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TESTING THE "WEAK FORM EFFICIENT MARKET" HYPOTHESIS: AN ANALYSIS ON EUROPEAN AND ITALIAN EQUITY MARKETS.

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INTRODUCTION

"Considerate la vostra semenza:
fatti non foste a viver come bruti,
ma per seguir virtute e canoscenza".

Dante Alighieri, Divina Commedia, Inferno canto XXVI, 116-120.

The purpose of the thesis is testing the Weak Form of Efficient Market Hypothesis (from now "EMH") on Ftse Mib and Stoxx Europe 600 daily data, from the introduction of the euro, in 1999, up to February 2016, by implementing and comparing different quantitative tests.

Our research is organized in three parts.

1. In the first one, we describe the market microstructure in terms of the financial markets types and roles. The market is a real or a virtual place where people, acting as buyers and sellers, meet each other and conclude transactions; they trade stock, bonds, derivatives or other financial instruments. O'Hara (1995) defined the market microstructure as "the study of the process and outcomes of exchanging assets under a specific set of rules. Microstructure theory focuses on how specific trading mechanisms affect the price formation process". In particular, we study the order-driven type of market, where all buyers and sellers can trade without the presence of the dealer. Traders display the size of the trade and the price at which they want to sell or to buy an instrument, according to specific rules: order-precedence rules match the sellers to buyers and trade- pricing-rules create price from trade.
Next we describe the different market players, focusing on informed traders: people who collect, gather and act on information about fundamental instrument values. Types of informed traders are: value traders, news traders, technical traders and arbitrageurs. We want to evaluate whether the information can affect the price and how. On the other side, there are uninformed traders who do not know whether instruments are fundamentally undervalued or overvalued. We analyse their role and their impact on the market.

2. In the second part, we start from the definition of the market efficiency and how its concept has been developed in the literature. After we address EMH from a mathematical perspective, describing the most used models.
The first market efficiency definition has been given by Fama, in 1965. He classified the efficiency into three categories: *weak* when the market reflects all market information, *semi-*

strong when the market reflects all public market information and *strong* when the market reflects all public and private information. This concept has been extensively studied: Grossman and Stiglitz (1980) found that efficiency and competition cannot exist together; Schwert (2003) studied the impact of the market anomalies (e.g. size effect, the value effect, the weekend effect, and the dividend yield effect): when anomalies become widely known their effects seem to disappear or to be quite weak. Blakey (2006) looked at some of the causes and consequences of random price behavior. Lo (2004) considered the financial market from a biological evolution perspective, defining the market as "a co-evolving ecology of trading strategies: the creation of new strategies may alter the profitability of pre-existing strategies, in some cases replacing them or driving them extinct." Finally, Ball (2009) highlighted the limitations of the concept of market efficiency, identifying it as a possible responsible of global financial crisis.

Addressing the EMH form the mathematical perspectives, we examine the *weak* efficient market, where the prices follow a random walk, fully reflect all available information and fluctuations are independent of each other. So, price changes are unpredictable and fluctuate in a random way, according to the *characteristics* of Brownian Motion. Many authors have tested the EMH: Malkiel (2007) and Darné (2013) studied the Chinese market, Dat Bue Lock (2007) examine Taiwan Composite Stock Index, Kim and Shamsuddin (2008) the Asian stock market and Okpara (2010) the Nigeria Market. They found prices followed a random walk and so the analyzed markets were considered weakly efficient.

Nevertheless, other authors believe the price variations are not random: Mandelbrot wrote the price movements are not independent or Brownian and they are influenced by past events, which could alter the future prices values. In capital markets returns, there are patterns or trends and they persist over time and over scales, discovering in the time series a fractal structure. If details are observed at different scales, there is always a certain similarity to the original fractal: the rules are precise and the results are predictable. Other authors expanded the fractal theory: Dubovikov *et al.* (2003) implemented a new approach to the fractal analysis, identifying new fractal characteristics and Kristoufek (2013) analyzed whether the predictions of the fractal markets hypothesis are still valid also in turbulent periods.

Lo and MacKinlay (1988) implemented a variance ratio test for measuring how volatility changes, in order to check the random walk hypothesis. They found the variances increased faster than linearly, with the return horizon, so the time series they analyzed did not exhibit random walk behavior. Other studies supported this theory: Darrat and Zhong (2000) investigated Shanghai and Shenzhen Exchanges; Bahadur (2009) studied the Nepalese Stock Market; Hiremath (2014) analyzed the Stock market returns in India on the National stock exchange (NSE) and Bombay stock exchange (BSE); Abbas (2014) examined the daily stock returns on Damascus Securities Exchange. Dhar (2001) reached the same conclusion, studying how the different investors expectations - contrarians and momentum traders - affected the price and Pavlenko (2008) got to the same point, applying the mean reversion theory to the stock price analyzing the PFTS index.

3. In the third part we put together and integrate different tests available in the literature, in order to analyze the weak efficiency, from various points of view. As each test measures a different feature of random walk, our goal is to compare them, to verify the coherence, or to highlight the differences and complementarities among the methodologies. We use the following tests: normality test, the unit root tests, autocorrelation test, the GARCH model, the Lo and MacKinlay variance ratio, R/S analysis, long run dependency test and runs test. If the outputs show features of random walk, the analyzed market can be considered weak efficient.

We make a comparison between Stoxx Europe 600 and Ftse Mib and Indexes daily prices, to analyze the Italian and European scenarios, from January 4, 1999 to February 11, 2016 time frame. The reason why we consider Stoxx Europe 600 and Ftse Mib is because it fhe first represents the overall european economic situation while the second one the Italian equity market.

Finally we comment and discuss the results, in order to evaluate the efficiency or inefficiency of the analyzed markets.

PART I.

1. THE MICROSTRUCTURE OF THE MARKET

"These are the forms of time, which imitates eternity and revolves according to a law of number." Plato, Timaeus 37c-38b

A market is a real or a virtual place where people, acting as buyers and sellers, meet each other and conclude transactions. In more specific terms, the aim of capital market is to trade stock, bonds, derivatives or other financial instruments.

In order to understand how it works, it is necessary to outline its structure. Many authors studied the microstructure of the market because it is affected by many variables and factors such as rapid structural, technological, and regulatory changes. Some concrete examples can be the huge increase in trading volume, transformations in the regulatory environment, new technological innovations, the growth of the Internet, and the propagation of new financial instruments.

Maureen O'Hara (1995) describes market microstructure as "the study of the process and outcomes of exchanging assets under a specific set of rules. While much of economics abstracts from the mechanics of trading, microstructure theory focuses on how specific trading mechanisms affect the price formation process."
According to Madhavan's survey (2000), Lyons (2000) pays attention on microstructure of foreign market; Keim and Madhavan (1998) concentrate on execution costs about institutional traders; Coughenour and Shastri (1999) focus on the estimation of the components of the bid-ask spread, order flow properties, the NASDAQ controversy, and linkages between option and stock markets.
Moreover, Hong and Wang (2000) studied the microstructure through the examination of volumes and prices.
The study of market microstructure is important and interesting because it is related to various fields of finance, as Madhavan (2000) writes: "A central idea in the theory of market microstructure is that asset prices need not equal full information expectations of value because of a variety of frictions. Thus, market microstructure is closely related to the field of investments, which studies the equilibrium values of financial assets. But while many regard

market microstructure as a sub-field of investments, it is also linked to traditional corporate finance because differences between the price and value of assets clearly affect financing and capital structure decisions." [1]

This part of the present work is mainly based on studies of Harris (2003), since he provides a very detailed and complete description of markets and trading structures. He describes how market works and how it is organized.

In order to understand the market microstructure, it is important to know the characteristics of market quality and how market structure (trading rules and information systems) influences these features. The characteristics of market quality are liquidity[2], transaction costs[3], informative prices[4], volatility[5] and trading profits[6].

Trading rules and trading systems characterize the market structure. They detect who can trade, what they can trade and when, where and how they can trade and what information trades can have.

In order to arrange trades, the exchanges and traders utilize execution systems: *quote driven* system and *order driven system*. In the first, the dealer arranges trades when he trades with his clients, instead in the second, order precedence rules match buyers to sellers and trade pricing rules establish the prices of the resulting trades. There are also *brokered trading systems* in which brokers arrange trades for their clients helping buyers and sellers match each other. Finally, *hybrid markets* mix the features of all these types of systems, e.g. NYSE and NASDAQ.

In the **quote driven market** dealers act in all trades. Their task is to participate and to quote at which a buyer can purchase and at which a seller can sell. This type of market is called also dealer market because dealers supply and provide all liquidity. They establish the prices through bid and ask quotations. The bid is the price at which the dealers bid to buy, and the

[1] The author studies the market microstructure through four categories: price formation and price discovery, market structure and design issues, information and disclosure, informational issues arising from the interface of market microstructure with other areas of finance.

[2] Liquidity is the ability to trade quickly high volume at low cost. It has four *dimensions*: immediacy related to how quickly are trade; *width* linked to the cost of a trade at a given size; *depth* dealt with the size of a trade at given cost and *resiliency* referred to how quickly prices return to the previous levels after a large trade that changed prices.

[3] In order to have a successful trade, the transaction costs have to be small and well managed.

[4] Information is a fundamental component to share price formation.

[5] Volatility causes a relevant impact on the market. The traders have to manage it and it can be a source of profit even it brings high potential risks.

[6] The trading is a *zero sum game*. It means that total gains of winners are equal to total losses of the losers. To make money, a trader has to trade with a trader who will lose.

ask is the price at which the dealers offer to sell. Who want to sell, receive bid prices, instead, who want to buy, pay ask price.

Dealers and traders choose when they want to trade, indeed the client trades with a dealer who makes good prices and good offer. If traders want to trade with each other, the intermediation of a dealer is necessary.

If the traders do not have credit relationships with dealers and the dealers do not consider that the traders are trustworthy and creditworthy, the last ones have to trade with the intermediation of brokers who attest that the traders will arrange the trades. Furthermore, the dealers can avoid trading with traders that are not their preferred clients and with traders who are well informed about the future changes of price because in this way, the dealers probably will make losses.

The quote driven structure is quite common and some examples are: the Nasdaq Stock Market, the London Stock Exchange, the eSpeed government bond trading system and the Reuters 3000 foreign exchange trading system.

In this thesis we concentrate our attention on order driven markets in which there is not a dealer that arranges the trades; instead, this type of market is characterized by order and trading rules that preside the system.

1.1. ORDER DRIVEN MARKETS

The order driven market is a financial market in which all buyers and sellers can trade without the presence of the dealer. The traders display the price at which they want sell or buy an instrument and the size of the trade. They can offer or take liquidity. All markets are regulated by trading rules to arrange trades and trade pricing rules to form the prices.

The order driven market includes: oral auctions, single price auctions, continuous electronic auctions, and crossing networks.

In the single price auctions, the trades are arranged at the same price following a market call.

In continuous electronic auctions, buyers and sellers continuously try to arrange trades at prices that change through time, at any time a new order arrives.

In crossing networks, the trades are matched at prices obtained from other markets.

The most common type of the order driven markets is the auction: many options, futures and stock exchange trade as an **oral auction**. In this type, the trading rules discover sellers and buyers with the best available prices. Indeed, in order driven markets, whoever take or supply liquidity, are traders. There can be dealers in the market, but they trade as common traders and they cannot choose the clients, even if in some type of order driven markets dealers provide the most of liquidity.

Harris (2003) describes an oral auction as exchange in which "traders arrange their trades *face-to-face* on an exchange trading floor. Some traders *cry out* their bids and offers to attract other traders. Other traders listen for bids and offers that they are willing to accept."

Trades occur when a buyer authorizes a seller's offer (called *take it* to accept the offer) or when a seller permits a buyer's bid (called *sold* to accept the bid).

Since buyers and sellers are not agree on the trade price and quantity, they continue to offer and bid. *Offering liquidity* means that traders make bid or offer to trade; instead, *taking liquidity* stands for when traders consent to make trade accepting the bids or offers.

As written before, all types of market are governed by the market trading rules in order to organize the trading and to ensure the fairness.

Open-outcry is the first rule. It establishes that traders must publicly explicit all bids and offers so that all traders can act on them in order to ensure the fairness of each traders in the markets.

To help trader to evaluate market conditions and to protect clients from dishonest brokers, the open-outcry rule imposes moreover that all traders must accept publicly so that when they arrange trades, they are aware of situation.

1.1.1. The Rules of the Market

The charm of the Exchange Market is preserved by efficient and well-controlled market place. The rule, the guidance and the monitoring of trading keep the order of the market. One market purpose is to procure to investors, intermediaries and issuers an efficient[7], liquid, solid and well-regulated market in which it is possible to raise capital, fulfil investments and make trading.

The market rules plan the trading and guarantee the honesty and fairness among traders and also protect brokerage customers from not honest brokers. The regulations procure efficient exchange of information, that is meaningful for arrange trades. In general all types of markets

[7] In the second part we examine and analyze the definition of market efficiency.

are regulated and controlled by rules. In this section, we will examine the guidelines and regulations of the order driven market.

All types of order driven markets apply **order precedence rules** to match the sellers to buyers and **trade pricing rules** to create price from trade.

1.1.2. Order Precedence Rules

The order precedence rules in an **oral auction** establish bids or offers that traders can accept. The primary order precedence rule is always price priority. The secondary precedence rules depend on market: futures markets use time precedence and U.S. stock exchanges use public order precedence and then time precedence. Now, we concentrate on the features of these rules.

