in literature, on the basis of GARCH construction.

ARCH effects have generally been found in future markets (Schwert, 1990), individual stock returns (Engle and Mustafa, 1992) and index returns (Akgiray, 1989). An interesting point about their specification is that most of empirical works choose low orders of lags p and q as long as typically GARCH(1,1), GARCH(1,2) or GARCH(2,1) are sufficient to model volatility dynamics of very long financial time series. Exceptions to this rule of thumb are usually motivated by seasonality phenomena (such as weekend effect according to which returns volatility is higher during periods near to the market closure) that sometimes appear in the data and could lead to an higher order of models. Furthermore, Bollerslev et al. (1992) pointed that presence of ARCH effects needs to be taken into account in the residuals analysis from application of traditional market models and when nonlinearities in stock returns are searched. As regards the former case, an example is provided by Morgan and Morgan (1987) who demonstrated that corrections for the returns conditional volatility leads to underestimation of market risk and overestimates abnormal returns. For what concerns nonlinearities present in the financial markets, many studies argue that most of chaotic behaviors can be explained by the dynamics of conditional variance (Schwert, 1989; Scheinkman and LeBaron, 1989; Hsieh, 1991).

The first type of GARCH extension regards the model for conditional mean of returns. In (4.1) an uncorrelated, zero mean process is considered. Actually, returns show a slight degree of serial correlation at least for a low order of lags. In this case, then, it is useful to introduce the class of AR(m)-GARCH(p, q) models. Through this way, an autoregressive structure is introduced in the conditional mean process and, at the same time, a GARCH framework is kept for modeling conditional variance.

We have seen that ARCH (and consequently GARCH) models allow for an unconditional excess kurtosis even if erratic component series $\{\epsilon_t\}$ is assumed to follow a Normal distribution. Despite of this, the excess kurtosis provided by these models has been considered not enough for fitting heavy-tailed distributions found in practice. In order to overcome this limitation, some examples in literature proposed to adopt GARCH models with errors distributed according to heavier-tailed distributions than the Guassian one: even though several proposals have been made, the most common consists on assuming Student-t distributed innovations where the degrees of freedom ν represent a parameter that needs a further estimation process. In general, dealing with heavy tails distributions represents a cumbersome issue for estimation purposes. This is confirmed also by some studies (such as Baillie and DeGennaro (1990)) which argue that assumptions on the error distributions assume a crucial importance in order to avoid spurious results. In contrast with this approach, some nonparametric or semi-parametric estimation procedures for (G)ARCH have spread in literature (Engle and Gonzalez-Rivera, 1991; Bühlmann and McNeil, 2002). Another limitation of the basic GARCH formulation in (4.4) is represented by the inability of catching phenomena such as the above described leverage effect. Indeed, conditional volatility at time t is explained by its past values and squared returns. In such a formulation, signs of previous returns have no impact in predicting future volatility values. This constitutes the main reason for which Nelson (1991), proposed the class of exponential GARCH or EGARCH models, in which the conditional variance is result of an asymmetric function of past values. In particular:

$$\log(\sigma^2_{t|t-1}) = \omega + \alpha\epsilon_{t-1} + \beta\log(\sigma^2_{t-1|t-2}) + \delta(|\epsilon_{t-1}| - \mathbb{E}\left(|\epsilon_{t-1}|\right)) \tag{4.5}$$

where the leverage effect is given by the difference between absolute residuals and the expectation of absolute residuals. In this model, volatility process $\{\sigma^2_{t|t-k}\}$ is seen as a multiplicative function of lagged innovations rather than an additive one. Furthermore, α and δ parameters measure respectively the impact of the size and sign effects on volatility.

While nonnegativity constraints are imposed on parameters of GARCH models, in case of EGARCH these are not necessary since dependent variable is represented by the logarithm of the conditional variance (which guarantees positive forecasts).

Other GARCH extensions

In order to catch the popularly assumed financial trade-off between risk and expected performance of a security, Engle et al. (1987) proposed GARCH in mean (GARCH-M) models. They assume that an increase in conditional variance is associated with a rise in expected returns including the volatility term $\sigma^2_{t|t-1}$ in the generating returns process as follows:

$$r_t = \mu + \gamma\sigma^2_{t|t-1} + \sigma_{t|t-1}\epsilon_t \tag{4.6}$$

where $\sigma^2_{t|t-1}$ follows a GARCH process and γ is the coefficient that reflects the impact of volatility on asset expected return. Although it might appear that risk-averse investors would require higher risk premium when financial risk increases, empirical studies have shown that there is no full agreement in literature about this topic. In particular, authors that used ARCH-M model to test this relationship showed that significance of the parameter for the conditional variance entering in (4.6) is sensitive to distributional assumptions (Bollerslev et al., 1992) and modifications of the conditional variance and mean equations of the model (Glosten et al., 1993). Moreover, Pagan and Ullah (1988) argued that parameters in the conditional mean model are not asymptotically independent with those of the variance, then any misspecification in the latter might lead to inconsistent and spurious results about the parameters of the former. Even the issue about the constancy of the linear relationship between returns and volatility has been challenged by several studies (Chou et al., 1992; Gennotte and Marsh, 1993) which provided also theoretical arguments against this hypothesis.

As we have seen, GARCH models assume that persistence of shocks to conditional variance (measured by squared returns) behaves according to ARMA structure. But actually, slow-decaying autocorrelation patterns of volatility commonly found by empirical works (mainly of those that used high-frequency data) led Engle and Bollerslev (1986) to propose the class of integrated-GARCH (I-GARCH) processes whose formulation apparently resembles that of ARIMA models.

In this framework, then, given the presence of unit root in the conditional variance process, shocks to volatility do not decay over time and unconditional second moment does not exist. For instance, in (4.4) when $\alpha_1 + \beta_1 = 1$ the process takes the name of IGARCH(1,1). However, this construction has been criticized by an interesting work of Lamoureux and Lastrapes (1990) in which the authors argue that, unlike random walk behavior of asset prices, I-GARCH effects lack of theoretical motivations. They argued, instead, that high persistence of conditional variance is mainly due to structural deficiencies of GARCH models whose formulation does not take into deterministic shifts of the process (for instance through time varying parameters). The idea of modelling structural breaks (or jumps) present in unconditional variance leads to the final class of model we would like to present.

In order to model asymmetric impacts of volatility, besides EGARCH, another type of tools that gained popularity is represented by qualitative threshold (G)ARCH (QTARCH or G-QTARCH) processes proposed by Gourieroux and Monfort (1992). Their structure deviate from each of those above described since: it is based on Markov Chains design and depends from a specific state or regime which, in turn, is a function of the process that one aims to study. Once the process exceeds a threshold value, a particular state will be determinant rather than another one. For example, a representation of G-QTARCH(p,q) model is the following:

$$\sigma^2_{t|t-1} = \omega + \sum_{i=1}^{p}\sum_{j=1}^{J} \alpha_{ij}\mathbb{1}_j(\epsilon_{t-j}) + \sum_{i=1}^{q} \beta_j \sigma^2_{t|t-j} \tag{4.7}$$

in which the distribution of the innovations is divided into J disjoint intervals (each with constant conditional variance) and $\mathbb{1}_j(\epsilon_t)$ is 1 if ϵ_t is contained within the j-th set, 0 otherwise.

This type of specifications has, above all, computational difficulties as long Maximum Likelihood estimation results infeasible. In the context of threshold models, then, it would be preferable to consider a Bayesian approach.

4.3.2 Some models for conditional mean

Although, from the point of the considered time series models, our focus has been oriented on those for heteroskedasticity, it seemed necessary to devote a section of this chapter to a brief discussion about some interesting and important statistical tools used in literature to forecast conditional mean of stock prices.

Long memory processes

In order to address slow-decaying autocorrelation patterns exhibited by stock prices and volatility proxies (absolute or squared returns), some long-memory processes have been implemented. A refinement of the traditional ARIMA framework, produced the class of fractionally integrated ARMA (ARFIMA) models. The main motivation consisted on the fact that sometimes serial correlations of asset prices decay at a slower rate than for ARIMA model. By introducing a non-integer fractional integration parameter d, autocorrelation pattern of the process becomes even more persistent over time. Actually, despite their theoretical elegance, these models are of nontrivial estimation, lack of a clear economic interpretation, are not extendible to multivariate processes and need a long sample period to produce reliable results. Finally, Ray (1993) show that by increasing the autoregressive order of (seasonal) ARIMA models, in comparison with (seasonal) ARFIMA, one could obtain better results in terms of long-term forecasts and Man (2003) reported that an ARMA(2,2) can produce competitive short term predictions when compared to ARFIMA models.

State space models

State space models started spreading among statisticians and econometricians during the end of 80s, many years after their and wide diffusion in engineering field, mainly after Kalman (1960) work. They define a wide variety of forecasting models whose main advantage consists also on handling non-stationary time series. This class is such wide that most of the traditional models (*e.g.* ARMA) can be formulated as a specific state space representation. Harrison and Stevens (1976) proposed a specification of state space class known as Dynamic Linear models (DLM) and a Bayesian approach to estimate them.

Bayesian time series analysis, in fact, is essentially based on state space models even though they have been implemented also within the frequentist framework (Harvey, 1984, 1990).

Their formulation is built on a pair of equations with time-varying parameters: a state and an observation model. The former establishes how the state vector (unobservable component) evolves over time, the latter, instead, provides the link between this latent factor and the observed quantity of interest.

A Normal Dynamic Linear model can be generally formulated as:

$$\begin{aligned} Y_t &= F_t^{'}\theta_t + \epsilon_t, \quad \epsilon_t \sim N(0, V_t) \\ \theta_t &= G_t\theta_{t-1} + \omega_t, \quad \omega_t \sim N(0, W_t) \end{aligned} \tag{4.8}$$

where Y_t is the observed quantity of interest, θ_t is the state vector, $F_t^{'}$ is the row vector of covariates and G_t is defined as *transition* or *evolution* matrix of dimension $p \,\mathrm{x}\, p$ with p as the number of covariates.

Usually, one-step-ahead forecasts are computed exploiting a recursive algorithm, known as Kalman filter, which has proved to be efficient under Normality assumptions.

However, if non-Gaussianity hypothesis can be overcome by using the family of conjugate prior distributions, flaws of these models arise when data are non-linear or when covariance matrices V_t and W_t are not known and, then, need to be estimated. In those cases, Kalman algorithm is not enough so that computer intensive methods, such as Markov Chain Monte Carlo and Importance Sampling techniques, need to be implemented for inferential purposes.

In literature, some works have tried to inspect and analyze state space forecasting power in comparison with other models and the most recent among these studies (Makridakis and Hibon, 2000) concluded that simpler methods tend to perform better. Actually, the apparent complexity appeared because state space models estimation was performed by maximum likelihood.

Nonlinear models

Threshold and regime switching models started spreading in financial field after Tongs' publications (Tong, 1983, 1990). A popular example is the class of self exciting threshold AR (SETAR) models since their piecewise linear structure attracted attention in financial literature. The drastic changes among regimes represented a drawback for these models; in order to avoid them, smooth transition AR (STAR) models were introduced to allow for a more gradual state shifts. Sarantis (2001), indeed, empirically proved that STAR models get better forecasting results than linear AR and random walk on short and medium term horizon. However, they generally suffer from a limitation shared by nonlinear forecasts which consists on the fact that predictive distributions are not Normal and often analytically intractable. For this reason, the process of nonlinear multi-step ahead prediction works through simulation approach, exploiting Monte Carlo or bootstrap techniques.
Among nonlinear models proposed by financial academics and scholars, Artificial Neural Networks (ANN) assumed a crucial role. The underlying idea is that inputs get filtered through hidden layers (whose number needs to be pre-specified: larger it is, more complex the model is) before reaching the output variable through specific functions. They represent a relative recent tool in financial forecasting context as long as their early days date back to the 90s. Their popularity, in this field, is essentially due to the following properties:

- Their structure is data-driven and self adaptive. As opposed to the traditional time series models, in fact, very few a priori assumptions are made about the problem under study as long as they are able to trigger a process of learning from data. For instance, they do not assume any particular prior assumption about a specific data generating process or statistical distribution;

- ANNs are recognized as universal functional approximators. Each traditional statistical model, in fact, assumes an underlying function that links past (input) with future values (output). Often classic forecasting methods have problems in estimating this underlying functions due to complexity of real data and Neural Networks represent good alternatives for solving these issues.

- Non-linearity of ANNs makes them feasible tools for fitting time series stock prices. Although other non-linear models have been proposed in finance, however their parametric nature implies that, in order to work, they generally need an underlying framework of hypotheses about the process of interest. Actually, formulating assumptions about non-linear processes is not a simple task since too many non-linear patterns might occur and a single model cannot catch all of them. Once again, flexibility of ANNs is very helpful since formulating realistic assumptions about laws that guide processes when very little is known (such as financial markets) is often a really though exercise.

- They can easily address problems of missing, incomplete or fuzzy data.

Sometimes, however, strengths of ANNs have been overvalued and this fact led Chatfield (1993) to question whether these models had been considered as the holy grail for financial predictions. Moreover, several papers (Church and Curram, 1996; Conejo et al., 2005; Tkacz, 2001) reported that ANNs forecasting performances can be outperformed by more traditional and naive models such as random walk. Hill et al. (1994), instead, questioned their universality arguing that ANNs are likely to work better than traditional models only if applied to high-frequency data.
However, if on one side, empirical evidences showed that, in finance, there is still no full agreement about a definitive dominance of Neural Networks over alternative

models, on the other side it is universally recognized that ANNS's risks are represented by model complexity and over-parametrization.

4.3.3 Some considerations about time series forecasts framework

It is worth noting that the theoretical backgrounds of technical analysis and time series forecasts are quite different each other.
In the latter case, in fact, the approach to the study of financial markets is extremely dominated by statistical analysis of past observations. In particular, this approach is based on specific tools like histograms, autocorrelograms, tests and guided by concepts like volatility clustering, heavy-tails or non-linear relationships between returns and volatility.
In general, each of these aspects assigns a scientific degree to the decision making process in which the analyst (or trader in this case) is involved. In fact, it is on the basis of the probabilistic laws that govern financial markets that time series models can produce reliable results in terms of analysis and prediction. As a consequence, time series forecasts should be considered in order to improve the use of technical analysis and, above all, for reaching a greater confidence in trading activity, as we will later see.
Finally, it should be highlighted that the increasing complexity reached by the theoretical construction of the time series models analyzed so far, has not guaranteed a substantial improvement of the forecast accuracy. This fact is related to the idea that models, for construction, represent simplifications of the real phenomena under analysis. As regards the specific field of financial markets, this issue is even more present since statistical and econometric modeling should also take into account the

irrational and, for this, unpredictable behaviors of market agents.

Despite, over time, the concept of data generating process has left the room for models that could, in principle, adapt themselves more easily to the data structure (leading, for instance, to the implementation of artificial neural networks for financial time series) several studies conclude that past stock prices or returns do not provide enough information for predicting, in relatively accurate way, future financial markets' dynamics.

Chapter 5

Empirical results

5.1 Introduction

This chapter is devoted to the presentation of the empirical results of the work. Firstly, a description and an exploratory analysis of the data will be presented, with a particular focus on the reasons for which some specific time series models have been considered for generating trading results.

The following section will be devoted to the presentation of the methodologies adopted to generate trading signals in case of: technical analysis, time series models and combinations between them. Moreover, in the last part of this methodological subsection we will deal with the particular rule implemented for computing trading returns, also called 'Double-or-Out' strategy.

Finally, the presentation of trading strategies outcomes will involve the analysis of the results produced both by the individual and the combined rules.

5.2 Data

5.2.1 Data description

For our study, we considered the daily time series with values of S&P500 index for the period ranging from 31 December 2004 to 15 October 2012 whose historical values are depicted in Figure 5-1. This equity index includes the 500 largest US companies for capitalization and it represent a good proxy for the health status of the American economy since their total market value accounts for the 80% of the whole American stock market.

Figure 5-1: S&P 500 index historical values from 31 December 2004 to 15 October 2012

The choice for that particular sample period responded to methodological reasons: some of the chosen strategies, in fact, needed the first 200 observations for generating trading signals. For comparing strategies results, then, the period 31 December 2004-14 October 2005 was used for model estimation and strategy results will be shown only for sample period included between 15 October 2005 and 15 October 2012. Moreover, since the aim of our study has consisted on analyzing how the considered trading strategies had performed during three approximately different periods in terms of volatility levels, the results presentation will be generally carried out by subdividing the sample period into three sub-samples of equal length. In particular, what has been defined as first sub-period (end 2005-early 2008) was characterized by relatively low volatility levels and stable stock markets. During the second one, ranging from early 2008 to the mid of 2010, instead, the market crashed and, as a consequence, perception of risk by investors reached the highest level. Finally, the last sub-sample, which included the observations from mid 2010 to 15 October 2012, was treated as a medium-volatility phase in which markets tried to recover from the financial crisis.

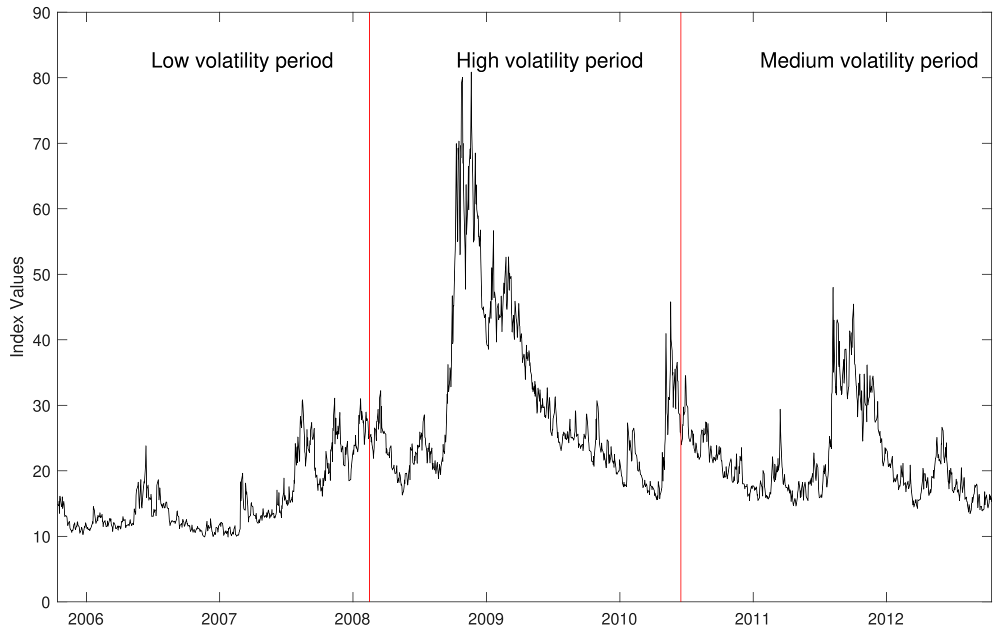

Figure 5-2: Vix index historical values for considered sample period

An indirect and commonly used indicator for gauging risk present in the market is the Chicago Board Options Exchange Volatility Index (also known as VIX) which computes and records the implied volatility on the basis of call and put options prices on the S&P 500 index.

In order to give a graphical representation of the different volatility levels recorded during that periods, in Figure 5-2 are plotted the historical values of VIX index.

5.2.2 Distributional features

In Table 5.1 are gathered the main statistics for the log-returns distribution.

	S&P 500 returns
Mean	0.00000089
Min	-0.09461020
1st quartile	-0.00540390
3rd quartile	0.00643880
Max	0.10957107
Skewness	-0.1950
Kurtosis	4.6271
Jarque Bera test **(p-value)**	4139.6 (0.0000)
Kolmogorov-Smirnov test **(p-value)**	0.4757 (0.0000)

Table 5.1: Summary statistics and distributional features of the S&P 500 returns for the 2005-2012 period.

These summary statistics tend to confirm some of the distributional features described in the previous chapter, namely: a zero mean, leptokurtic and slightly negative skewed distribution. Moreover, the Normality hypothesis is refused, with high confidence levels, both by Jarque Bera and Kolmogorov Smirnov tests, given their 0 p-values in parenthesis.