Price Priority

According to Harris (2003), "the Price Priority gives precedence to the traders who bid and offer the best prices. Traders cannot accept bids/offers at any inferior price. Buyers can accept only the *lowest offers* and sellers can accept only the *highest bids*."

Honest traders, obviously, look for the best possible price. They preserve the rule so that they can contest dishonest brokers who do not offer or bid good prices. It is a *self-enforcing* rule[8]. In order to enforce this regulation, the exchanges do not make to respect it with a particular procedures because, maintaining the rule on their book, they condemn dishonest brokers.
Any traders at any time who offer or bid prices that make better current best bid or offer, obtain the price priority rule.

Time Precedence

"The time precedence gives the precedence to the trades whose bid or offer first improves the current best bid or offer. While they have time precedence, no other traders may bid/offer at the new best bid/offer", as defined by Harris (2003).
Since traders keep their bids or offers and since their quotes are not accepted, traders hold their time precedence.

[8] It means that it includes in itself the authority and it procures itself for enforcement. The price priority rule is the only self-enforcing rule.

This type of rule stimulates *price competition* among traders. Indeed, if a trader, who wants to make a trade ahead of a trader who keep the time precedence, must make better the price in order to trade.

The price improvement has to be not so small. The minimum price increment or the smallest amount by which a trader can improve the price (called *tick*) represents what traders has to pay in order to acquire the time precedence. If the incremental price is very small, the traders, who want improve the price, do not obtain a good advantage. Time precedence is meaningful only when the minimum price increment is not very small. The tick size determines the impact on price competition varies by tick size. If the minimum price increment is too small, the price competition decreases because the time precedence rule is not meaningful. If the tick is too large, traders hesitate to trade because they have to pay more to improve the price.

Harris (2003) explains: "The time precedence is not a self-enforcing rule. Most traders do not care whose bid/offer they accept as long as they get the same price. Traders who have time precedence must defend it when someone improperly attempts to bid/offer at the same price."

An example of a strategy that exploits the time precedence is the *leapfrog strategy*. If a trader wants to trade before other, he has to jump over each other's price with improved price. He has to improve his bid or his offer in order to have the precedence over other traders. Time precedence encourages traders to play leapfrog strategy by jumping over each other's prices with improved price.

Public Order Precedence Rule

Harris (2003) designates public order precedence rule as the "the rule that allows public traders to take precedence over a member even when the member has time precedence."

In order to reduce the asymmetrical information that affects floor traders, some equity exchanges impose that their members have to not trade ahead of a public trader who wants to trade at the same price.
Other aims of this type of rule are to give public traders more access to their markets and to increment investor confidence in the market because the public order precedence rule ensure that the members of exchanges cannot step in front of their orders.

1.1.3. The Trade Pricing Rule

The trade-pricing rule used in oral auctions is simple and, according to Harris (2003), “it requires that every trade takes place at the price proposed by the trader whose bid or offer is accepted.” Large and aggressive traders use this rule in order to lower their trading cost, so it is also called *discriminatory pricing rule*. It decreases trading cost because the traders that are most willing to trade would not make such a good offer if they knew the full order size.
To trade one at a time, large traders often divide their orders into different parts. The first piece is traded at the best prices initially available and the remaining portion is traded at progressively inferior prices since the traders deplete the available liquidity and the market finds the true order size. Thanks to this rule, it can be possible to discriminate among traders who want to trade obtaining their best price and who are willing to trade only at inferior price gaining their worst prices.

In exchanges that run oral auctions, in order to match buyers and sellers and enforce trading specific rules, it is necessary conduct all trading in each securities or contract at its assigned post or in its assigned pit. Trading Floors can be *trading pit* [9]in the Future markets and *trading post* [10] in the stocks, options, and bond markets. This configuration ensure transparency so all traders can see clearly all other traders.

1.1.4. Rule Based Order Matching Systems

Rule based order matching systems exploit trading rule to arrange traders from the orders that traders submit to them. These types of rules are used by most exchanges, some brokerages and almost all electronic communications networks. If traders want to arrange trades, it is possible only by submitting and cancelling order. Most systems accept only limit orders. The quantity that traders will accept must be clear. Rule based order marching systems process price and quantity information to arrange their trades.
The market collects the orders before the call if it is a *call market*; instead if it is a *continuous market*, the system tries to arrange them at any time new orders enter.
Call markets concentrate their attention on all trades on the same instrument at the same time.

[9] Harris (2003) defines a trading pit as “a place on an exchange floor designated for trading a particular contract or set of related contracts. They are depressions in the floor that have steps all around the sides. The traders stand on the steps and on the bottom of the pit”.
[10] “A trading post is a place on the floor of an exchange designated for trading specific securities”. See Harris (2003).

In these, orders occur at specified times and are collected at one time, and the exchange forms buy and sell prices then. They produce more impact and more surplus for traders buy they are utilized when the volume traded is little.

Instead, in the continuous market, a trade can occur at any time as long as the market is open. Buyers and sellers can carry on trading continuously. The price is determined by auctions or bid ask spread quotes.

Continuous markets can trade more volume than call markets because they may trade at more than one price but, in order to measure the ability of the market to create trader surpluses, volume is not a good measure to calculate trader surpluses. Indeed, nevertheless the uniform pricing rule is used to trade lower volume, it produces a higher surplus than continuous market when the continuous market elaborates the same order flow and if exchanges maximize the difference between the buyer's estimation and the seller's estimation for each trade, the total surplus drops.

1.1.4.1. Order precedence Rules

Order matching systems rank all buy and sell orders according to their precedence rule. The orders with the highest precedence rule are matched the first. Indeed, as we have seen before, the rules are hierarchical. The primary order precedence rule is the *price priority*, the secondary precedence rules are: time precedence, display precedence and size precedence.

Given the same primary precedence, markets use their secondary precedence rule to rank the orders. Markets use these regulations since they rank all orders according to their precedence. Harris (2003) explains *time precedence* as a rule that "gives orders precedence according to their time of submission." There are two types of this rule: the <u>Floor time precedence rule</u> and the <u>strict time precedence</u> rule. The first is called floor time precedence because it is the equivalent rule used in oral auctions. It establishes that, at given price, the first order arrives has the precedence over others. The other orders, that not matched, remain and they are put in order according to another secondary precedence rule. <u>Strict time</u> precedence puts in order all orders in rank with respect to their submission time given the same price. Types of markets that use only price priority and strict time precedence to rank the orders are called *pure price time precedence systems*.

Display precedence gives the priority to orders that traders display over orders that traders do not show, given the same price. This rule exists to ensure transparency and to stimulate the traders to show their intentions and their orders. Indeed, if only a part of an order is displayed and the remaining part is hidden, the system divides the order and it usually treats the two parts separately.

Size precedence depends on which market a trader acts. In some markets the small orders have the precedence over the large orders. According to Harris (2003), "when two or more orders have the same size and they cannot all be fully filled, some markets allocate available size on a *pro rata basis*". Pro rata basis means that the orders are filled according and in proportion to their size.

Traders can issue orders with restrictions in size. These types of order generally have lower precedence than the order without constraints because they are harder to fill. Traders may indicate if they want fill all entire or they can determinate a specific minimum part in order to partially fill.

The aim of this type of order execution is to avoid paying fixed costs for every small trades such as settlement fees, costs of accounting for each trade and exchange fees.

1.1.4.2. The Matching Procedure

The matching procedure begins after the market ranks the orders. If the market is a call market, the matching procedure starts immediately after the call market. If the market is a continuous market, it occurs at any time a new order enters.

The first orders matched are whose are the highest-ranking. If the buyer is willing to pay what seller demands, the trade is concluded. The trade pricing rules establish the price of the trade.

If there is one order that is smaller than the other, this will fill completely; whereas the remaining part will be matched with the next highest-ranking order.

If two orders have the same size, they will completely be matched. The system then will fill the next highest buy and sell orders. This keeps on since all possible trades are filled.

According to Harry (2003), "since the market processes orders ranked by decreasing price priority, the last match that results in a trade often involves two orders that bid and offer the same price. The next match does not result in a trade because the buyer's bid price is below the seller's offer price. "

1.1.4.3. The Trading Pricing Rules

Every type of market has its rule. It varies according to different structure. In single price auctions the uniform pricing rule governs the trade, in continuous two sides auctions and a few call markets the discriminatory pricing rule is used and in crossing networks the derivative pricing rule settles the trade.

Now, we pass to describe all these types of rule.

Uniform Pricing Rule

Stock markets and most electronic futures markets use uniform pricing rule in order to open their trading section. These rules are quite common and are used in **single price auctions**.
The price of all trades is the *same* market clearing price. The last match of a trading brings to the clearing price. If the buy and sell orders in this match specify the same trade price, that price must be the market clearing price. Any other price would be either too high to satisfy the buy order or too low to satisfy the sell order. Matching by price priority ensures that this market clearing price is also feasible for previously matched orders. These matches involve buy and sell orders with higher price priority. Since all buyers with higher price priority is willing to trade at higher prices than the market clearing price, and all sellers with higher price priority are willing to trade at lower prices than the market clearing price, all matches can trade at the market clearing price[11].
If the bid or offer in the possible last trade defines different prices, the buy order will bid a higher price than the sell order offers. The market can clear at either of these two prices or at any price between them. The market rules will specify the clearing price in this unusual event.

When the **supply is equal to demand**, the single price auction clears the price. The list of the total volume offered by the sellers at each price is called supply schedule, instead the list of the total volume offered by the buyers. Harris (2003) specifies that "It slopes upward because sellers will sell more at higher prices than at lower prices."
If the price is below the clearing price, there is excess demand: buyers want to buy more than sellers offer.
If the price above the clearing price, there is excess supply: sellers offer more than buyers want.
Since the price and quantities are discrete, single price auctions often have excess supply or demand at the market-clearing price. If there is excess supply or demand, all traders have to fill their orders at the price and which sell or buy order will be filled as the first is decided by the secondary precedence rules (Figure 1).

[11]The Cambridge Business English Dictionary defines it as "the price of goods or services that exists when the quantity supplied is equal to the quantity demanded".

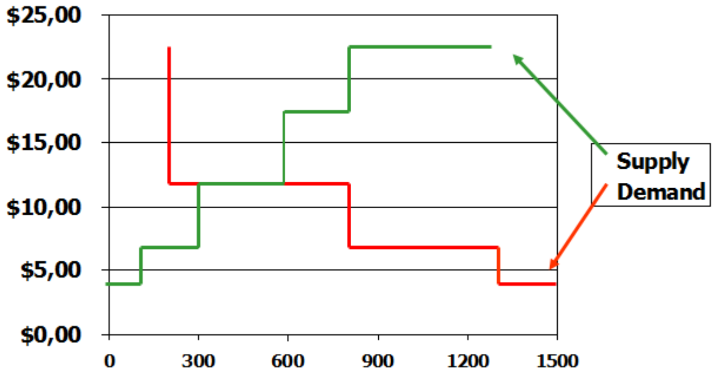

Figure 1. The supply and demand schedule plot
Source: author's elaboration

After the trade and the formation of the price, the seller or the buyer can benefit from surplus. The trader surpluses depend only on **valuations** of sellers and buyers. Indeed, it is the difference between the trade price and their valuations. In particular, for seller it is the difference between trade price minus the seller's valuation and for buyer valuation minus the trade price. The sum and the distribution of the surpluses do not depend on the trade price because buyers want to purchase a low price and sellers want to obtain high price. So, auction maximize total surplus because it matches by buyers who most value the item and the sellers who least value it. Trader surpluses will be positive if sellers sell at price above their valuations and buyers bid at prices below their valuations. Obviously, all would like to obtain maximum profit.

It is not easy to measure trader surpluses. We never know exactly their valuation about trades; we only can suppose them through their orders. For example, if a trader submits a limit order[12], we can suppose that his valuation correspond more or less to limit order because a rational seller never set limit price below his estimation.

The total trade surplus is maximized in the single price auction if the traders are satisfied by outcome of the auction. This means that *no trader regrets trading* or no potential trader regrets not trading. No trader will regret trading if he does it rationally. If traders imposed that their limit prices are equal to their estimations, all traders will be satisfied by the auction outcome.

Traders regret not trading when they fail to trade and wish that they had and when traders do not trade aggressively enough to take part in the auction.

[12] Harris (2003) defines it as "an instruction to trade at the best price available, but only if it is no worse than the limit price specified by the traders. For buy orders the trade price must be at or below the limit price; for sell orders, the price must be at or above the limit price". Traders who are not risk averse and for whom monitoring orders is not much costly use this type of orders.

Every buyer who estimates the instrument more than clearing price and every seller who estimates the instrument are included in the resulting trade; other buyers and sellers that do not estimate the values in this way do not take part in it. Since the same clearing price determines the successful buyers and successful sellers, there is not a lower estimation for a successful buyer than for successful seller.

Discriminatory Pricing Rule

In order to set the price of trade, the rule in the **continuous two side auctions** systems is the discriminatory pricing rule.

The order book contains the standing orders that attend to fill. The buy and sell orders are ranked according to their precedence. The best bid is the highest bid and the best offer is the lowest offer. Whenever a new order arrives, the matching systems try to arrange it with an order on the opposite side with the highest precedence. A trade occurs only if the order accepts the terms of the new order. If the new order is a buy order, it is necessary to specify that the trader will pay at least the best offer price, the same thing for the sell order.