In order to offer a graphical flavor of returns distribution, in Figure 5-3 are plotted its Kernel density estimator (with Gaussian smoothing function) and the superimposed theoretical Normal distribution, for comparison reasons. The deviation of SP500 returns from the Normality assumption is corroborated also by the graphical analysis. In fact, despite their bell-shaped distribution, the Normal one seems not to fit the

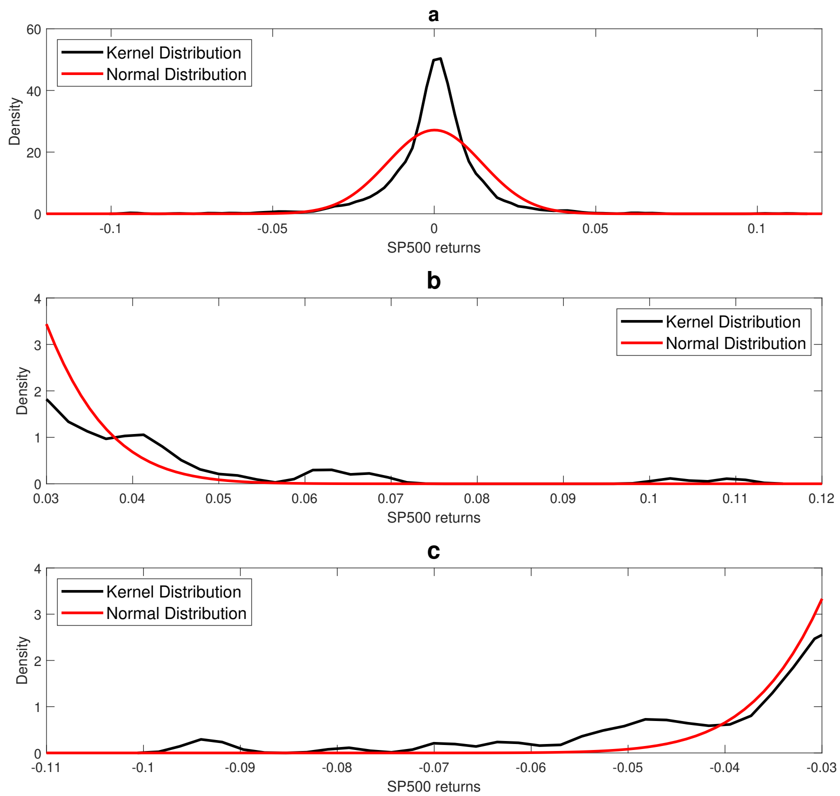

Figure 5-3: Empirical distribution of S&P 500 returns. In (a) the full interval is considered, while (b) and (c) focus respectively on the right and left tail.

data very well neither in the center, because of the peak of the return distribution is much higher than for the Normal, nor in the shoulders which appear tighter. Finally, a particular focus is devoted to the behavior of returns distribution for extreme values analysis: the empirical density estimator plot confirms the well known leptokurtic property for both of the tails.

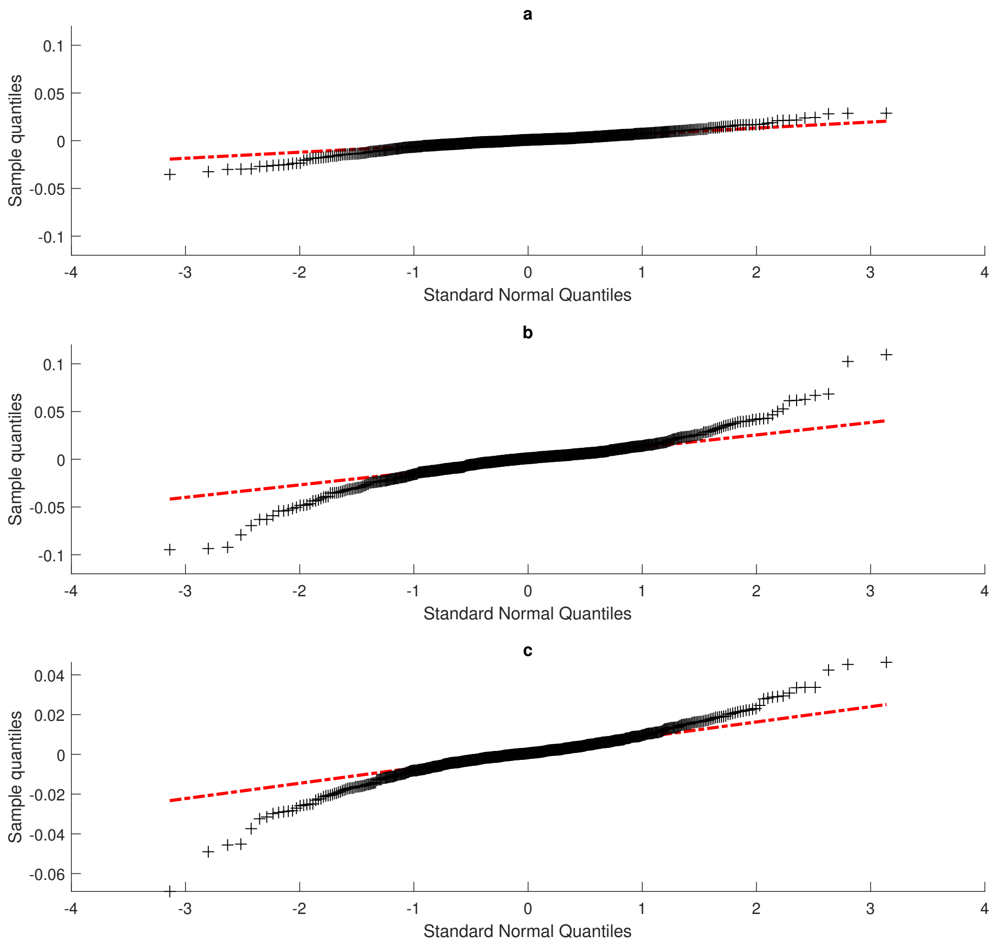

Figure 5-4: In (a), (b) and (c) are reported the Quantile-Quantile plots of S&P 500 returns, respectively, for the low, high and medium volatility period.

Normal Q-Q plots of Figure 5-4 proves, once again, the substantial deviation from Gaussianity. In particular, Normal distribution seems not to fit very well the data especially for the most turbulent period among those considered. During the high volatility phase, in fact, markets recorded huge losses but also extreme positive peaks; within this context, then, Normality assumption showed its inadequacy.

5.2.3 Autocorrelation and volatility analysis

As regards the serial correlation structure exhibited by S&P500 returns, Figure 5-5 reports both their graphical representation and their estimated autocorrelation function. The left hand side shows the typical dynamics of simple financial returns,

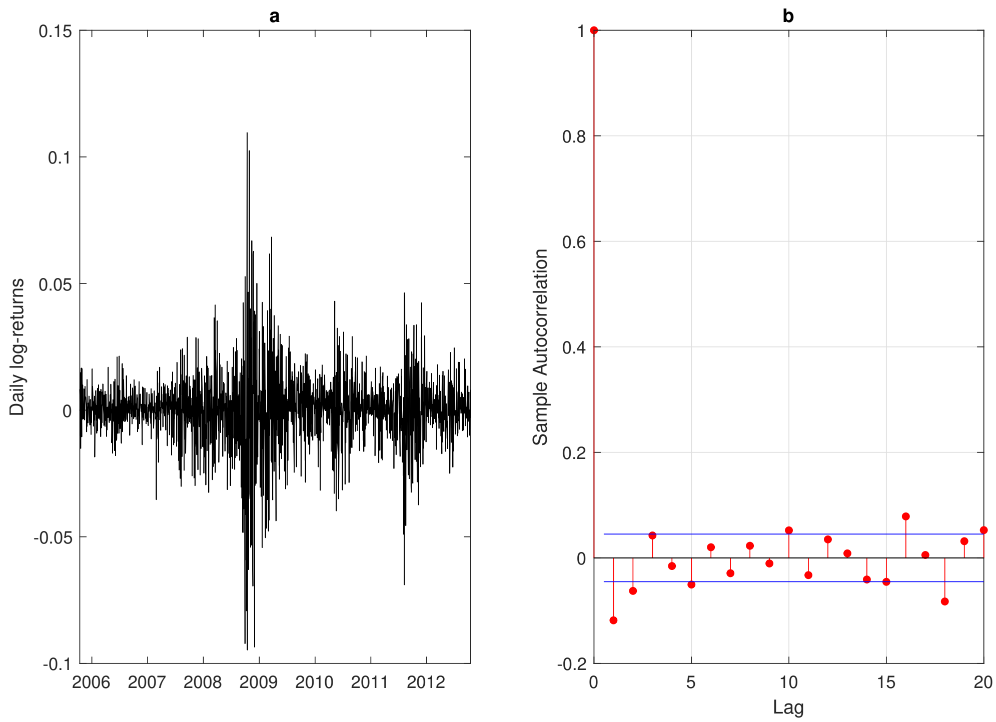

Figure 5-5: Plots of S&P500 returns (a) and their sample autocorrelation function (b)

namely: absence of any type of trend factor, series that fluctuates around a constant zero mean value and that appears to be stationary. The estimated autocorrelogram in Figure 5-5(b) confirms the low degree of serial correlation, typical of financial returns data. In this particular case, a highly significant negative correlation is reported for the first lag of the series. After that, returns process proves its short memory feature as long as it records a fast rate correlation decay, apart from some significant values appearing at high order of lags whose presence seems mainly due to randomness.