If it is possible trade the new order, it is called marketable. Two examples of marketable orders are: market orders[13] and aggressively priced limit orders[14]. The matching system fills this with the highest- ranking order on the opposite side of the market.

If the new order is not marketable, the new order will wait until it is possible to match with another order on the opposite side.

If this trade is only partially filled, the remaining part will be matched with the next highest ranking order on the other side. This process does not stop until the new order fills completely or until no further trades are feasible. The residual part remains in the order book unless the trader commands otherwise.

Comparison between discriminatory pricing rule and uniform pricing rule.

Large impatient traders tend to trade more with the discriminatory pricing rule than the uniform, given the same set of standing orders. This is due to the fact that the trading of the

[13] Harris (2003) defines market orders as “an instruction to trade at the best price currently available in the market. Market orders usually fill quickly, but sometimes at inferior prices. The execution of a market order depends on its size and on the liquidity currently available in the market”.

[14] This type of orders is the easiest to fill because they are orders with the highest prices if it is a buy limit order and with low prices if it is a sell limit orders.

first part of order is completed at better price than the remaining part. Instead, if the market uses the uniform pricing rule, the price is the same for the entire order.
Who use standing limit orders want to trade under the uniform pricing rule because they want that all traders obtain the same price for all the large order. In this way, the traders issue dissimilar orders when they act on the various type of market structure.

The two rules provoke different impacts on the trade price. In the markets in which the rule used is the discriminatory pricing rule, the trade price is the limit price. Instead, in markets regulated by the uniform pricing rule the limit price not often is the trade price. If the order is very huge relative to the other orders in the auction, the limit price is the trade price.

In order to move to a uniform pricing rule, continuous trading markets must use *halt rule* to stop trading. If there is a large order imbalance that makes prices go too far or too quickly, continuous markets stop trading. The trading halt indeed, acts to shift from the discriminatory pricing rule to the uniform pricing rule.
If large traders split their orders, they create *delays* for the execution of their trades but the traders may be dampened from breaking orders if these lags are long.
Trading halts rule are useful also for decrease volatility. This occurs because traders are on guard to unusual demands for liquidity. According to Harris (2003), “if traders step in to supply liquidity, prices may not change as much as they would have changed if the market immediately processed the orders that caused the imbalance”.

Derivative Pricing Rule

Crossing networks use the derivative pricing rule in order to make trade. Indeed, the price of a trade is determined elsewhere from other markets that trade the same instruments. They are the only order driven markets that are not auction markets where prices are regulated in order to match buyers and sellers. This type of market identifies if traders want to buy or sell at the crossing prices.
The most relevant crossing networks are call markets and the financial instruments are U.S. equities. Preceding the call, traders submit orders to buy or sell. Following the call, the order precedence rule of this type of market connects the buy orders with the sell orders and these orders assume the shape of trade if it is possible to trade at the crossing price. When crossing networks do not decide the market clearing prices, obviously there is excess demand or supply at their crossing prices. Indeed, if the buy order is greater than the sell order, the sell order

will be filled completely. The same happens for the opposite case, always according to their order precedence rules.

In the crossing networks it is possible for buyers and sellers meet each other without any impact on price. Traders prefer act in this type of market because, although most order volume does not fill completely, the crossing commissions are very low. So they can continue to cross the orders. This type of market fills only a part of the total order volume that a trader would to submit.

All three major crossing networks are completely confidential and anonymous systems: the orders of the traders and the imbalances after the crossing are not showed. This is due to the fact that traders want submit the remaining part of the orders in other type of markets. They want this confidentiality because they do not want to manifest their plan of the trade. Even if the crossing network exhibited the entire order, traders would submit only a part of their orders in order to not manifest the entire size. Since these networks profit only from filled orders, they want traders to submit their full order sizes.

Some crossing networks work in continuous way. At any time new orders arrive, continuous markets try to arrange trades. These networks attempt to arrange trades whenever orders arrive. The orders that cannot be filled wait in order book or are transferred to other markets.

If the price is not credible and if the traders do not believe that it is fair, they will not trade. For these reason, the crossing networks must use prices feasible taken from other markets.

These other primary markets accuse crossing networks to not compensate them properly. Crossing networks obtain their price and they skim the cream of their order flow. The crossing networks would compensate properly because the primary market produce the prices that allow to crossing network to work successfully.

Crossing network customers reply that, when they do not take part in trade, they should not pay to discover the price. Crossing market traders moreover sustain that the prices created in primary markets are associated with them because their orders, submitted in primary market, create the feasible prices.

Problems with Derivative Pricing Rule

The derivative pricing rule brings to two problems. Traders who trade at derivative prices must consider these.

The first is connected to the notion of a stale price. Stale price is "an old price of the asset that does not reflect the most recent information."[15] This situation occurs when traders arrange trades at predetermined prices. Since in the derivative pricing rule the price comes from the price set in another market, when it was determined it was fair but at the moment of trade, it may not still be fair.

This occurs because instruments can change overtime. The stale price deals with the problem of adverse selection.[16] The well-informed traders choose the side of the market in order to trade with the uninformed traders.

The second problem deals with price manipulation. Harris (2003) explains that "a manipulated price is a price that a trader has deliberately changed in order to obtain some advantage. The potential for price manipulation exists whenever traders agree to trade at a price to be determined elsewhere in the future." Indeed, the traders could try to manipulate the price that will be convenient in the future for their trade. Obviously, the buyer aims for lower price, and the seller for higher price. If they both try to manipulate the price, the impact of their action will be deleted. Moreover, if the trade is large, they may have a lot of expenses and disadvantages.

Price manipulation is outside the law in the United States under Section 9(a) (2) of the Securities Exchange Act of 1934 and in the most of rest of the world but it is often difficult to identify.

So far we have described how the market microstructure is composed and how does it works through the specific rules. Now, we pass to outline the individuals and the actors who dominate the market.

[15] Definition from http://www.nasdaq.com/investing/glossary/s/stale-price

[16] It happens when a buyer has more information than seller and vice versa about the instrument traded. Indeed, when buyers and sellers have different information (this situation called asymmetric information), traders with better information about the security will benefit from trade in the market at the expense of the other trader.

1.2. THE TRADERS IN THE MARKET

"What registers in the stock market's fluctuations are not the events themselves but the human reactions to these events, how millions of individual men and women feel these happenings may affect the future. Above all else, in other words, the stock market is people. " (Bernard Baruch)

Traders are people who act in the market. They are numerous and they are classified according to how to act in the market. They are "Individuals who take positions in securities and their derivatives with the objective of making profits. Traders can make markets by trading the flow. When they do this, their objective is to earn the bid/ask spread. Traders can also take proprietary positions in which they seek to profit from the directional movement of prices or spread positions".[17]

They have a *short position* if they want to sell something that they do not have. They hope that price will drop so that then they can buy it a lower price. They make money when they sell high and buy low. Instead, they have a *long position* when they have something. They make money when prices go up: buy low and sell high.

The trading industry is divided in two sides: the buy side and the sell side. The first side is composed of traders who purchase exchange services; the second side sell liquidity to the other side.

The buy side includes: investors, borrowers, hedgers, asset exchangers and gamblers.

Investors are individuals, corporate pension funds, insurance funds, charitable and legal trusts, endowments, mutual fund and money managers. They trade stocks and bonds in order to move wealth from the present to the future for themselves or for their clients.

Borrowers are homeowners, students and corporations that use mortgages, bonds and notes in order to move wealth from the future to the present.

Hedgers are farmers, manufactures, miners, shippers and financial institutions. They conclude futures contracts, forward contracts and swap to reduce business operational risk.

Asset exchangers are international corporations, manufacturers and travellers that exchange currencies and commodities to acquire an asset that they value more than the asset that they tender.

Finally, gamblers are individuals who trade various instruments in order to entertain themselves.

[17] Source: http://www.nasdaq.com/investing/glossary/t/traders

The sell side of the trading industry is composed by dealers, brokers and brokers-dealers who offer exchange services to the other side.

Market makers, specialists, floor traders, locals, day traders and scalpers are dealer that act in order to earn trading profit by supplying liquidity.

Brokers are retail, discount, full-service, institutional, block brokers and futures commission merchants that work in order to earn commissions by arranging trades for clients.

Finally, brokers dealers are wirehouses that earn trading profits and trading commissions.

Several agencies help traders to settle the trades in order to facilitate trading. They are: exchanges, clearing agents, settlement agents, clearinghouses, depositors and custodians.

Exchanges are place where traders meet in order to conclude trades.

Thanks to clearing agents, buyers and sellers are matched and trades are cleared. Harris (2003) explains that "A trade *clears* if the buyer and seller both report that they traded with each other, and their reported terms of trade are identical. If the records do not match exactly, the clearing agent reports the discrepancies to the traders who then try to resolve them."

Settlement agents help to settle the trades of traders. Indeed, buyers give to them cash instead sellers give to them securities. When the trade and both part have finished their action, the settlement agents transfer cash to the sellers and securities to the buyers.

The net settlement is a relevant part in the settlement process. Thanks to the netting process, it can be possible reduce the number of transaction because for each client the SA nets the buy and sell position each security in order to obtain a one single net security position and also it nets all credits and debts of clients in order to achieve a single net money position for each client.

Clearinghouses act as a buyer for every seller and vice versa also in the derivative contracts such as in futures, options and swap markets. They issue and they guarantee their contracts also for the traders who are not clearing member. These traders must have clearing members who act for them. Generally, the clearing members are the owners of clearing houses and they are jointly liable for settling all trades. Clearing Houses must take care to the credit quality of members and the potential settlement risks that they can impose upon other traders. Clearing House is like a mutual insurance company because the clearing members must settle the trade if a trader fails to do it. If a clearing member cannot settle, the Clearing House can impose its other members to do it.

Finally, in the depositories and in custodians, clients hold their cash and their securities.

In order to map and rank traders, we divide them in principals and agents. The last one are: brokers, block traders and buy-side traders.

The *principals* are divided in three categories: utilitarian traders, profit-motivated traders and futile traders.

Utilitarian traders: investors and borrowers, asset exchangers, hedgers, gamblers, fledglings, cross-subsidizers and tax-avoiders. They trade because they believe that they will obtain benefit in addition to the profits from trading.

Profit motivated traders are speculator or dealers that rationally expect to make money from their trading. The last ones include market maker, specialists and block facilitators. Speculators can be informed traders composed by value traders, news traders, information-oriented technical traders and arbitrageurs (pure or statistical) or parasitic traders divided into order anticipators (front-runners, sentiment-oriented technical traders and squeezers) and bluffers (rumourmongers and price manipulator).

Finally, *futile trader*s are: inefficient profit-motivated traders, pseudo-informed traders, victimize traders and rogue traders. They think that they are profit motivated but in fact they are not. Their estimations are not rational because they have not real advantages to trade successfully.

We want to concentrate our attention on informed traders because in the second part we are going to analyse the definition of market efficient in which the information have a relevant and meaningful role and if traders keeping the news can beat the market and forecast the price changes. For this reason, we examine how informed traders act in the market and their profitability considering the transaction costs. Moreover we also study the uninformed traders because, as we will delineate, they have an important role in the financial market during the trade.

1.2.1. Informed Traders

Informed traders are traders who collect, gather and act on information about fundamental instrument values. When they note that current prices are differ from the fundamental value that they have estimated, they want to trade. Indeed, they construct and form feasible opinions and they can understand if the instruments are undervalued or overvalued. They sell when their valuations are below the current price and they buy when their estimations are above the current prices.

Informed traders estimate fundamental values. They may found their valuations on *private information* that only they obtain or on *public information* that any trader can have.

What does "fundamental value" mean?

Harris (2003) defines the fundamental value as "the value of an instrument is the value that all traders would agree if they knew all available information about the instrument and if they could properly analyse this information." "Fundamental value or intrinsic value is the expected present value of all present and future benefits and costs associated with holding instrument. It is not perfect foresight value, but depends only on information that is currently available to traders. Perfect foresight value depends on all current and future information about values. Fundamental value is the best estimate of perfect foresight value."

The difference between fundamental value and market value is noise. The market value is the value represented by the price at which a seller can sell or a buyer can buy the security. In particular, it is "The price at which a security is trading and could presumably be purchased or sold. What investors believe a firm is worth; calculated by multiplying the number of shares outstanding by the current market price of a firm's shares."[18]

Value traders try to discover the fundamental value, instead the dealers are interested in identify market values that produce two sides order flows.

Informed traders make prices more informative because after their trade the prices reflect their estimates of fundamental value. Indeed, their trading strategy is to sell when the price is above their estimates of fundamental value and to buy when the price is below their estimates: when they buy, the price tends to push up and when they sell, the price tends to push down.

When they trade each other, the impact on price is zero. In this way the market price reflects an average of their different value estimates. The market price thus evaluates the intrinsic value of the instrument better than any trader can measure it.[19]

Not all estimations on price are the same: it can happen if informed traders found their valuations on different data or one or more traders make a mistaken analysis. In this way they make the price less informative. However, in the long run the price becomes more informative because traders who have committed the mistakes, usually exit from the market if not able to recognize and correct them.

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[18] Source: http://www.nasdaq.com/investing/glossary/m/market-value

[19] For the algebraic illustration see Harris (2003), p. 225.

Informed traders trade in order to make profit, not to make price more informative. Their transaction costs are the impacts on price, so when the price impacts are small, they make more profit.