In line with the stylized facts described in the previous chapter, presence of volatility clusters arises also for S&P500 returns series. In order to detect it, Figure 5-6 plots its squared returns and their estimated autocorrelation function. The squared

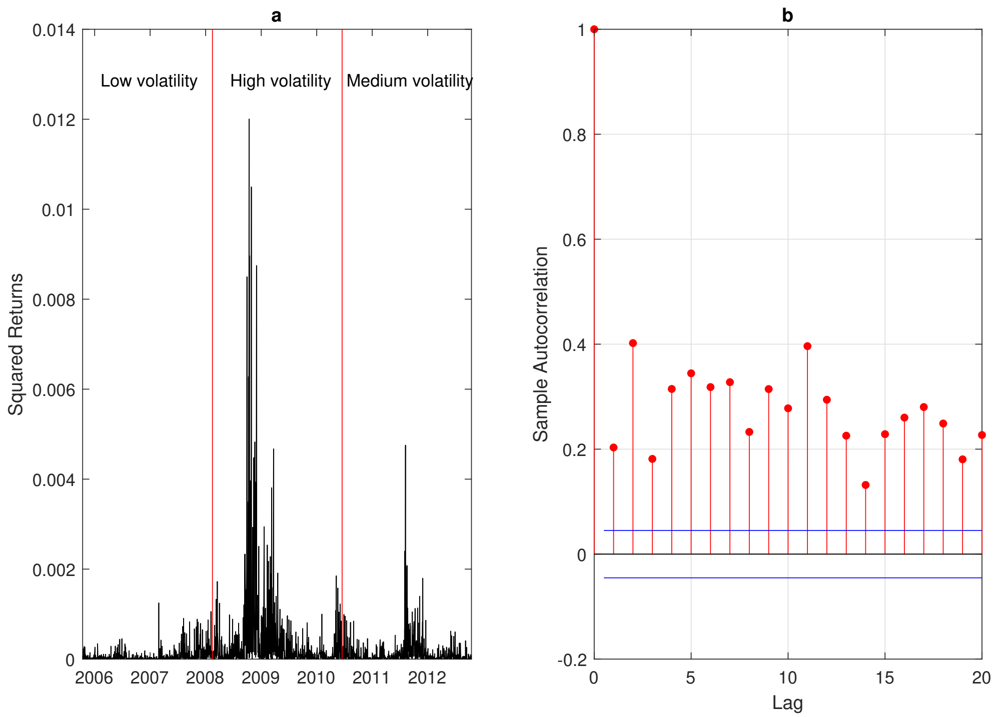

Figure 5-6: S&P500 squared returns series (a) and its respective estimated autocorrelation function (b).

returns series spots very well the presence of GARCH effects in the data. Periods of low and high turbulence, in fact, tend to group each other over time because of the well known conditional heteroskedasticity dynamics. The persistency feature is confirmed even better by the slow decaying pattern exhibited by the sample serial correlation function of squared returns in Figure 5-6(b). The autocorrelogram values, in fact, are all statistically significant at high confidence levels, with no exception.

On the other hand, scatterplots in Figure 5-7 were shown in order to visually assess the presence of asymmetric volatility effects in the S&P 500 time series. At the

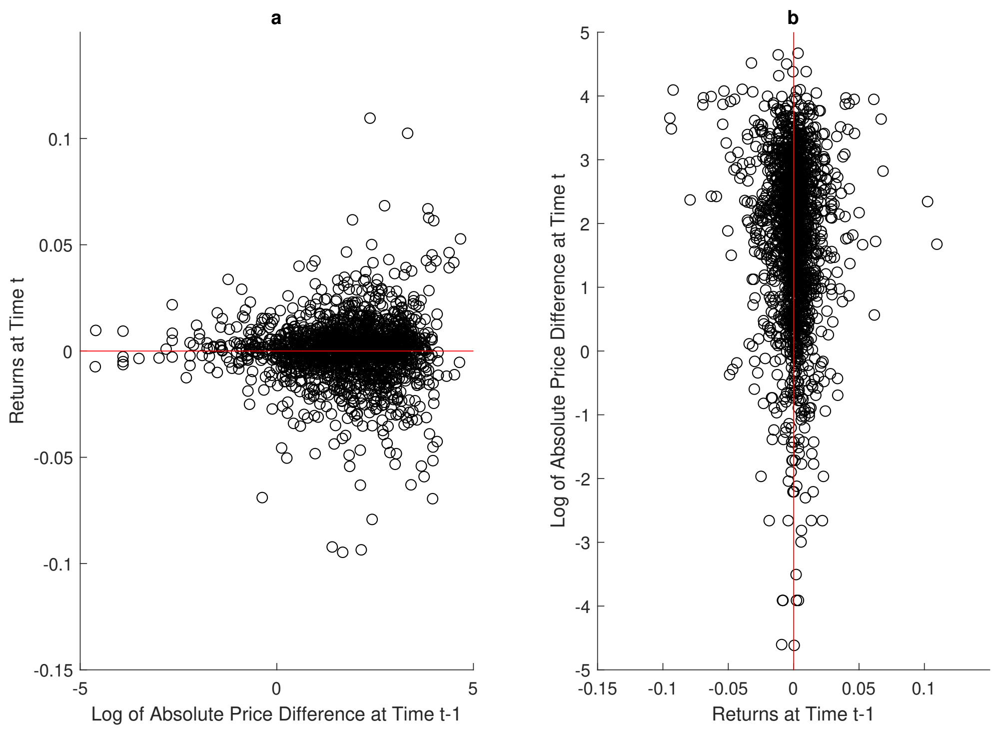

Figure 5-7: In graph (a), past volatility is plotted against current returns while in (b) is shown the relationship between past returns and actual volatility.

same time, the analysis was focused also on evaluating which one, among volatility feedback and leverage effect, played a more prominent role in our dataset. Given the latent nature of volatility, we used a proxy measure represented by the log of absolute daily difference quotations of S&P 500 index. A single day was chosen as time lag. In the left plot of Figure 5-7, a funnel effect is clearly present. In fact, when the level of past volatility increases, also the variability of future outcomes rises. The data under analysis suggest that days of low volatility are usually followed by positive than negative returns, while there is such not evident relation for high daily variability

$r_t = \mu + \phi_1 r_{t-1} + \sigma\epsilon_t, \quad \epsilon_t \sim IN(0,1)$				
	Value	**StandardError**	**TStatistic**	**PValue**
μ	9.8408e-05	0.00032628	0.30161	0.76295
ϕ_1	-0.1184	0.013286	-8.9118	5.023e-19
σ	0.00019542	2.6284e-06	74.348	0

Table 5.2: AR(1) parameter estimates

levels since data points distribution appear quite symmetric for positive and negative returns. Figure 5-7(b), instead, tends to spot more clearly a possible leverage effect because negative returns are likely to feed future extreme volatility levels more than what occurs for past positive outcomes. Then, the asymmetric effect present in the data tends to support more clearly the reasons of those authors who sustain that volatility-returns casualty link is triggered by negative performances of the markets rather than stock prices variability.

In order to further analyze the properties of S&P500 returns during the 2005-2012 period in Table 5.2, 5.3 and 5.4 have been gathered the full sample parameters estimates of the time series models that we will later use for trading signals generation, namely AR(1), AR(1)-GARCH(1,1) and AR(1)-EGARCH(1,1). In order to study the statistical significance of their estimated coefficients, also the p-values of the individual t-tests have been reported.

$r_t = \mu + \phi_1 r_{t-1} + \sigma_{t\|t-1}\epsilon_t, \quad \epsilon_t \sim IN(0,1)$ $\sigma^2_{t\|t-1} = \omega + \alpha_1 r^2_{t-1} + \beta_1 \sigma^2_{t-1\|t-2}$				
	Value	**StandardError**	**TStatistic**	**PValue**
μ	0.00029906	0.00020643	1.4487	0.14741
ϕ_1	-0.11285	0.028371	-3.9777	6.9591e-05
ω	2.9011e-06	7.7145e-07	3.7605	0.00016957
α_1	0.11225	0.011571	9.7004	3.0037e-22
β_1	0.86811	0.013594	63.858	0

Table 5.3: AR(1)-GARCH(1,1) parameter estimates

$r_t = \mu + \phi_1 r_{t-1} + \sigma_{t\|t-1}\epsilon_t,$ $\log(\sigma^2_{t\|t-1}) = \omega + \alpha_1 \epsilon_{t-1} + \beta_1 \log(\sigma^2_{t-1\|t-2}) + \delta_1(\|\epsilon_{t-1}\| - \mathbb{E}(\|\epsilon_{t-1}\|))$				
	Value	**StandardError**	**TStatistic**	**PValue**
μ	0.00020356	0.00019333	1.0529	0.29238
ϕ_1	-0.06462	0.026315	-2.4557	0.014063
ω	-0.1845	0.022264	-8.2868	1.1636e-16
α_1	0.13277	0.01688	7.8652	3.6844e-15
β_1	0.9794	0.0024741	395.86	0
δ_1	-0.13398	0.011769	-11.384	5.0145e-30

Table 5.4: AR(1)-EGARCH(1,1) parameter estimates

As regards the first model, results in Table 5.2 confirm, at high confidence level, a negative relation between past and actual returns. Parameters of AR(1)-GARCH(1,1) reported in Table 5.3 are all statistically significant except for trend factor whose estimate can be, once again, considered equal to 0. Conditional variance dynamics seems well modeled by GARCH(1,1) structure since all their coefficients are statistically non-zero. This issue, then, support presence of GARCH effects for returns series. Finally, interesting considerations emerge from outcomes of Table 5.4. In particular, significant positiveness of α_1 and β_1 confirm respectively clustering effects and persistence of conditional volatility dynamics. The asymmetric behavior instead, is proved by the negative significant estimated δ_1 that precisely measures the impact of leverage effect.

In general, the results of models estimation clearly refuse an hypothesized presence of a particular trend coefficient in returns series. It is worth underlying that, in this case, the term trend does not have the same meaning that technicians assign to it. The fact that trend coefficient is not significant for each time series model considered simply implies that long-run mean value of S&P 500 returns is, statistically, equal to 0.

5.3 Adopted methodologies

After having analyzed the statistical properties of the dataset, from here on, our focus will shift to the explanation of the methodologies adopted for generating the empirical results. From this point of view, the methodological framework that we have followed has been inspired by the approach implemented in Fang and Xu (2003). Before describing the methods used for emitting trading signals, it is worth specifying that a general assumption underlying each of rule provides for the 'buy' or 'sell' transactions take place just before the end of each trading day. In such a way, daily returns are simply computed comparing closing prices of consecutive days.

Furthermore, from here on, we will refer to returns as the daily difference of log-price series, even though we actually should call them log-returns.

5.3.1 Technical trading strategies

As regards the choice of technical strategies for generating the trading signals, double crossover rules have been considered. These are widely used techniques in which two moving averages are computed and trading signals are produced in correspondence of intersections between these two price filters. Many technical strategies are based on moving averages since they represent very simple and intuitive tools useful for filtering the noise present in the data and spotting, in such a way, possible trends. Given a time series of asset prices X_t, a moving average can be expressed in terms of the lag operator L as:

$$M_m[X_t] = \frac{1}{m}\sum_{i=1}^{m} L^i(X_t) \tag{5.1}$$

On this basis, the parameters characterizing double crossover rules consist on the triple $\{m_1,m_2,d\}$ where m_1 and m_2 represent respectively the shorter and longer window lengths and d the bandwidth, a percentage coefficient that, on the basis of the stock price at time $t-1$, determines the threshold value beyond which a trading signal is generated. In general, the window parameter determines the smoothness of the resulting series $\{M_m[X_t]\}$: greater this value is, smoother the result. On the other hand, moving averages with shorter window size react more quickly to the shifts of the original series. The introduction of the bandwidth d responds to the necessity of reducing the number of trades induced during that times, in which, an asset price is moving in one direction but it quickly orients towards the opposite way.

Double crossover strategies, then, generate 'buy' signals whenever longer moving average crosses from below the shorter one, while triggers of 'sell' actions occur in the opposite case. In a more formal way, we can express 'buy' and 'sell' days respectively as τ_i^B and τ_i^S in which,

$$\tau_i^B \equiv \inf\{t : t > \tau_{i-1}^B, M_{m_1}[X_t] - M_{m_2}[X_t] > dX_{t-1}\} \tag{5.2}$$

$$\tau_i^S \equiv \inf\{t : t > \tau_{i-1}^S, M_{m_2}[X_t] - M_{m_1}[X_t] > dX_{t-1}\} \tag{5.3}$$

where $\{M_{m_1}[X_t]\}$ and $\{M_{m_2}[X_t]\}$, with $m_2 > m_1 \geq 1$, are the series of moving averages used as rough estimates for the market trend.

As concerns the strategies parameters, we chose to consider the ones selected by Fang and Xu who, in turn, referred to the 10 double crossover models analyzed in Brock et al. (1992): {1,50,0}, {1,50,0.01}, {1,150,0}, {1,150,0.01}, {5,150,0}, {5,150,0.01}, {1,200,0}, {1,200,0.01}, {2,200,0} and {2,200,0.01}.

5.3.2 Time series trading strategies

In Section 4.2 we developed the topic about statistical properties of financial returns on the basis of the empirical findings discovered in literature. In Section 5.2, instead, we tested for and, finally, confirmed the presence of the above cited features in our dataset. From here, emerged the necessity of including these considerations on the construction of our trading rules. In particular, considered the significant results obtained in Subsection 5.2.3 and that those ones represent widely used classes of models for describing financial returns dynamics, we based time series trading strategies on AR(1), AR(1)-GARCH(1,1) and AR(1)-EGARCH(1,1) forecasts. For the generations of daily trading signals, the implementation of this method relied on rolling techniques estimation of time series models, in order to produce sequentially, each day, an updated out-of-sample forecast for the day ahead. By taking inspiration

from Fang and Xu's work, for reducing risks of data snooping bias, each model was fitted on the basis of the same window lengths of the long moving averages used in the technical trading rules: 50, 150 and 200 days.
At each time t, then, a buy signal for $t+1$ was generated if

$$\mathbb{E}\left(r_{t+1}|I_t\right) \geq \delta \tag{5.4}$$

while a sell signals arose when

$$\mathbb{E}\left(r_{t+1}|I_t\right) < \delta \tag{5.5}$$

where I_t is the information set at time t and δ is assumed to be 0.

5.3.3 Combined trading strategies

The methodology implemented for generating trading signals when more than one approach was merged consists on emitting 'buy' ('sell') triggers at time $t-1$ if both the technical and the time series rule produce 'in'('out') signals based on actual information set, I_{t-1}.
As we will later appreciate, this method can, in principle, exploit the different predictive aspects of both the strategies. In general, the inclusion of more than one type of market forecast helps to reduce the number of trading operations and consequently the amount of transaction costs. Relying on more than one approach, it should also make the trading strategy less sensitive to the frequent early or false signals that may arise exploiting single indicators.
In this framework we followed the method proposed by Fang and Xu which consists on using the longer length of each moving average rule as window size for the time

series model. For instance, the {1,50,0} moving average rule was combined with an AR(1)-GARCH(1,1) model with 50 as window length for its rolling estimation.

5.3.4 Trading returns computations

In oder to evaluate performances of the trading strategies, we followed a symmetric method used also by Brock et al. (1992) and Bessembinder and Chan (1998) that consists on assuming that a trader borrows at risk-free interest rate and doubles its equity position when buy signals are generated, simply holds the S&P500 index when no opposite signal is emitted while when 'sell' signals occur, he liquidates his stock properties in favor of the risk-free asset. For its functioning, this scheme takes the name of 'Double-or-Out' strategy. Hence, at each time t, following this procedure, investor returns $r_d(t)$ can be formulated as

$$r_d(t) = \begin{cases} 2R_t - r_t^f, & \text{if} \quad \text{buy signal is generated at t-1} \\ R_t, & \text{if} \quad \text{no opposite signal is generated at t-1} \\ r_t^f, & \text{if} \quad \text{sell signal is generated at t-1} \end{cases} \tag{5.6}$$

where R_t is the S&P500 daily return and r_t^f is the risk-free interest rate which, in our case, has been assumed equal to 0.

In this framework, then, portfolio value of the investor is not function of time but, instead, in each trading day it is considered independent on the previous one. In order to get more realistic results, trading returns have been computed net of transaction costs (a 0.3% was considered), arising whenever buy and sell operations have taken place.

5.4 Results

5.4.1 Individual trading strategies

Figure 5-8 and 5-9 report cumulative returns of technical analysis and time series based trading rules.

The difference between the two graphs can immediately be spotted in terms of results of the worst strategies of each approach. Despite the best rules tend to get similar final results, in the worst case scenario, a trader would have gained a negative final result only following a moving average approach. Moreover, the worst technical strategy has been the one with the smallest m_1, m_2 and with 0 bandwidth value. This might probably be due to the combination between functioning of the returns computation strategy and the presence of transaction costs that increased the trader losses when frequent whipsaws took place.

Moreover, by observing the two graphs, another type of consideration can be done about the consistency of trading strategies results over time. In fact, neither for technical analysis nor for time series case, a specific rule clearly dominates the others over the whole sample period. For instance, if the {1,150,0.01} moving average rule performed very well until 2007, at least other five strategies obtained better results at the end of 2012. This might mean that market conditions changes have great impacts on the profitability of trading strategies. Furthermore, the graphs highlight that both classes of rules generally succeeded in staying out from the equity market during most of the high volatility phase triggered by the 2007 crisis.

In Table 5.5 and 5.6 are reported some performance indicators of technical and time series trading strategies subdivided according to the volatility periods. The comparison among the two approaches has been performed on the basis of three measures:

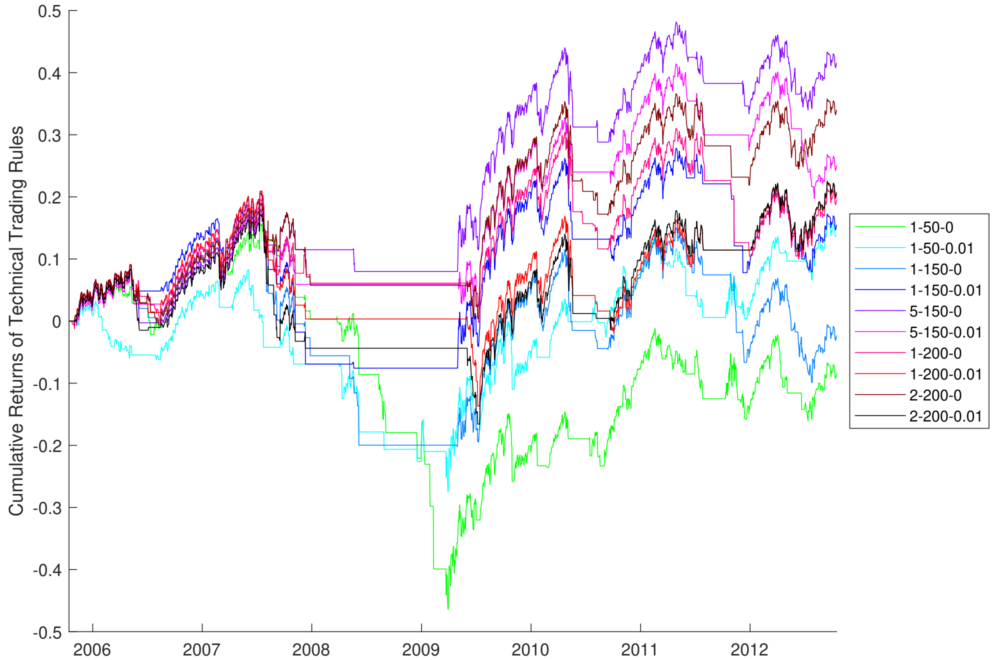

Figure 5-8: Cumulative returns of technical trading strategies

excess returns with respect to a Buy&Hold strategy in which the investor buys the equity asset and holds it in her portfolio until the end of the sample, a downside risk indicator represented by the maximum drawdown which measures the maximum loss in the equity line from a negative peak (before a new positive peak is achieved) and percentage of days (during each of the three periods) in which the trader has held S&P500 index in its portfolio.