Informed traders act on liquid market because in this type of market the price differs significantly from fundamental values, so they can trade profitably.

Informed traders want prices go toward their evaluations about intrinsic value only after they have taken position in one side of the market.

Since the price impact generates transaction costs, informed traders must minimize them in order to trade as profitable as possible. They then should decide if trading aggressively or not.

Aggressive trading is profitable when they suppose that their private information become public so they must trade when they are more informed than other traders because they make profit when the price differs significantly from fundamental value. The second case in which the informed traders can make money is when they think that they are not the only one to trade in the same information. Who is the first to trade, he will profit most. In order to trade profitably, they must trade as quickly as possible.

Another strategy is called *stealth trading*: informed traders can decide to trade slowly because they believe that they will not lose their advantage. So, it will difficult for other traders understand that the first have informational advantage.

The notion and the study to discover how to quantify fundamental values attract all type of informed traders. Fundamental or intrinsic value changes constantly as the situation and variables change. People that understand these changes trade on them. In particular, as we will examine later, news traders first trade and make money. Value traders recognize their mistakes and trade on the resulting profit opportunities. Informed technical traders make money recognizing systemic and predictable mistakes of the news or value traders.

If the values change because the common valuation factors change and if the arbitrageurs believe that the similar instruments are not correctly priced relative to each other, they make profits.

Like the value traders, arbitrageurs can recognize this situation and they trade profitably if the price changes cause them to conclude that similar instruments are no longer priced correctly relative to each other. If it is not true, they will make losses.

When uninformed traders make small trades on the same side of the market or large trades, they make price go away from fundamental values. It is hard to distinguish if the change of value is due the trading of informed or uniformed. Value traders are the most able traders to recognize this situation but they must to be very sure because there is a risk to trade with news traders and they will lose. Also technical traders can recognize and so make money when the uninformed traders trade.

In the next section we try to analyze how the trading of informed is profitably and how they affect the liquidity and the market.

1.2.1.1. Profitability of Informed Traders

If informed traders are able to forecast the future price changes and the impact on prices, their trading profits must cover: their costs of acquiring and processing their information, their commission costs, the value of their time and all other normal costs of doing business.

Liquidity is the variable on which the success to trade of informed traders bases. When no traders are willing to trade, the liquidity is not so expensive because there is not competition. In this case, the trader will make a successful trade. Although the trade is profitably, a question arises: why no one wants to trade? The answers can be two. The first is because informed traders have unique and reliable information that no one trader has and they have valuated correctly the fundamental value and thanks to the cheap liquidity, they make profits.

The second is because, even if their valuation is not correct, the low price liquidity, that they acquire, increases their profits.

Liquid market, indeed, is "a market allowing the buying or selling of large quantities of an asset at any time and at low transactions costs."[20] Liquidity is the ability to quickly trade large size at low cost.

To trade profitably, the informed traders have to act in a very liquid market. If they are very well informed but they trade in a very illiquid market, they do not make money. It is better to be a less informed trader in liquid market rather than very well informed trader in an illiquidity market.

The most successful informed traders trade gathering material information more efficiently and with less price impact. Instead, the traders, who collect material information at high cost or who trade poorly, can fail. A trader can be stay in business and he is not successful if only covers their total expenses.

[20] Source: http://www.nasdaq.com/investing/glossary/l/liquid-market

If the trade becomes very profitably, many traders enter in the market and they compete each other. So, in this way profits drop. Even if the trading becomes less successful, the trade of informed makes the price more informative closer to fundamental values. More traders in the market bring less opportunity to profit.

Obviously, informed traders do not want to communicate their information because they cannot understand if they are better or less informed with respect to other; they have to use indirect methods to predict their profitability, which is the most important obstacle for informed traders.

According to Harris (2003) "the entry and exit of informed traders is a slow process because traders cannot easily predict how profitable their operations will be. Since informed do not share this information, their usually do not know how well informed they are relative to other informed traders. They therefore must use alternative methods to predict their profitability".

To sum up, the trade is successful when the trader estimates the fundamental value base on news that other traders do not have and with different methods to use to analyse the data available.

Moreover, the valuations have to be orthogonal and *not correlated* with each other. Indeed, if the traders estimate the value with the same model and based on the same info, the results will be equal and will be highly correlated. They must compete with each other to make profit from their analysis.

Precision and *orthogonality* are the two features that increase profits and make successful the trading. The valuations about fundamental value have to be precise and orthogonal. The most successful traders must have unbiased and accurate estimates of value. These have to be uncorrelated with the valuations of other traders.

Of course, the valuations cannot be perfectly orthogonal and completely precise. A trade-off can exist. A trade can be successful with precise but highly correlated valuations or with orthogonal but imprecise value estimates.

People often study past performance if they want to predict future profitability. It analysis is reliable only if the variables that were important for past performance will last to be relevant for future performance. [21]

So far, we analyzed the profit of informed traders, how they move the price to fundamental value, and how the price becomes more informative thanks to their trading. Nevertheless, a

[21] Analysts can use analytic or statistical methods to establish if the performance is related to luck or skill.

paradox arises: if prices reflect quite the information, as we have seen before, informed traders will not want to trade because they know that their trade will not profitably. So, if informed trading does not make money, informed traders will not trade and prices will not reflect correctly the information. We propose two solutions of this paradox.

The first can be that the fundamental value is well known by everybody. In this way, prices reflect the information even if there are not informed traders in the market. This argument can be not real because generally the values are not very known. The second solution is linked to this point. Prices do not reflect very well the information. When these diverge meaningfully from fundamental value, informed trading will be profitable. Hence, by making the price more informative, they eliminate other profit opportunities, and at a certain point they do not trade further. If prices or values change, prices then may be very different from values so that informed traders can again make money by trading. Since prices and fundamental values change, the informed traders make prices more informative but not always. Indeed price can differ from fundamental value because they do not change in the same way or because only price or only the intrinsic value change or because the uninformed traders act in the market.

1.2.2. Uninformed Traders

Harris (2003) gives a definition of uninformed traders: "they do not know whether instruments are fundamentally undervalued or overvalued. Either they cannot form reliable opinions about values or they choose not to. Uninformed traders include utilitarian traders, futile traders and some types of profit motivated/oriented traders".

As we have seen before, informed traders do not trade profitably if they trade with other informed traders. The better informed will profit at expense of the less one that eventually decide to stop trading because they understand that they are losers. So the informed traders make money only if they trade with uninformed traders. Since uninformed traders can sustain their losses because they obtain other valuable services from the market[22] they continue to trade.

Generally, the uninformed traders do not want to trade with informed traders because they do not wish to lose. If the uninformed traders know that there is an informed trader in the trade, the first will not trade anymore. So since informed traders want to trade profitably, they have to hide their identity and pretend to be uninformed traders. Indeed informed trading is most

[22] Uninformed traders can be investors, borrowers, hedgers, asset exchangers or gamblers.

profitable in markets with uninformed traders and in which traders can easily identify informed traders. In which type of markets the price reflects less the information.

The impact of noise traders[23] on market liquidity can seem irrelevant. Glosten and Milgrom (1985) instead demonstrated that the noise traders reduce the permanent impact of trades and the temporary price impact of trades.

Bloomfield *et al.* (2005) proved that "noise traders who trade as contrarians[24] for behavioral reasons will increase volume, and will also reduce the temporary price impact as they attempt to reverse recent price movements. Noise traders who act as momentum traders[25] will increase bid-ask spread and temporary price impacts as they pile on to prior trades." They also have showed that the volume is bigger in a market in which there are noise traders rather than a market without noise traders. Their findings suggest that "noise traders are more active when security prices appear to be farther away from their expected values, consistent with their acting as either rational momentum traders (who are reacting quickly to price movements)". They increase depth[26], submitting more limit orders than market orders. [27]

Generally, noise traders sell when prices increase, and buy when prices go down. The authors explain that "this strategy can potentially work well in term of earning small profits by providing liquidity when the underlying value of the security is stable. But this is exactly the wrong strategy when security prices are adjusting to valuable new information".

The models proposed by Froot *et al.* (1992) and by Allen *et al.* (2006) consider the situation in which there are investor in short term period who are rational and have a good information on fundamental but they cannot receive dividends and they have to sell their instrument to have returns. The authors have demonstrated that "First, when informed traders have short trading horizons, they are unable to engage in arbitrage and stock prices are perturbed by noise trader demands. Second, even when informed traders have long trading horizons, informed traders' arbitrage remains imperfect and noise traders still (although less severely)

[23] Uninformed traders are also called noise traders.

[24] Momentum trading strategy consists in buying when prices are going up and selling when prices are going down. This strategy destabilizes the price in the market.

[25] Contrarian trading strategy consists in buying when prices are decreasing and sell when the prices are going up. This strategy stabilizes the price in the market.

[26] One of the four dimensions of liquidity that it is dealt with the size of a trade, given the cost.

[27] The authors explain: "The results thus far indicate that noise traders can influence market behavior, but exactly what they are doing in the market is less clear. As a first step to understanding their behavior, we consider their trading strategies, and in particular the taking rate of limit orders. The Taking Rate is defined as the number of shares a trader trades by submitting market orders divided by the total number of shares he trades (where the denominator consists of both market and executed limit orders). The higher the taking rate, the more the trader transact by demanding rather than supplying liquidity. The Taking Rate also speaks to the aggressiveness or trading urgency (as opposed to patience) demonstrated by traders."

affect stock prices." So, the stock prices are affected by the uninformed traders and the impact on prices is more meaningful when trading horizons are short. Moreover they continue "even when informed traders have long trading horizons, short sales constraints limit their arbitrage and noise traders still affect stock prices, although their effect is less severe compared to that in short-horizon sessions."

To sum up, noise traders produce effects and impacts in the market. They decrease spreads and the temporary trades impact on price and their presence permit to informed traders to reduce the losses. Indeed, more money noise traders loose, more profits come to informed ones. The noise traders generally make liquidity rather than take it. These impacts are generally positive, but there are some negative aspects. In fact, when they trade they obstacle the adjustment of prices toward the fundamental value, especially if the market is least efficient.

Now, we want to analyze the types and the trading strategies of the informed traders in order to understand better what we will explain in the second part. In particular, we will analyze if the arbitrage, fundamental and technical analysis can be work in the financial market.

1.2.3. Types Of Informed Traders

1.2.3.1. Value Traders

Value traders are informed traders that collect and analyse through economic models all available information in order to evaluate fundamental value. They gather information about sales, costs, economic activity, interest rate, management quality, potential for competition, growth options, labour relations, input prices, prospects for new technologies, and other info useful to discover the true value.

The aims of value traders are: to forecast and to discount future cash flow, to value the option associated with the assets underlying the instruments, and to value any options associated with ownership of the instrument itself.

These categories of traders include financial analysts, statistician, actuaries, macroeconomists, industry economists, marketing professionals, accountants, engineers, scientists, computer programmers, librarians and research assistants.

As a normal informed they buy instrument when they think that it is undervalued and otherwise when they believe that it is overvalued. So they make money when the current price is far away from fundamental value.

Large value traders usually are organized in pyramid with many steps of management. They are constructed as pyramid because in this way they can avoid estimation errors. The structure is composed of *analysts* and *portfolio managers.* Analysts work at the bottom level and they gather information and construct opinions about values of the instruments. After, portfolio managers examine the opinions about values of these analysts. The portfolio managers controls and guarantees that the analysts use feasible and consistent assumptions when they form and construct their opinions about their securities. Moreover they ensure that these analysts have considered all possible variables and information and they have not ignored relevant news. All successful traders must pay attention to their analysis to ensure that they have used unbiased assumption based on all possible information in order to make reliable opinions about values of securities and to avoid mistakes.

Value traders contrast the trading of the bluffers[28] because the first recognize when the prices move far from fundamental value and so prevent the bluffers from trading profitably.

Informed traders as bluffers act on information but the first trade on information that they collect about fundamental in order to make prices more informative, instead bluffers do not gather information about fundamental but they create their information in order to make price less informative and to fool other traders.

Since value traders understand the fundamental value, Harris (2003) sustains that “They often supply liquidity to large traders. They are the liquidity suppliers of last resort.”

Indeed, another aspect that we have to consider in order to delineate better the value traders is that they trade also *to provide liquidity to the market.*

The price deviations from intrinsic value also caused when dealers can adapt the prices even if they understand that their clients are uniformed. These price adjustments could be larger if dealers believe that no other traders will act on the opposite side of the market.

Value traders can decide if they want to trade *directly* or indirectly with the uninformed traders. In the first case value traders offer limit orders that uniformed accept or block brokers ask value traders to complete the orders for uninformed traders who demand liquidity. Value

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[28] Harris (2003) defines bluffers as traders who “profit by encouraging traders to sell when the bluffers want to buy and to buy when the bluffers want to sell. They do this by producing or distributing information that their victims use to form opinions about future prices.”

traders permit uninformed trade to trade when they are willing to trade. When value traders act in this way, they supply immediacy to the uninformed liquidity demanders.

In the second case, value traders can act with uniformed traders *indirectly*. If uninformed demanders want to sell a stock immediately, they sell to dealers who accept order. Since dealers do not recognize if these traders are uniformed or informed, they adjust the price because they think that they will be not easy match with the traders on the other part of the market in which case they will be exposed to more inventory risk than they would like to bear. In this way price drops below the fundamental value and the trade becomes successful. In order to recover the target inventory, the dealers have to diminish the quotes. When happens this, the value traders purchase from dealers at discounted prices.

Their trading makes the market resilient. The market is resilient[29] when it is difficult for uniformed traders modify the prices. The resiliency of the market is due to the trading of value traders because, when the price moves far from intrinsic value. In particular, according to Harris (2003): the market is resilient when value traders are well capitalized, well informed and willing to trade.

The price at which value traders want to trade is called *outside spread* that depends on the risks and costs of their business. The risks of their business are the adverse selection and the winner's curse.

Value traders meet with the adverse selection risk when they offer liquidity to traders that demand it. They do not know if these traders are well informed or not informed. In order to avoid this type of risk, they attempt to know all variables and news about the fundamental value. To protect themselves, they increase their spread to recover from uninformed traders the losses if they trade with well-informed traders.[30]

The second factor that affects the outside spread is the *winner's curse*. It can be related to buyer or seller. Accordingly to Harris (2003), "buyers can suffer the winner's curse when they compete to buy something that has a common, but unknown value when its value is the same for everyone." People can try to discover the true value through different models that brings different results. Some valuations can be closer than others.

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[29] Resiliency is one of the four dimensions of liquidity. It measures how fast price returns back to the previous level after an impact caused by a large trade.

[30] Dealer acts in the same way in order to cover from the losses of trading with informed traders: he widens the spread and this additional widening is adverse selection component that provokes price changes. The bid–ask spread is composed by: transaction cost component (this part compensates dealer for their normal cost of doing business) and adverse selection component, called also permanent spread component. Glosten and Milgrom (1985) estimated adverse selection component as the product of the pricing error times the probability of trading with an informed trader.

The winner's curse occurs when the buyers conclude the trade at price higher with respect to the instrument really worth. Although they win the auction, they pay more for an instrument. This happens because the highest bidders in the auction are the buyers who overestimate values. Harris (2003) explains: "If they bid at price near their value estimates, and if they pay those prices, they will regret trading if their estimates to prove to be too high. On average, those estimates do prove to be too high because extreme estimates rarely are as accurate as estimates closer to the mean estimate. Bidders who pay prices near estimates of value tend to pay too much if they win the auction."

If they take into account the consequences of to be the highest bidder in the auction, the highest bidder could understand that this estimate is highest among all buyers. In order to overcome the winner's curse they can lower their bid to reflect what they learn about their estimations on value if they win the auction. They have to decrease largely if they compete with many traders.

A relevant consequence is that when a trader keeps in contact with a foolish bid, only choice is to lose the auction. A trader cannot trade profitably with people that have strategies to lose money!

Value traders suffer from winner's curse because they act only if the current price goes away from their estimates. Of course, if their estimation is wrong, they fail and they regret trading. They make mistakes if they use wrong economic models or they don't consider relevant information.

The second feature that affects the outside spread is the *costs of value trading*. In particular these costs are the direct costs for business, such as their expenditures for research: costs to acquire and analyse data about instruments.

The spread of the dealer is narrower than the outside spread of value traders. This is due to the time, the size, the research costs, and the exposures to adverse selection; the winner's curse and total volume.

1.2.3.2. News Traders

They are info traders who try to forecast how instrument will change, collecting and gathering *new* information about instrument values. The new information is a material information because it influences instrument values.

They are different from value traders because the last ones estimate the value of an instrument from all available information. The news traders, instead, believe that the price reflects all information but not the news. Their aim is to valuate and to estimate how value will be modified by their new information.

They add their estimates about news change impact to current price, in order to estimate the total instrument values.

To trade successfully, they have to collect and act on news *before* other traders. If the information is available public, they must be fast to trade because other traders can easily collect and interpret the news. The trade will be profitable only for the traders that act before on their news.

Insider Traders

Moreover, the news traders use inside information in order to trade and to make money.

Inside information is "Material information about a company that has not yet been made public. It is illegal for holders of this information to make trades based on it, however received"[31].

In many countries such as USA, this type of trading is illegal in order to ensure the fairness in the market under the Rules 10b5-1 and 10b5-2 adopted by the SEC.[32]

People who sustain the restriction of insider trading believe that the restriction increases the investor confidence in the market because the trading with the inside info is not a fair trade. Furthermore, if the insider trading is restricted, the transaction cost for uninformed traders would be reduced because a relevant part of informed traders could not trade. This would make the market more liquid for uninformed traders.

Insider trading rules ensure that the manager labour market act efficiently and they maintain publicly traded companies productive. Without the regulation, shareholders would know less about the company and corporate directors would lose the control over manager.

Nevertheless, identify the insider trading is not easy. The inside information can be very well hidden: the successful trade can be due not to inside information but thanks to precise estimation, accurate valuation, good advice or skilled speculation.

[31] Source: The Entrepreneur's Dictionary of Business and Financial Terms.

[32] Rule 10b5-1 provides that a person trades on the basis of material nonpublic information if a trader is "aware" of the material nonpublic information when making the purchase or sale. The rule also sets forth several affirmative defenses or exceptions to liability. The rule permits persons to trade in certain specified circumstances where it is clear that the information they are aware of is not a factor in the decision to trade, such as pursuant to a pre-existing plan, contract, or instruction that was made in good faith. Rule 10b5-2 clarifies how the misappropriation theory applies to certain non-business relationships. This rule provides that a person receiving confidential information under circumstances specified in the rule would owe a duty of trust or confidence and thus could be liable under the misappropriation theory".
Source: http://www.sec.gov/answers/insider.html.

Not all people want to restrict the insider trading. They believe that it brings price efficiency because they think that, since insider traders have the knowledge about the new, they make prices more informative. They also consider hard to detect the insider trading, so the costs of enforcement this law would be high. Moreover, insider trading could incentives the entrepreneurial behaviour by manager, according to Manne (1966). Indeed, managers who have smart ideas can benefit implementing these ideas buying stock in their firm before the plan is revealed and selling the stock when the new information is in the price. Insider trading permits them to become entrepreneurs.

As we have seen before, news traders must act on information before the price reflect the news, i.e. if information cannot be used to predict future changes of price. In this case, the information is in price.

The information can be old and can be *already* in the price. It is called *stale information*, when all traders understand the significance of the news or when they push the price towards their estimation of fundamental.

No one can trade profitably on stale information. When a trader acts on it, he is called **pseudo informed** trader because he believes that he is well informed but in fact he is not. They are uninformed traders; they buy when prices are already high and they sell when the price is already low, so they lose.

Successfully news traders must understand if the new information is already in price or not before they trade. They must evaluate the instrument from the first principles. They generally trade wrong because they do not estimate accurately as value traders do.

1.2.3.3. Technical Traders

Technical traders identify recurring price pattern in order to forecast the trend of price. Harris (2003) defines them as "Information-oriented technical trading consists on recognizing ad trading on mistakes made by informed traders. By correcting the mistakes, technical traders cause prices to reflect more accurately the information that the informed traders have. Information-oriented technical traders identify violations of abstract statistical proprieties that characterize informative prices."

In fact, they can act as dealer when they offer liquidity to uninformed traders and with their trading, make the price more informative.

They can act also as order anticipator when they attempt to front-run the uninformed traders; in this case they also called sentiment-oriented technical traders and they make the price less informative.

When they try to identify predictable patterns, they analyse price and volume. They estimate frequency distribution, run regression or construct models like neural models.

A shortcoming of technical analysis is its effort on recognizing the pattern of the price rather than the economic analysis of intrinsic value through fundamental information. It is difficult the profitability of the technical analysis in efficient markets. Indeed, to trade successfully, the technical traders must accurately do predictions on price changes. Harris (2003) sustains that in efficient markets, price changes are unpredictable because prices are close to value and because value changes are unpredictable, so the price cannot be forecasted in reliable way.[33]

1.2.3.4. Arbitrageurs

Harris (2003) defines arbitrageurs as traders who "simultaneous buy and sell similar instruments. They try to identify instruments that are inconsistently priced relative to each other. They buy the cheaper instruments and sell the more expensive ones. They profit if the cheaper instruments appreciate and the expensive ones depreciate, if the cheaper instruments appreciate faster than the expensive ones, or if the expensive instruments depreciate faster than the cheaper ones."

The term "similar" refers to the fact that their values depend on common fundamental factors that is a variable upon which instrument values depend, such as: macroeconomic variable (interest rate, GDP, unemployment, inflation), industry (sales, wages, prices, product innovations, competitive conditions), physical (weather, agricultural pests, solar activity), political (legislative, executive, judicial, military interventions) and social data (crime, social unrest). This leads to implement the *law of one price.*

Their trading corrects the price because they make the price more informative and facilitate to rationalize the security prices because they trade when they understand correctly that an inconsistency of priced instruments exists. If the two securities depend on the same factor (e.g. soybean), the price of both of them should replicate the common factor and should both reflect the equal information about the common factor.

[33] In the second part of this work, we analyze the efficiency of the market and we try to understand if the price trend can be predicted.

Arbitrageurs, in order to trade profitably, must not estimate correctly the single instrument, but *the differences in value*. Their strategy consists in simultaneously buying and selling similar instruments in order to preserve themselves against price changes. In particular, if all instruments are undervalued so the price goes up, they trade profitably if they buy and they make losses if they sell. If all instruments are overvalued so the price goes down, they earn money if they sell and they lose if they buy.

Lamont and Thaler (2003) explain: "The risks to arbitrageurs are particularly large in situations without a specified terminal date. One risk is that after taking a position, the valuation disparity widens, causing the net wealth of the arbitrageurs to fall."

The transaction costs in the trade are represented by the price impacts. The less impact on price provokes more money; their trade will be profitably if, after they set their positions, the prices will adapt and modified correctly with respect to their proper relations. Arbitrageurs, instead, lose money when they wrongly believe that securities are not correctly priced relative to each other. This occurs when only the price if an instrument changes and the price of a similar security does not modify.

PART II.

2.1. CAN THE MARKET BE EFFICIENT?

In the first part, we have described the structure and the actors in the market. Thanks to this description, we are able to understand and know the rules that govern the market and how the traders operate on it.

In this second part we attempt to discover if the market is efficient and if the price changes can be forecasted.

2.1.1. What does "market efficiency" mean?

"A professor who espouses EMH is walking along the street with a graduate student.
The student spots a $100 bill lying on the ground and stoops to pick it up.
-Don't bother to try to pick it up,- says the professor.
-If it was really a $100 bill it wouldn't be there.- "
B. Malkiel

The primary task of capital market is to allocate the ownership of the economy's capital stock. The market, indeed, should provide an accurate signals for resource allocation: Fama (1965) wrote "that is, a market in which firms can make production-investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time "fully reflect" all available information. A market in which prices always fully reflect available information is called efficient."

In general terms, the market is efficient when the price reflects fully information in a correctly way. In fact, the information is never in the price. The efficiency of market depends also on the cost of acquiring information. If the cost is very high, no one informed trader would obtain and act on it because their trading would not be profitable. The first author who gives the definition of market efficiency was Fama.

In order to test the Efficient Market Hypothesis, mathematical models assume that price follows a random walk.[34] Indeed, if prices of financial instruments fully reflect the

[34] In the following part, we concentrate our attention on Random Walk theory and what this implies.

information available, hence the price fluctuations would have the same features of independence of news that affect the market. So, the price changes fluctuate in a random way with the features of Brownian Motion. It is a stochastic process without memory and it cannot be possible to forecast the future prices changes. There is not any correlation with the past.

Hence, can market be really efficient?

Some authors believe that the market is structurally inefficient. Even if all participants had all available information at the same time, the information cannot be translated by everyone in order to sell or buy securities. Agents having different investment plan and financial liquidity, there are always at each level of price buyers and sellers.

The efficiency is a limit condition toward which markets can aim but they can reach it only in determinate situations. An example can be taken from diffusion of some important data in American economy in short term. Data on exchange ratio dollar/marco and on Treasury bond provoke unexpected price fluctuations to a level that the market will be in equilibrium. Generally, speculators act on the market betting on fundamentals, betting the risk of to assume a position.

Before the Fama's studies, at the beginning of 1900, Bachelier laid the groundwork because he compared financial market to fair play in which sellers and buyers acting on the market produce prices of financial instruments that are fair and they reproduce the correct value. Obviously, the fact that, the trade is a zero sum game and all investors have the same necessary information to promote financial investments, induce to deduce that *it is impossible to beat the market*. In order to amplify the returns, rational investor has to anticipate, with different and risky strategies with respect to others actors in the market, the future price changes identifying the potential price trend. In order to understand this, we propose two examples.[35]

At the beginning of analysis, a technical trader, considering for example the charts of the time series of price, can identify signals to sell or buy. Indeed, if the price follows a positive trend, can he buy the financial instrument with the prospect to sell it?

This situation, according to definition of efficient market, would be impossible because, given the huge volume traded and the numerous investors, the technical trader can be anticipated by

[35] Taken from Mandelbrot, B. B. and Hudson, R. L. (2004).

other traders who sell or buy in the same. This caused that they forerunner the trend of market and eliminate the prospective of returns created by the initial investors.

Another example can deal with the financial analyst who identifies an error in the financial structure of a company after examining the balance sheet and income statement. He can propose to give less weigh on portfolio to the financial instrument of this company, with the aim to short sell it, speculating downward on the stock analyzed. If it occurred, in a financial market characterized by numerous traders that would do the same action making the effect null, this would be reflected in the price bringing to reach the fair value of the security.