Excess return indicator has been introduced in order to assess whether these strategies were able to 'beat the market' or, alternatively, the best choice, for a trader, consisted in passively holding the equity asset gaining a 13.73%, -18.95% and 25.62% respectively in the first, second and third subsample. From this point of view, the outcomes for both approaches suggested generally similar conclusions. Active strategies, in fact, have demonstrated an extraordinary profitability when markets dropped. In

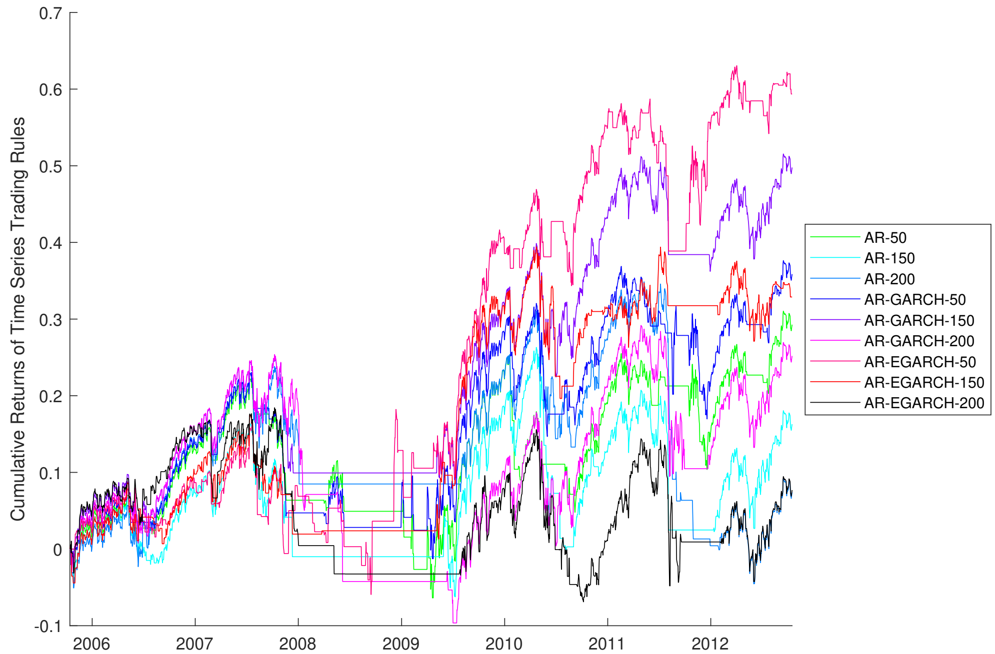

Figure 5-9: Cumulative returns of time series trading strategies

order to give a mild idea, it is enough to say that average excess returns for technical trading strategies was 27.7% during high volatility phase while it recorded a -13.11% and -16.96% respectively in low and medium volatility periods. Time series rules, on the other hand, recorded even better results during bearish markets (34% of excess returns) and suffered smaller losses during the first sub-sample of observations (-8.8%). This pattern is also effect of the percentage of days in which the trader has held the equity portfolio: in particular, when markets performed badly, percentage of trading days in which the trader held the S&P500 index substantially decreased, reaching an average value of 44% for both strategy approaches. Hence, because of the presence of negative equity returns it was sufficient to invest in a 0% risk-free asset to get a daily positive excess returns. Some differences emerge in terms of trading operations quantities during low and medium volatility periods. Technical strategies, in fact, produced generally less trading signals both in the former and in the latter phase (respective mean value of 78% and 71% for time series case, 70% and 67% for the technical rules).

Although, in principle, technical trading rules should have performed quite well in markets with trends, Table 5.5 suggest that, at least, those ones chosen did not possess any predictive power during bullish periods.

The outcomes of time series-based trading strategies in Table 5.6 suggest slight better results than moving average rules (*e.g.* the average excess return reduces from -13.11% to -8.88% during low volatility phase) but, in general, they show a similar pattern even in terms of risk measure, represented by the maximum drawdown indicator. It is interesting to analyze whether, among the class of time series models chosen, there is one that performs generally better than the others.

Also in this case, there is no definite answer in the sense that data in Table 5.6 suggest that none of the class of models dominates the others in terms of excess returns or risk measure.

A consideration arises observing Table 5.7 that, on the basis of Table 5.6, computes mean and standard deviation of excess returns with respect to the different class of models independently on the window lengths adopted. If on one side, it is confirmed that no class of models was superior along the three subsamples, results of AR(1)-GARCH(1,1) suggest that these models were, at least, the most consistent during low and medium volatility periods. In fact, during both of them, their trading signals generated the best results in terms of excess returns and variability, as they had the smallest standard deviations.

As regards the window size, instead, it does not help to track any particular excess return pattern neither for the time series nor for the technical analysis strategies.

		1-50-0	1-50-0.01	1-150-0	1-150-0.01	5-150-0	5-150-0.01	1-200-0	1-200-0.01	2-200-0	2-200-0.01	Average (Std. dev.)
Low volatility phase	**Excess return**	-0.1345	-0.2063	-0.1930	-0.2065	-0.0224	-0.0781	-0.0762	-0.1338	-0.0796	-0.1810	-0.1311 (0.0616)
	Max drawdown	0.0152	0.0151	0.0241	0.0270	0.0091	0.0117	0.0133	0.0202	0.0130	0.0213	0.0170 (0.0055)
	Perc. of days holding S&P500	0.6599	0.5170	0.7364	0.6769	0.7058	0.6752	0.8078	0.7279	0.8044	0.7279	0.7039 (0.0784)
High volatility phase	**Excess return**	-0.0028	0.2577	0.2302	0.3906	0.3870	0.3702	0.3044	0.2272	0.3597	0.2453	0.2770 (0.1121)
	Max drawdown	0.0476	0.0207	0.0147	0.0127	0.0122	0.0089	0.0125	0.0144	0.0123	0.0126	0.0169 (0.0106)
	Perc. of days holding S&P500	0.5212	0.4720	0.4584	0.4397	0.4584	0.4414	0.4109	0.3973	0.4126	0.4007	0.4413 (0.0364)
Medium volatility phase	**Excess return**	-0.1512	-0.1186	-0.2643	-0.2332	-0.1529	-0.2456	-0.2357	-0.0922	-0.1418	-0.0608	-0.1696 (0.0671)
	Max drawdown	0.0149	0.0134	0.0245	0.0195	0.0141	0.0208	0.0204	0.0108	0.0142	0.0108	0.0163 (0.0044)
	Perc. of days holding S&P500	0.6859	0.6010	0.6910	0.6214	0.6808	0.6129	0.7419	0.6961	0.7385	0.6927	0.6762 (0.0468)

Table 5.5: Performances of technical trading rules

		Ar-50	Ar-150	Ar-200	Ar-Garch-50	Ar-Garch-150	Ar-Garch-200	Ar-Egarch-50	Ar-Egarch-150	Ar-Egarch-200	Average (Std. dev.)
Low volatility phase	**Excess return**	-0.0736	-0.1473	-0.0524	-0.0901	-0.0380	-0.0660	-0.0771	-0.1178	-0.1328	-0.0883 (0.0349)
	Max drawdown	0.0170	0.0188	0.0161	0.0202	0.0166	0.0206	0.0267	0.0193	0.0247	0.0200 (0.0034)
	Perc. of days holding S&P500	0.6565	0.8537	0.9252	0.6650	0.9167	0.9660	0.5867	0.6956	0.7585	0.7804 (0.1305)
High volatility phase	**Excess return**	0.2365	0.2942	0.3282	0.3184	0.4020	0.2096	0.5567	0.5120	0.2540	0.3457 (0.1145)
	Max drawdown	0.0208	0.0235	0.0143	0.0175	0.0142	0.0191	0.0171	0.0145	0.0149	0.0173 (0.0031)
	Perc. of days holding S&P500	0.5314	0.4261	0.3803	0.5705	0.4754	0.4194	0.4414	0.3990	0.3582	0.4446 (0.0658)
Medium volatility phase	**Excess return**	-0.0742	-0.1867	-0.4045	-0.0736	-0.0690	-0.0945	-0.0900	-0.2681	-0.2470	-0.1675 (0.1113)
	Max drawdown	0.0179	0.0195	0.0421	0.0255	0.0153	0.0193	0.0249	0.0212	0.0263	0.0236 (0.0074)
	Perc. of days holding S&P500	0.6842	0.7148	0.7793	0.6757	0.8302	0.9015	0.5705	0.5399	0.7216	0.7131 (0.1087)

Table 5.6: Performances of time series trading rules

	Ar	**Ar-Garch**	**Ar-Egarch**
Low volatility phase	-0.0911 (0.0498)	-0.0647 (0.0261)	-0.1092 (0.0288)
High volatility phase	0.2863 (0.0464)	0.3100 (0.0965)	0.4409 (0.1634)
Medium volatility phase	-0.2218 (0.1679)	-0.0790 (0.0136)	-0.2017 (0.0973)

Table 5.7: Average excess returns in function of the different classes of models. Standard deviations are between parentheses.

5.4.2 Combined trading strategies

As regards the combination between technical and time series trading rules, with intent of good illustration, we chose to analyze the promising outcomes for the strategies that mixed moving average indicators and AR(1)-GARCH(1,1) forecasts. These are firstly graphically reported in Figure 5-10 in terms of their cumulative returns. The difference with plots of Figure 5-8 or 5-9 is substantial.

First of all, the best combined strategy more than doubles the final return of the best individual technical and time series rules. Secondly, in Figure 5-10, the worst rule outperforms many of the strategies based on a single approach. Thirdly, quite just after one year of signals emissions, three clusters of strategies clearly emerge and those with the best performances kept their competitive advantage until the end of the sample.

Despite these differences, Figure 5-10 spots, once again, the ability of trading strategies in predicting negative performances of the market and consequently staying out from the S&P500 investment. However, after the crisis, buy signals started again to produce positive results for most of the trading rules.