Thanks to these examples, we can deduce that, passing from one trading instant to other, the traders in the market "zero sum game" and fair play, after assimilating information, would make indifferent the use of information, moving the price of security towards to its fair value.

In order to define the efficiency of market, Fama (1970) formulated the following model:

Events occur at the moment t-1 and t+τ, C=0, 1, n.
Define Φ (τ-1) as the set of available information at time t-1 that is relevant to determine the price of the securities.
Define Φ m (τ-1) as subset of Φ (τ-1).
P (j, t-1) is the price of security j at the time t-1 for j=1, 2, n with n stands for the numbers of securities.
f (p, 1+t+r…p *n*, *t+r* I Φ (τ-1)) the join probability function of securities prices at time t-τ fixed by the market at time t-1 given the information subset Φ m (τ-1).
The information set Φ (τ-1) includes the state of the world at time t-1 according to the information dealt with real variable such as monetary aggregate, GDP, dividend, consumption and others. The actors in the market have the same available information in order to choose their investment. We assume that we know the consequences of current state of world (i.e. t-1) for the join probability distribution of prices of securities in future time. This means that Φ (τ-1) implies the join function f (p, 1+t+r...p n, t+r/ Φ (τ-1)).

The process to create prices works in this way: on the basis of information Φ m (τ-1), the market fixes a distribution of prices for time t-1. On this basis and in relation to determine the prices in equilibrium, the market determines the appropriate current prices for each security. Thus we can affirm that the market is efficient if Φm (t-1) =Φ (t-1), i.e. if the information set that the market use to determine the security price include, and so it fully reflects, the complete available information. As result, this implies also that market known the consequences about available information of join return distribution. (This seems to underline that actors in the market, having the knowledge about the parameters in the model proposed, can formulate the approximate valuations of security prices).

These conclusions contrast with the theory of Keynes (1937)[36]. He affirmed that the actors in the market, during the phase of selection which security choose in portfolio, proceed following the opinion that the remaining part n-1 actors in the market would have had according to stock to be sold or bought and not pondering on macroeconomic variables or on expected return of financial instrument.

Fama (1965) specified that the market conditions consistent with efficiency are:

- There are no transaction costs in trading securities;
- All available info is costless available to all market participants;
- All agree on the implications of current information for the current price and distributions of future prices of each security.

In this type of market, the information is reflected perfectly in the price.

As we understand, this description of market is very not real. A world without transaction costs and a world, in which the information is simple and costless, do not exist in reality. These conditions are not necessary condition to efficient market, they are only *sufficient*. Indeed, we can say that a market efficient ca be efficient if the *sufficient numbers of investors* have ready access to information.

According to Fama (1991), "But though transaction costs, information that is not freely available to all investors, and disagreement among investors about the implications of given information are not necessarily sources of market and inefficiency, they are potential sources. All three exist to some extent in real world market". It is important to valuate and measure the impact on process to form price.

[36] Keynes, J. M. (1937). The general theory of employment. *The quarterly journal of economics*, 209-223.

2.1.1.1. Three levels of efficiency

The efficiency level of market can be analyzed from three different perspectives. The three views are weak, semi-strong and strong form efficient.

The market is **weak efficient** if the prices reproduce all information in past prices. In this way no one can forecast the changes of price in the future having information about the past. In this level the price follows a random walk, so the technical, statistical and chart analysis are futile. An example of weak efficiency is *weekend effect*, analyzed by Cross (1973), and French (1980). If a trader buys financial instrument on Friday with the perspective to sell on Monday, he will obtain negative returns because some traders would not exploit the opportunity to sell short securities on Friday to rebuy on Monday, not obtaining profit.

Another analysis done by Roll (1988), examines that prices of security of small companies, often lose the pre-Christmas a value between two and three percent and on the first month of the New Year. It is called January effect.

The second level is when market is **semi-strong efficient**. This means that the prices reproduce all public available information. This brings that no one anyone individual can forecast the future price changes only from public information. Contracts, public news, past prices, volumes in all securities and other variables are in public news. The trade will be profitably for informed traders if they have access to information not public.

Public information means data from income statement and balance sheet, reports and balance sheet that are available for everyone in order to promote the regularity and transparency of the market.

Finally, the market is **strong efficient** if all available public and private information is in the prices. In this type of market no one informed traders can be make money. In these markets, instruments common known are traded. Samuelson (1973) sustained that the strong efficiency level refers to the information public available with respect to confidential information that are reflected stock market prices. So, it could be argued that the outsiders and insiders would be unable to beat a benchmark, as they have fully corporate information. In fact, this form of efficiency information is entirely foreign to the market, although it is improved with the latest regulation on insider trading and market manipulation. The presence of information asymmetries due to the rapidity with which a shareholder can obtain data of the company in which he has a job management with respect to minority shareholders, will make always unfair use of the information, given that, between the moment in which it is detected the relevant news in order to speculate and the moment will be transmitted to the market, in this time lag, the insider may place an order for buy earlier than others outsiders, earning a profit thanks to the corporate position privileged.

Fama (1970) tested these hypothesis. The findings are strongly in support. Although the results show that there is a statistically evidence for dependence in following prices fluctuations, the remaining part of findings is not enough to demonstrate that the market is inefficient. Hence, he affirmed: ”a consistency evidence of positive dependence in day-to-day price changes and returns in common stock exists”.

This kind of positive dependence imply a positive and near to zero correlation that it is demonstrated also through the Alexander filter[37]. If we amply the concept of market efficiency, we state that we do not reject the hypothesis of efficient market. Other authors demonstrated that a positive dependence exists but it is not used to trade profitably. Moreover, Fama in the same work wrote “shows that large daily price changes tend to be followed by large changes, but of unpredictable sign”.

Finally, as noted earlier, the strong-form efficient markets model, in which prices are assumed to fully reflect all available information, is probably best viewed as a benchmark against which deviations from market efficiency (interpreted in its strictest sense) can be judged.

To sum up, the proof in support of the efficient markets model, in the Fama’ s words, “is extensive and contradictory evidence is sparse.” Indeed, many researches have tested and proofed the market efficient hypothesis. In the next section, we outline the development of definition of efficient market and how it is changed according to the real world and to the economic and financial circumstances.

[37] It is a trading strategy in which technical analysts construct rules consisted on percentage changes in price from previous lows and highs when they want to buy or sell. The filter rule is based on the conviction that increasing prices keep on going up and decreasing prices keep on going down. It is often viewed as subjective screener, because it is set by an analyst's interpretation of a stock's historical price history.

2.1.2. The development of the concept of market efficiency

Fama was the first that defined the concept of efficient market. After this author, many and many have studied if the market is efficient. In the past years, Grossman and Stieglitz (1980) have found “the impossibility of efficient market”.

Their results show that if the market is efficient, price reflects fully information. Nevertheless, if the acquisition of information is costly, then nobody will want to acquire it. However, if the information is not obtained, the market will not be efficient and it does not produce information to anyone. If we add perfect competition, characterized by small and atomistic price takers, hence individual can acquire info, trade on the basis of it without moving prices.

If prices don’t change due the perfect competition, then their information is not in price. So, the market cannot be efficient and competitive at the same time: *efficiency and competition together do not exist.*

They construct a model in which prices reflect partially the information of arbitrageurs. They obtain compensation, paying the information. They have shown that when traders have not to pay a lot or when they have very precise information, there is equilibrium and the information is revealed by the market. If the beliefs of arbitrageurs are heterogeneous, an impulse arises to create a market.

Nevertheless, the heterogeneous beliefs are endogenous, so the information became expensive and the price system becomes informativeness. The creation of new market depletes these beliefs, which gave rise to them and this causes the elimination of the market. Grossman and Stieglitz (1980) assert “If the creation of markets were costless, as is conventionally assumed in equilibrium analyses, equilibrium would never exist. There is a fundamental conflict between the efficiency with which markets spread information and the incentives to acquire information”.

Finally, Grossman and Stieglitz (1980) conclude: “Thus, we could argue as soon as the assumptions of the conventional perfect capital markets model are modified to allow even a slight amount of information imperfection and a slight cost of information, the traditional theory becomes untenable. There cannot be as many securities as states of nature. if there were, competitive equilibrium would not exist.”

The concept of efficiency is extensively studied, analyzed and questioned by a huge number of academics and researches.

2.1.2.1. Does market efficiency mean absence of anomalies? More recent studies

Schwert (2003) studied the market anomalies and he shows that when anomalies are published, practitioners implement strategies analyzed by the papers and the anomalies subsequently undermine or vanish. In other words, research findings induce the market to become more efficient.

In particular, anomalies in the market are empirical evidence that the market is not efficient and they are not consistent with maintained theories of asset-pricing behavior that do not identify the market inefficiency or inadequacies in the underlying asset-pricing model. It is studied in the academic literature that it seems that anomalies vanish, nullify, or weaken. Schwert (2003) investigates if "profit opportunities existed in the past, but have since been arbitraged away, or whether the anomalies were simply statistical aberrations that attracted the attention of academics and practitioners." If we consider the anomalies in relation to behavioral theories in order to create new asset pricing models, we can create models that explain and outline some of these inefficiency and anomalies, but they cannot make forecasts for the behavior not yet tested and studied.

Indeed, the well-known anomalies in the finance literature do not maintain in various sample periods. In particular, it seems that *the size effect and the value effect vanish* after the papers that outline them were published. At about the same time, investors implement the trading strategies analyzed in the academic papers. For example, the weekend effect and the dividend yield effect have lost their essence and their forecast power after the papers that made them well known.

Moreover, Schwert (2003) continues: "the evidence that stock market returns are predictable using variables such as dividend yields or inflation is much weaker in the periods after the papers that documented these findings were published."

Another author who investigated the market efficiency was Blakey (2006); in particular, he concentrates his attention to circumstances according to the market is efficient. They are:

there are no participants use market power, new information circulate very rapidly, and prices reflect the unbiased valuations of who act in the market who take decision rationally. In this way, the information known by everybody is already in the price and only news can affect the price. He wrote: “The impact of new information on perceived risk is randomly positive or negative (because any known bias is already reflected in the price). Price fluctuations are the market’s responses to new information and are also randomly positive or negative.”

Most practitioners think that the price pattern is affected by at least four factors that are fundamentals, sentiment, liquidity, and manipulation and that they can gain a statistical advantage if they positioned on the profitable side of each factor. Blakey (2006) asserted that “a belief that sentiment plays a central role in price behavior is perfectly consistent with high levels of randomness.” The author explained that the variations in sentiment increase in the short and medium term the perception of fundamentals. If the sentiment is meaningful in order to determine the price pattern, the efficient market hypothesis are invalidated.

As we have said in the first part, the liquidity and the manipulation, that can be legal or illegal, bring to fail the correctly reflection of the info in the prices.

Individuals who trade and affect the equilibrium between supply and demand can manipulate also in legal way the market. For example, institutional traders that buy or sell large amounts do not want a negative effect on the price that they obtain or purchase. So, they do small trades in the opposite side of the market with respect if they buy or sell in order to increase or decrease the price. This attracts the traders who gather and strengthen the short-term trend, thereby procuring raised supply or demand in the way that the institutional trader is searching for.

Another example is correlated with the “window dressing”. Some mutual funds, at the end of each quarter, purchase small amounts of other stock. In this way, they raise the apparent value of their holdings that they present to shareholders. Blakey (2006) explained: “Underwriters of secondary offerings who receive an overallotment option are able to short stocks prior to the announcement of the secondary offering and then cover their shorts using their overallotment. Thinly traded stocks are very vulnerable to being manipulated via relatively small quantities of purchases or sales. This explains the eternal popularity of “pump and dump” schemes run.”

2.1.2.2. The Adaptive Markets Hypothesis by Andrew Lo (2004)

Andrew Lo was another author that criticizes extensively the market efficiency and he asserted[38] that "the degree of market *inefficiency* determines the effort investors are willing to expend to gather and trade on information, hence a nondegenerate market equilibrium will arise only when there are sufficient profit opportunities, that is, inefficiencies, to compensate investors for the costs of trading and information gathering." The investors can see these profits as 'economic rents' that those willing to engage in such activities collect. Who are the providers of these rents? Black (1986) provides an answer and he affirms noise traders because they are traders who act on what they believe to be information but it is a noise.

The efficient market hypotheses are so questioned because they are not well defined and empirically rejectable hypothesis. In order to make it more practical, it is necessary to delineate additional structure, e.g. informational structure or preference of investor. In this way test of EMH would be a test for other hypothesis. For example, the stock market are too volatile and this can be due to the inefficiency of market, risk aversion or dividend smoothing.

An example provide by Farmer (2002), in which the market is structured with a non-equilibrium market mechanism in which it is possible to obtain analytic results, holding a good degree of reality. The traders are computational entities that use strategies built on limited information and they make money or losses thorough their actions. He notes that successfully strategies continue to persist and accumulate capital during time; instead the strategies that provoke losses may vanish.

Lo (2004) gives an interpretation of this situation. He views the financial market "*as a co-evolving ecology of trading strategies*. The strategy is analogous to a biological species, and the total capital deployed by agents following a given strategy is analogous to the population of that species. The creation of new strategies may alter the profitability of pre-existing strategies, in some cases replacing them or driving them extinct."

Many studies analyze that, as the strategies evolve and fit to the situation, the market adapts and become more efficient. Nevertheless the mean of efficient is different from the efficiency of the classical EMH. Prices modify over time as result of the interaction of intrinsic

[38] Lo, A.W. (2008), Efficient markets hypothesis, in S. N. Durlauf and L. E. Blume (eds.), The New Palgrave Dictionary of Economics, second edition, Palgrave Macmillan, London.

dynamics and different trading strategies. It is not necessary that the prices reflect 'true values'; if the market is seen as a machine whose task is to determine prices properly, its inefficiency can be substantial. Lo (2004) wrote: "Patterns in the price tend to disappear as agents evolve profitable strategies to exploit them, but this occurs only over an extended period of time, during which substantial profits may be accumulated and new patterns may appear."

It is a biological perspective in which markets, instruments, investors and institution interact and evolve according to the law of economic selection. Under this view, they compete and adapt. [39]

This evolutionary view to see the market was influenced by studies of Wilson (1975).[40] It is necessary to re-conduct the EMH to behavioral alternatives: the adaptive markets hypothesis (AMH). Wilson applied the principles of competition, reproduction, and natural selection to social interactions, yielding surprisingly compelling explanations for certain kinds of human behavior, such as altruism, fairness, kin selection, language, mate selection, religion, morality, ethics and abstract thought. Lo (2004) continues "Prices reflect as much information as dictated by the combination of environmental conditions and the number and nature of 'species' in the economy or, to use the appropriate biological term, the *ecology*. By 'species' I mean distinct groups of market participants, each behaving in a common manner. For example, pension funds may be considered one species; retail investors, another; market-makers, a third; and hedge-fund managers, a fourth." He compares the profit opportunities in a determined financial market to the amount of food and water in a given local ecology (more resources, less competition).

Lo and Repin (2002)[41] have found that physiological variables associated with the autonomic nervous system are highly correlated with market events even for highly experienced professional securities traders. They argue that "emotional responses are a significant factor in the real-time processing of financial risks, and that an important component of a professional trader's skills lies in his or her ability to channel emotion, consciously or unconsciously, in specific ways during certain market conditions."

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[39] Farmer and Lo, (1999); Farmer (2002).
[40] Cited in Lo (2004).
[41] Cited in Lo (2004).

Indeed, for example, if we analyze the relation between risk and reward, it is determined also by the preferences of various populations in the market ecology (e.g. regulatory environment and tax laws).

The main implications of this view of market efficiency are four:

1. As we have just seen, the first is that is not stable during the time because it depends on relative sizes, preferences of individuals and institutional aspects[42]. These features change over time and this modification affects also the relation between risk and reward.
2. The second implication is that the arbitrage opportunities can exist in AMH (this is not possible in EMH). When they are exploited, they vanish but new profitable situations appear and other disappear as the economic and financial situation changes.
3. The third implication is that investment strategies will increase and decrease, they perform successfully in determine situation and bad in other. In the AMH view the good strategies may vanish for a time and then they come back when the environmental condition become adapt for trades.
4. The fourth implication is that innovation is the most important thing in order to survive and the survival is the only action that is relevant, so the evolution of strategies and of the markets and financial technologies are the means to survive.

2.1.2.3. The Ball's explanation on EHM

In his works Ball (2009) gives an explanation about what EHM imply. He asserts that the collapse of Lehman Brothers and other large financial institutions during the financial crisis represent a failure to follow the lessons of efficient markets in a world that is far from.

The EHM imply, according to Ball (2009) two insights. The first is that the notion that competition strengthen a correlation between profits and costs. If revenues are excessive, new entry decreases or depletes them. The second, proposed by Fama, is to view price fluctuations as a function of the flow of information to the marketplace. If we consider these two insights together bring to the EHM: competition among people who act in the market provokes the return from using information to be comparable with its cost.

[42] They can be how the society is structured, the regulatory environment and tax laws.

This fundamental idea leads directly to a prediction about financial markets' reactions to publicly released and widely-disseminated information such as corporate quarterly earnings reports. In competitive equilibrium, the profit from use public information should be linked to the cost of exploiting it. But to a first approximation, there is no cost to acquire public information, and so the gains from exploiting it should be competed away to zero.

From these, forecast that an individual cannot foresee to gain above-normal returns from exploiting publicly available information, as it already is in prices. The EMH irreversibly changed the way of thinking on how financial instrument of the markets behave.

No one should act on info: "if all investors passively indexed their portfolio, the market would cease to be efficient, because no investors would be acting to incorporate information into prices", explained Ball (2009).

The individual who act in the market believes that, since market prices already reflected all available information, there is not profit from creating information and, as consequence, prices of financial instrument differ substantially from their fundamental value.

Many sustained that the market should have forecasted the financial crisis but the EMH does not mean that one can foresee the trend of stock prices in the future in general way and in particular, the crisis. The EMH imply that we are unable to predict crisis. If we were able to forecast an event in the market, current prices would be not efficient because they would not reproduce the information incorporated in the prediction. Under the EHM, an individual can forecast that large market fluctuations will occur, but when they occur, is impossible to predict. In particular, the bubble or the collapse of large financial institutions.

Ball (2009) pointed out that the EHM do not specify "how much information is available, whether it comes from accounting reports or statements by managers or government statistical releases, what its reliability is, how continuous it is, the frequency of extreme events, and so forth. The theory addresses only the demand side of the market. The EMH says only that, *given* the supply of information, investors will trade on it until in equilibrium there are no further gains from trading."

The information in EMH is treated as an objective commodity that has the same sense for all investors.

In reality, it must consider that investors have different opinion and sentiment about the information. The market operators take decisions not only on their own opinions but also on beliefs of others. This fact become meaningful in some determinate events and rapid fluctuations price, as occurs in October 1987.

In the EMH, the process of create information is supposed costless, and the price incorporates the info immediately and exactly. Of course, in the reality the transaction costs exist and it would necessary to consider them.

The EMH assume that the market is costless to act. This is impossible to believe it because there are pricing errors, even if they are less than transaction costs. The hypothesis do not consider liquidity effects and presume the trading is continuous. It is important to consider the illiquidity as price factor, as occurs in 2007 during the crisis because generally higher returns offset lower liquidity.

Moreover, it also ignores the tax for the participants in the market. Indeed, in the real world, the actors in the market have to pay taxes and fees on dividends and capital gains. It is meaningful to understand and consider this effects.

Ball (2009) also underlines that it is difficult to test the EMH. In order to do it, it is necessary to define and specify what is an "efficient" price in relation to information. He affirms that "Normally this is done by comparing the returns earned from trading on the information with the returns otherwise expected from passive investing."

To estimate expected returns, it was used the CAPM but it resulted a bad model because betas were difficult to measure accurately.

Other methods was the Fama-French three-factor model, which is a better model to forecast estimated returns but it is based on a foundation of empirical correlations.

Tests of the EMH concentrate the attention on the analyzing the flow of information into market prices. Obviously, many types of information can change and is not independent of modifications in some variables e.g. interest rates, risk, risk premiums, and securities' risks that many of these variables will be subject to long-term secular fluctuation but what is the exact order to construct an efficient price reaction cannot be known.

Another difficulty to the EMH is that, given the individual security level, some parameters like risk or betas are very complex to estimate because they are not constant and change as reaction of other modifications of other variables, e.g. companies' stock prices. Moreover, they can be modified as reaction of some announcements e.g. distribution of dividends.

In order to conclude and sum up the theories explained above, the efficient market hypotheses have limitations and the situation is much questioned. Among economists, a consensus does not exist. There were many advances in the statistical analysis, databases, and theoretical models surrounding the EMH but the results are not able to resolve if the market is efficient or inefficient. The main result of all of these studies is to harden the resolve of the proponents of each side of the debate.

Nevertheless, the fact that the changes in stock prices are random and no one can predict them makes so hard to make money. Obviously, this is applicable to all participants in the market. Blakey (2006) affirmed that "The EMH provides a starting point for developing financial strategies that approximately match the performance of the overall market, which is as much as most amateurs can realistically hope for."

The anomalies in the theory of market efficient proliferate, such as price overreactions and under reactions, excess volatility, seasonal patterns in returns; and the relation between future returns and many variables such as market capitalization, market-to-book ratios, price-earnings ratios, accounting accruals, and dividend yields. Indeed, Blakey (2006) concludes: "No theory can explain all the data it is asked to explain: there are always anomalies. What is never totally clear is whether the market anomalies are due to imperfections in the markets themselves, imperfections in market efficiency as a way of thinking about how competitive markets behave, or defects in the research itself."

2.1.3. Anomalies in the market: Bubbles, Crashes and Black Swans

"It is easier to deceive
a multitude than one man"
Herodotus

In order to better understand the market's anomalies and efficiency, the behavioral finance provides psychological theory to explicate them in the stock market. Indeed, the market outcomes, the information structure and the features of market actors affect the investment plan of traders.

Investors are exposed to behavioral biases. This caused that their investment choices can be less rational, so the rational agent act in response to the mispricing of financial instruments caused by behavioral biases of irrational agents.

For example, it can happen that managers act in a determine way because they are optimistic and self-confidence or because they are aware to losses. In the efficient market hypothesis the investors are fully rational.

It is not adequate considering the market efficient hypothesis and the behavioral finance as antagonistic models. Behavioral finance provides important insights into the formation of expectations and the process by which valuations are determined. It is very useful in order to explain and understand bubbles and crashes that are phenomena that are very linked to the actions and psychology of individuals.

The term of Bubbles means that there is a *mispricing of financial or real assets*. Indeed, a bubble and crash can happen when the price differs from fundamental value. In particular, bubble arises when price increases substantially above the fundamental value, instead crash happens when price goes down very fast. As we have seen in the first part, the fundamental value is not known by everybody, so it is difficult to detect if there is a bubble or not. The objects of this can be one individual financial instrument at one time or many securities.

This extreme price change has implication for many people who act in the market. All individuals and institutions would have to pay very attention to this phenomenon and would have to try to understand if it occurs or not.

In particular, it has implications for many actors in the market: for traders because they are exposed to risk to lose money if the price changes very rapidly; for clearing houses because their clients would not be able to settle and conclude the trades; for exchanges and brokers because this would cause a huge volume and it can waste their trading systems and finally a bubble can have implication for micro economists and macroeconomists. The first because this extreme volatility can induce them to make a wrong decisions about the utilization of economic resources and about decision if to save or consume the money. The second because the price change can have a strong impact on economic activity, in particular on decisions about investment and on economic global situation.

In general, bubbles begin when buyers are *optimistic* about intrinsic value. The new technologies, the new market that arises can induce some individual to be optimistic, they don't understand when the information is already in the price or if there is a new information and they cannot perceive the real risk to buy and hold the security. Of course, if more trade buy at the same time, the price of instrument goes up. This induce to other trade to buy so the price continues to go up and so another traders will want to buy and so on. These kinds of traders can be momentum traders or order anticipators. Value traders and arbitrageurs can realize that there is a bubble but they are unable to contrast it because they do not have a huge amount to sell.

Prices can arise to a level in which traders want to realize and make money. So, they sell and if they are many because they are optimistic to trade profitably, they induce the price to fall down and the traders that yet have the security lose. The panic and the uncertainty provoke by the fear that prices can continue to go down, brings to other traders to sell and so the price decrease more and more until to cause crash.

The price changes as the bubbles and crashes are caused by fundamental or transitory volatility. The first is due to the information that changes the fundamental value and it has a permanent effect that means that the following price changes are not correlated to precedent ones; the second is due to the uniformed traders that demand liquidity and it has temporary effect that goes back when the value traders and arbitrageurs trade on the base on the differences between fundamental value and price.

There are many theories about the origin of bubbles and many authors have constructed and studied numerous models. Indeed, bubbles arise through *belief distortions*. Belief distortions happen because often the data available to determine if there is a bubble is not sufficient.

The author proposes two examples.

Brunnermeier (2012) explained "If there has never been a nationwide decline in nominal house prices, agents may extrapolate that house prices will also not decline in the future (extrapolative expectations). "People who act in the market participants often think in this way when the data miss."

Alternatively, belief distortions may arise on the time that is different rationale: Brunnermeier (2012) continued "while the asset price boom observed may be out of line with historical data, agents may choose to ignore this by arguing that something fundamental is different this time around, such that cautionary signals from history do not apply."

There are another models based on heterogeneous beliefs. In these, beliefs are heterogeneous because they have different prior belief distributions, as a result of psychological biases.

For example, if investors are optimistic about the precision of signals that they obtain, this brings to different prior distributions with lower variance as regard the noise of signal. Brunnermeier (2012) specified, "Investors with non-common priors can agree to disagree even after they share all their information. Also, in contrast to an asymmetric information setting, investors do not try to infer other traders' information from prices."

In models of rational bubbles, investors want to hold a security during the bubble because they believe that the price goes up in the future.

So far we have described how a bubble can form and what are the implications. Moreover we have outline how bubble burst and the consequences of crash.

Before to delineate some historical examples of bubbles and crash, it is interesting to briefly introduce the theory of Black Swan by Nassim Taleb (2007).

In his book, he explains how the man life is dominated by the uncertainty and risk. He thinks that it is impossible to manage the uncertainty and risk. He criticizes the economists who believe to predict and to forecast the fluctuations of price of financial instruments and more generally, the trend of economy. He fights against the idea that the events follow a Gaussian distribution. In this way, the events that are out of average are not considered. It is impossible apply a Gaussian distribution in the real world because uncertainty exists and it is important to consider. The world is not regular as a normal distribution; it is necessary to consider another distribution that fits better with the events of world.