If Figure 5-10 suggests that strategy combination contributed to improve trading

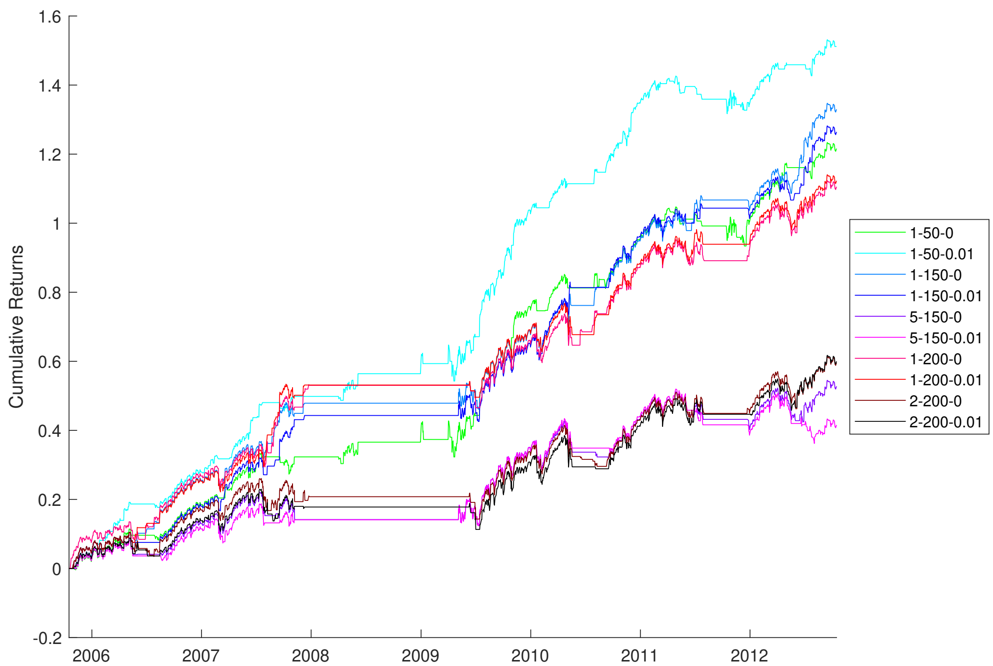

Figure 5-10: Cumulative returns of technical trading strategies combined with AR-GARCH models

performances, Table 5.8 further highlights the goodness of this choice.

		1-50-0	1-50-0.01	1-150-0	1-150-0.01	5-150-0	5-150-0.01	1-200-0	1-200-0.01	2-200-0	2-200-0.01	Average (Std. dev.)
Low volatility phase	**Excess return**	0.1859	0.3611	0.3415	0.3058	0.0045	0.0039	0.3931	0.3941	0.0707	0.0408	0.2101 (0.1581)
	Max drawdown	0.0059	0.0026	0.0059	0.0048	0.0078	0.0069	0.0063	0.0059	0.0091	0.0090	0.0064 (0.0018)
	Perc. of days holding S&P500	0.6071	0.4983	0.7347	0.6769	0.7058	0.6752	0.8078	0.7279	0.8044	0.7279	0.6966 (0.0870)
High volatility phase	**Excess return**	0.6788	0.8054	0.4724	0.5600	0.3847	0.3970	0.3513	0.3354	0.3043	0.3058	0.4595 (0.1620)
	Max drawdown	0.0100	0.0098	0.0074	0.0074	0.0088	0.0088	0.0085	0.0085	0.0091	0.0088	0.0087 (0.0008)
	Perc. of days holding S&P500	0.4652	0.4380	0.4346	0.4261	0.4414	0.4346	0.3786	0.3701	0.3769	0.3718	0.4138 (0.0336)
Medium volatility phase	**Excess return**	0.1474	0.1413	0.3118	0.1945	-0.0656	-0.1893	0.1583	0.1893	0.0184	0.0493	0.0955 (0.1376)
	Max drawdown	0.0103	0.0096	0.0064	0.0060	0.0105	0.0150	0.0083	0.0082	0.0102	0.0087	0.0093 (0.0024)
	Perc. of days holding S&P500	0.5986	0.5425	0.6684	0.6122	0.6701	0.6139	0.7364	0.6990	0.7364	0.6956	0.6573 (0.0604)

Table 5.8: Results of technical trading rules combined with AR-GARCH models

Table 5.5 and 5.6 clearly showed that trading strategies based on a single approach produced good performances during high volatility period but could not 'beat the market' for the remainder of subsample phases. On the other side, instead, Table 5.8 reports that combined trading strategies, on average, can get substantially better results even in those periods. The average excess cumulative returns, in fact, increase up to 21% and 9.55% respectively in low and medium volatility phases. Besides of this, dominance of active strategies is, a fortiori, confirmed for combined rules.

Furthermore, data suggest that mixing various trading approaches contributes to enhance the strategies stability and their consistency since maximum drawdown indicators of cumulative returns have significantly decreased with respect to those coming from the single approaches. Hence, this means that by relying on more than one predictive market indicators, trader's confidence might rise when operative decisions need to be taken. Outcomes, moreover, suggest that higher average excess returns are gained with a lower quantity of trading operations since the average percentages of days during which the trader has held the S&P500 index were lower than those of individual strategies in the respective subsample periods. As an example, in order to make a comparison between individual and combined strategies results and better understand how time series forecasts allow to improve technical strategies, we considered the individual {1, 50, 0} moving average rule and compared its results when this was combined with the trading signals coming from the AR(1)-GARCH(1,1) forecasts.

Figure 5-11 represents individual and combined strategy outcomes together with the S&P500 returns. Substantial differences in terms of returns have emerged until mid-2009. In particular, since 2007 strategies combination has led to avoid valuable negative peaks during the low volatility phase and, in general, the absence of 'buy' signals determined a pattern in which periods of no trading activities occurred more frequently, decreasing, in such a way, the volatility and (often) losses of the resulting returns series. Also during high volatility period, the integration with AR-GARCH forecasts were useful for avoiding great market losses, whose impact on the trading returns was amplified (both positively and negatively) as result of the 'Double-or-Out' strategy in which a trader doubles its investment in equity market after a 'buy' signal. Finally, this pattern follows also during medium volatility phase when, in general, the combined strategy was more able to be in the market when positive returns were generated.

Along the following pages, Table 5.9, 5.10 and Figure 5-13, 5-12 confirm, respectively

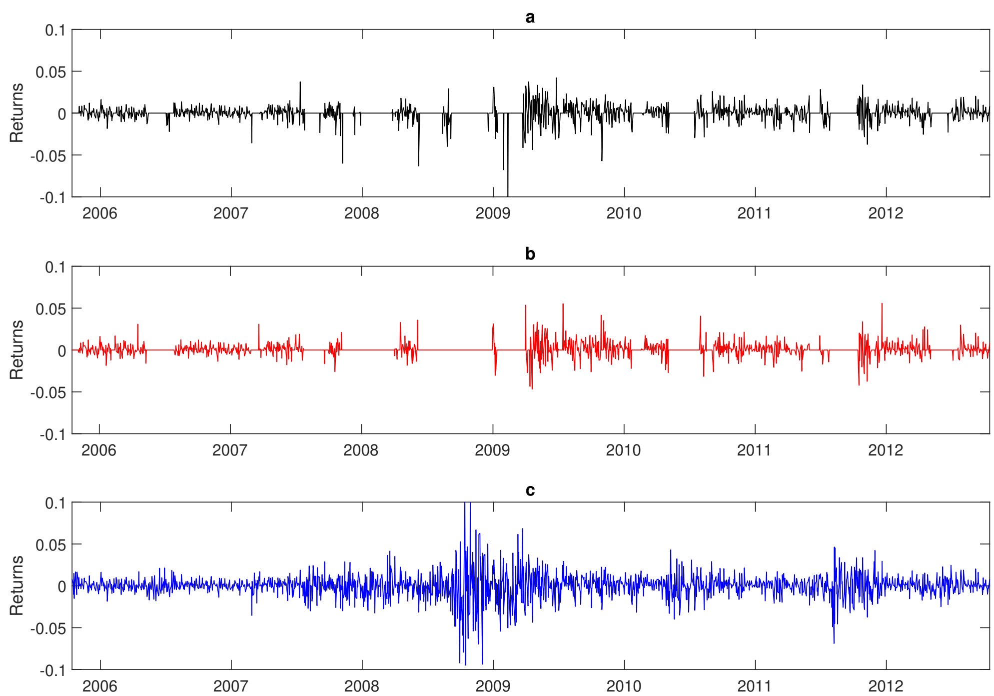

Figure 5-11: In (a) trading returns of {1, 50, 0} double moving average strategy are represented. (b) shows the plot of the same technical trading rule combined with AR(1)-GARCH(1,1) model. (c) depicts S&P 500 original returns.

in analytical and graphical forms, a general superiority of combined over the individual approach also when forecasts of other time series models were implemented. Further, it is worth noting that, in this framework, AR-GARCH and AR forecasts provide better performances than AR-EGARCH in terms of guidance for the technical trading strategies.

Despite these differences, an appreciable common element is represented by the fact that each strategies generally belongs to the same cluster of rules, independently from the time series model chosen. For instance, just to cite two cases, {1, 50, 0.01} and {5, 150, 0.01} strategies are always considered, respectively, the best and the worst ones in terms of cumulative returns. Rather than inferring that some specific technical trading strategies have superior forecasting power than others, this result might indicate that, despite the time series models implemented possess different theoretical properties, in practice, their forecast production and accuracy are quite similar each other.

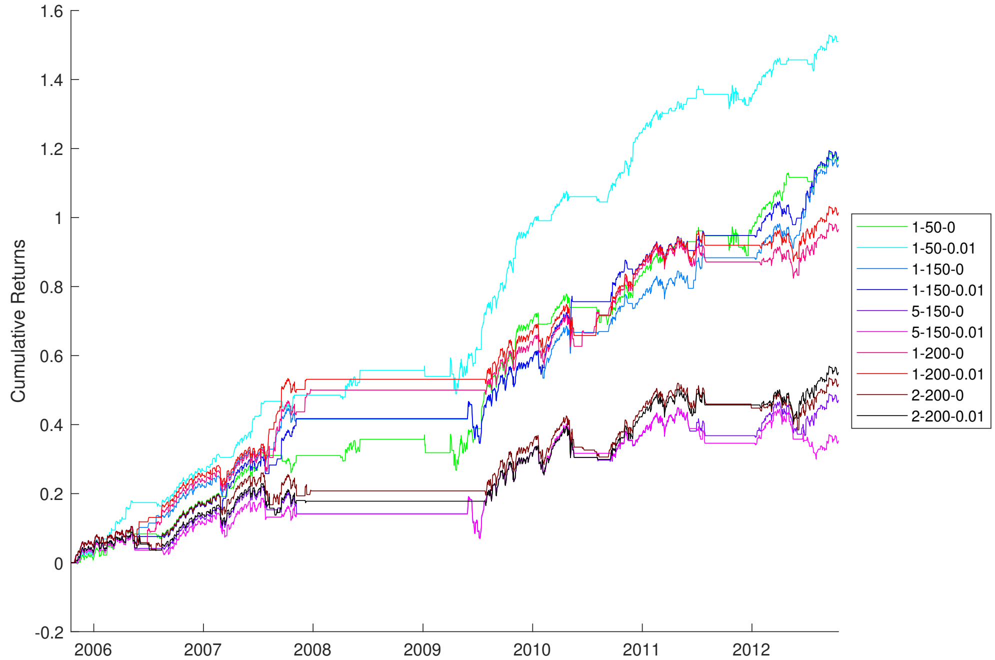

Figure 5-12: Cumulative returns of technical trading strategies combined with AR models

		1-50-0	1-50-0.01	1-150-0	1-150-0.01	5-150-0	5-150-0.01	1-200-0	1-200-0.01	2-200-0	2-200-0.01	Average (Std. dev.)
Low volatility phase	**Excess return**	0.1731	0.3483	0.2787	0.2802	0.0045	0.0039	0.3628	0.3941	0.0707	0.0408	0.1957 (0.1477)
	Max drawdown	0.0059	0.0026	0.0059	0.0048	0.0078	0.0069	0.0063	0.0059	0.0091	0.0090	0.0064 (0.0018)
	Perc. of days holding S&P500	0.6037	0.4949	0.7262	0.6735	0.7058	0.6752	0.8061	0.7279	0.8044	0.7279	0.6946 (0.0876)
High volatility phase	**Excess return**	0.6186	0.7645	0.4407	0.5283	0.3529	0.3653	0.3617	0.3162	0.3147	0.3162	0.4379 (0.1451)
	Max drawdown	0.0101	0.0098	0.0116	0.0116	0.0119	0.0119	0.0085	0.0085	0.0091	0.0088	0.0102 (0.0014)
	Perc. of days holding S&P500	0.4601	0.4346	0.3973	0.3888	0.4041	0.3973	0.3531	0.3463	0.3514	0.3463	0.3879 (0.0372)
Medium volatility phase	**Excess return**	0.1758	0.1933	0.2306	0.1642	-0.0899	-0.2196	0.0391	0.1004	-0.0702	-0.0091	0.0514 (0.1396)
	Max drawdown	0.0076	0.0058	0.0065	0.0061	0.0094	0.0143	0.0099	0.0083	0.0129	0.0089	0.0090 (0.0027)
	Perc. of days holding S&P500	0.6156	0.5527	0.6293	0.5765	0.6327	0.5782	0.6905	0.6582	0.6922	0.6565	0.6282 (0.0455)

Table 5.9: Results of technical trading rules combined with AR models

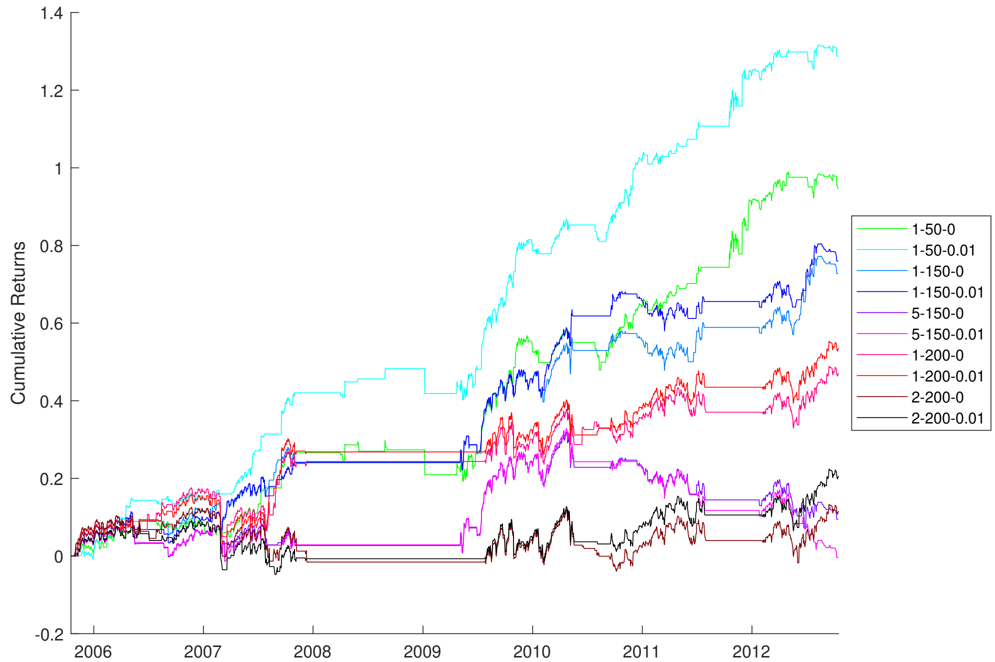

Figure 5-13: Cumulative returns of technical trading strategies combined with AR-EGARCH models

		1-50-0	1-50-0.01	1-150-0	1-150-0.01	5-150-0	5-150-0.01	1-200-0	1-200-0.01	2-200-0	2-200-0.01	Average (Std. dev.)
Low volatility phase	**Excess return**	0.1290	0.2831	0.1030	0.1042	-0.1103	-0.1082	0.1063	0.1309	-0.1529	-0.1442	0.0341 (0.1425)
	Max drawdown	0.0048	0.0023	0.0070	0.0079	0.0103	0.0111	0.0124	0.0125	0.0140	0.0137	0.0096 (0.0038)
	Perc. of days holding S&P500	0.4932	0.4133	0.6344	0.6020	0.6241	0.6054	0.6820	0.6224	0.6820	0.6259	0.5985 (0.0792)
High volatility phase	**Excess return**	0.4734	0.6220	0.4788	0.5664	0.3910	0.4034	0.2786	0.2331	0.2316	0.2331	0.3911 (0.1366)
	Max drawdown	0.0102	0.0077	0.0078	0.0069	0.0089	0.0089	0.0105	0.0105	0.0107	0.0107	0.0093 (0.0014)
	Perc. of days holding S&P500	0.3616	0.3430	0.3582	0.3497	0.3650	0.3582	0.3277	0.3209	0.3260	0.3209	0.3431 (0.0169)
Medium volatility phase	**Excess return**	0.1404	0.1785	-0.0577	-0.1146	-0.3900	-0.5025	-0.1162	-0.0324	-0.1656	-0.0863	-0.1146 (0.1976)
	Max drawdown	0.0067	0.0048	0.0096	0.0095	0.0179	0.0247	0.0100	0.0087	0.0119	0.0090	0.0113 (0.0055)
	Perc. of days holding S&P500	0.4796	0.4303	0.4643	0.4167	0.4677	0.4167	0.6497	0.6207	0.6514	0.6207	0.5218 (0.0955)

Table 5.10: Results of technical trading rules combined with AR-EGARCH models

5.4.3 Recap of the main results

As regards the results of individual approach, the comparison between technical analysis and time series based strategies highlighted that, excepted for the performances of their respective worst case scenarios, no substantial differences emerged in terms of average excess returns. Trading signals generated by time series forecasts produced slight better results in first and second sub-sample and quite similar outcomes during medium volatility phase (even though standard deviation of excess returns was higher for technical trading rules). Both of these approaches did not succeed to beat the market during relatively positive periods of the financial markets, while they constituted useful trading strategies for preventing huge losses occurred during the most volatile sub-sample period. Technical trading rules, in general, recorded lower percentage values of days in which the trader held the S&P 500 index, aspect caught also by Fang and Xu (2003).

On the other hand, outcomes of Subsection 5.4.2 suggest that integration between the two approaches contributed to improve substantially results of the individual strategies, in particular way for the low and medium volatility periods. Regardless of the time series models class, over the full sample period, combined strategies tended to group each other, approximately, into three clusters of rules according to their cumulative returns. As a consequence, unlike individual approach, results of combined trading rules were more consistent over time, since, in combined cases, some specific rules showed to clearly dominate some others throughout the sample period. Moreover, strategies integration led to smaller maximum drawdowns and number of days holding the S&P500 index which means that, in general, the trading activity was less risky.

Finally, results of Subsection 5.4.2 showed that AR(1)-GARCH(1,1) forecasts produce the most profitable outcomes among those of the time series models considered.

Chapter 6

Conclusions

This empirical work has confirmed the substantial positive effects of combining technical analysis indicators with time series forecasts for trading purposes, in line with findings of Cappellina and Sartore (2000), Dalan and Sartore (2003) and, above all, Fang and Xu (2003). Despite these two approaches are founded on the basis of different theoretical and philosophical premises about financial markets movements, the experiment has demonstrated, especially, the complementary role they can play in providing the trader a more complete framework of information in order to improve his decision making process. In particular, one main advantage of forecast combination consists on the continuous research of confirmation of the outcomes obtained by one predictive techniques through the use of the other approach. This becomes, inevitably, an interesting property for trading strategies as long as it reduces the risks inherent in each financial trading operation.

Instead, as regards the performances of the single rules, a final answer has not definitely been given since neither approach generated a general competitive advantage over the other: technical and time series trading strategies did not beat the market during relatively good periods for financial markets but, generally, succeeded in emitting no buy signals during crisis period when all financial indexes (included S&P500) recorded huge plunges.

Results, then, confirm that some sort of predictability in asset returns is present and can be exploited, above all, incorporating in trading strategies as much information as possible but in general we cannot generally infer that these results constitute proof in contrast with efficient markets theory. Despite of this, it is worth to note that some of the assumptions underlying the methodology used for computing trading returns might appear simplistic since we did not consider some other trading costs represented, for instance, by the bid-ask spread or specific financial taxations. Furthermore, in our framework, we did not take into account a real portfolio value moving in function of time and, above all, no consideration was made about the quantity of stock shares bought when buy signals occurred. It is also possible that some forms of data snooping biases may be present in our empirical work linked, for instance, to the fact that we did not implement the full universe of possible technical analysis techniques or time series models.

Nonetheless, since the primary purpose of our analysis relied on empirically testing whether time series forecasts would have improved predictive power of technical analysis techniques, we can conclude that this aim has been achieved.

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