Taleb defines Mediocristan a universe that fits correctly the Normal distribution and Estremistan a universe in which it is impossible to apply the Gaussian distribution, so it is necessary to introduce the Mandelbrot or Fractal Distribution. The last one can take in consideration the events that deviate from the mean and they are considered highly not probably. He extends this concept to the history and, sustaining the theory of Popper, he affirms that the inability to forecast the isolated events implies the inability to foresee the events of history. Indeed he defines the black swan is "a *highly improbable event* with three principal characteristics: it is unpredictable; it carries a massive impact; and, after the fact, we concoct an explanation that makes it appear less random, and more predictable, than it was.

Why do we not acknowledge the phenomenon of black swans until after they occur?” Part of the answer, according to Taleb, is that humans are hardwired to learn specifics when they should be focused on generalities. We concentrate on things we already know and time and time again fail to take into consideration what we don't know. We are, therefore, unable to truly estimate opportunities, too vulnerable to the impulse to simplify, narrate, and categorize, and not open enough to rewarding those who can imagine the "impossible."

In the past, there were many historical events of bubbles and crashes in which, the price was different from its fundamental value and, as we will describe, this brought a bad consequences.

2.1.3.1. Examples of Historical Bubbles and Crashes

The more ancient events of bubbles are from Mesopotamia and ancient Greek in which there was a problem of credit.

The best-documented ancient event are *Dutch tulip mania*, the *Mississipi Bubble,* the *South Sea Bubble.* All these events are characterized by the same mechanism described before. There is a huge rise of the price of a certain assets, in particular respectively in price of tulips, shares in Mississipi Company and in South Sea Company and then a tremendous falling down. These ancient events are also examples of potential contagion. Indeed, many British had purchased shares in Mississipi Company in Paris, and other from the Europe had bought South Sea Company in London.

Stock Market Crash in 1929

Coming back to 1900, the most significant crash is Stock Market Crash in 1929 when DJAIA dropped 13 percent on October 28 and another 12 percent on October 29. Before the price from 1924 to 1929 rose by almost 300 percent (Figure 2).

Many have analyzed that the bubble begun because a lot of uninformed traders, optimistic and enthusiastic for new technologies borrowed extremely to buy stocks.

Figure 2. Dow Jones Industrial Average, 1900-1950.
Source: Harris (2003)

The crash was caused because traders must sell financial instruments to satisfy margin calls following the decrease in stock prices over the previous month. Certainly, the quantity that was sold was also due to value traders who wanted to sell short, and to speculators who anticipated the sell orders that the margin calls would produce. Sellers in panic and confusion provoked prices to fall down. Even though panicked actors in the market usually do not move in successfully way, instead who sold during crash took a good decision and were lucky. If they did not sell their stock, they would have destroyed money in the next months and years.

Crash in the stock market, October 1987

Another fact is in the October 1987 in which DJIA lost 23 percent. It was a very complex event with many causes. The most notable cause of the crash was the use of portfolio insurance by institutional investors. Portfolio insurance is a dynamic trading strategy that portfolio managers use to replicate the combined returns of a portfolio plus a put option. It is hugely destabilizing to market prices. When they rise, portfolio insurance must buy stock.
Numerous factors contribute to the crash. The first can be that the prices were greater than fundamental value before crash.
Second, the enormous volumes that traders were willing to exchange during the crash were greater than the possibility of proceeding the trade of the New York stock exchange and its floor traders. The most important problem as regard to capacity implicated dot matrix printers on the floor that printed orders which traders sent to the exchange through the Superdot order-routing system.
Third, traders became in panicked when they watched the index futures market lead the stock market down. Generally, during the trading session, the index futures market leads the stock

market. This happens because index futures traders want discover the price of index risk. Instead, the cash stock market is made up of thousands of markets for individual stocks in which most traders are interested more in firm-specific risk than index risk. When prices began to fall down, they decline first in the index futures market. Traders who analyzed those declines in price understand that prices in stock market would soon go down.

Mini crash on October 13, 1989

Another crash was on October 13, 1989 in which markets fall down 7 percent. It happens after a consortium of banks that they would not sustain and to pay for leverage buyout of a parent of United Airlines, the UAL Corporation. UAL and other stocks dropped rapidly because traders had designated them as potential takeover targets. The index futures market also went down immediately and it provoked the cash market down. The market during this time was weakly because many traders had left the market removing much liquidity. The market fell down because the market was not able to manage the large demands for liquidity that traders who want to sell settled on it.

The Palladium Cold Fusion Bubble

In the same year, Martin Fleishmann and Stanley Pons published that they had obtained a cold fusion after super sating a palladium cathode with deuterium in an electrolytic cell. They asserted that the process could contribute to a clean, cheap and inexhaustible source of energy. After this announcement, some optimistic and enthusiastic traders start to purchase palladium futures contracts. The demand for palladium increase so that the price goes up by 24 percent. Then traders sold them and the price closed 6 dollars.

Another bubble deals with the removable computer disk drive. Iomega innovated the technology of Zip drive and so traders begun to buy its stock. The price increased until 1996 and the its price crashed.

The NASDAQ Bubble

The Nasdaq Bubble happened as the same facts of previous bubbles; it is called also dot com bubble. Indeed, the subjects were company of internet, telecommunications, computer and biotechnology sector. Traders, exciting and optimistic, traded on this market and put money in large and not diversified funds which in the past had a good performance. These funds placed money on the same stock held. This caused an increase of price until 2001 and this induced more investors to put money in funds. Of course, then the price dropped.

The development of internet more traders to enter in the market, even if they were not informed. The money placed by these traders, probably, contributed to the bubble of NASDAQ (Figure 3).

Figure 3. NASDAQ, 1995-2010.
Source: http://news.bbc.co.uk/2/hi/business/8558257.stm

The Japanese Asset Bubble

In the same circumstances the Japanese Asset Bubble occurred and it reached the top at the end of 1989. In Figure 4 it is possible to see the trend of Nikkei from 1982 to 2003.

In this time, the economy was characterized by productivity and efficiency. There were a credit expansion, uncontrolled money supply and acceleration of asset prices. It worked very well so many people invested in Japan. Japanese monetary policy probably contributed to the bubble. Interest rates in the mid-and-late 1980s were extremely low and the money supply grew very quickly. Many commentators said that there was simply too much money in Japan. Since Japanese investors -both individual and institutional- historically have not placed much of their money abroad, they invested the excess money locally. This money pushed up equity and real estate prices.

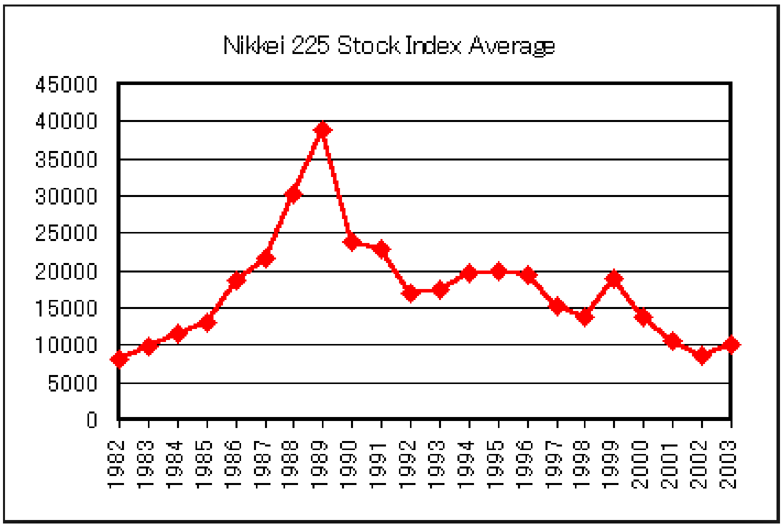

Figure 4. Nikkei, 1982-2003.
Source: http://www.grips.ac.jp/teacher/oono/hp/lecture_J/lec13.htm

Flash Crash

The Flash Crash refers to the very rapid price decline of US based equity products within an extremely short time period occurred on 6 May 2010. At that time, the major equity indices in futures were already down. This negative situation has been caused by bad news as regard the Greek debt and the diffusion of an unstable situation in the Euro zone. This get worst when an HFT selling algorithm belonging to the Waddell & Reed Financial started a sell program of important dimension causing notable price variation in US based equity products. In that case, the large fundamental trader started a sell program.

Analysing the Flash Crash is important concentrate the attention on the short time evolution of the sequence events, witnessing the portrait of a market extremely sensible and volatile. The sequence has been separated into five-phases by the SEC and CFTC.

1. From the opening to 2:32 p.m., prices were declining with stock index products sustaining losses of about 3%.
2. From about 2:32 p.m. through about 2:41 p.m. the market declining another 1-2%.
3. Between 2:41 p.m. and 2:45:28 p.m. volume exchanged spiked upwards and the market fell another 5-6% to reach intraday losses of 9-10%.
4. From 2:45 p.m. to 3:00 p.m. indices recovered while, individual securities and ETF experienced extreme price fluctuation with the presence of stub quotes.
5. From 3.00 p.m., prices of individual securities recovered and trading resumed in an orderly fashion.

The reason exacerbating this fall in prices is directly linked to the implementation of the sell order. It was calibrated on volume and does not take into account time and price.

Consequently, this large order was implemented employing only 20 minutes while the normal time is estimated in more than 5 hours. The sell pressure caused by the algorithm was initially absorbed by High frequency trader, Fundamental buyer in the future market and Cross-market arbitrageurs who transferred the sell pressure to the equity market by opportunistically buying E-mini and selling SPY or individual equity of S&P 500 index.

The major role in liquidity absorption played by the HFT, which initially sustained and stabilized demand and offer. Later HFT started to sell E-Mini contracts in order to reduce their long position, thus also them started to take liquidity worsening the situation. Moreover, to understand better the causes of this liquidity reduction, many liquidity providers were interviewed. In general, SEC and CFTC found that they significantly halted or reduced their trading activities during the afternoon of 6 May. Another reason contributed for the liquidity reduction is the reliability of quotation information. In those moments NYSE experienced a delay that went from 5 to 40 second. The products mainly responsible for these events were the E-Mini and the SPY two most active stock index instruments traded in electronic futures. Both are derivative product designed to mimic the behaviour of the S&P 500 Index (Figure 5).

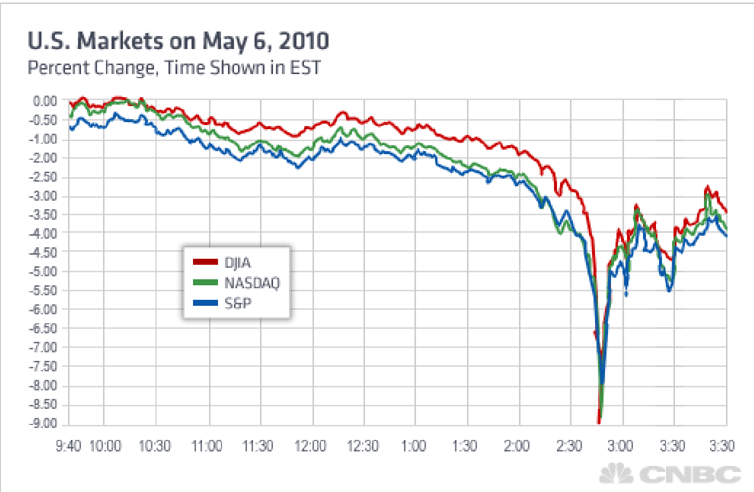

Figure 5. Dow Jones Industrial Average, NASDAQ and Standard & Poor’s, May 6,2010 from 9.40 am to 3.30 pm.
Source:http://www.hedgethink.com/education/hedge-fund-strategies/

Financial Crisis

The financial crisis 2007-2008 started in 2000 until 2006 when the prices of houses have increased so much, generating a housing bubble in the United Stated. This dynamic was favored by monetary policy of Fed characterized by low interest rate until 2004, as reaction to the dot com bubble and the event of September 2001. The low interest rates mean a low cost of money so that these encourage the demand of mortgages. The bubble moreover made convenient the mortgage concession because the bank, in the case of insolvency, can restore its position, confiscating and resell the house. In this way the bank can concede mortgages to also individual that do not have a good credit position, called subprime mortgages. Bank can cover and transfer the insolvency risk through securitization. Moreover, thanks to securitization, banks can expand their leverage (activity/Equity) and this provoked more profits but in this way they were exposed to a risk to huge losses. Through the securitization, complex derivatives were created and the role of rating agency was important. They impose the highest rate to these instruments, even if they were very risky. This process continued until 2004 when the Fed increases the interest rate as reaction to economic development. Nevertheless, this caused mortgages more expensive and so the insolvency cases increased. The demand to real estate dropped and the bubble crashed. Since entire situation through securitization was linked to bank sector, the crash moves to bank sector. The most important event was on September 15, 2008 in which Lehman Brothers failed.

Chinese Bubble

Until June 2015 there was a huge increase in Chinese Stock Exchange. The price of real estate was dropped, so individual invested and put liquidity in the capital market. The Govern moreover, in order to fight the corruption, prevented to transfer the money in real estate sector and to transfer money outside the China. So the liquidity remained in the country. In this way the majority invested in the Shanghai Stock Exchange believing that the govern would not permit that the financial market dropped. Scholarships and pensions are invested in the market and others have opened loans in order to have money to invest in the market.

After the decrease, who did not already sell, want to sell because the loan become more and more expensive. Pekin, in order to block this process, has decrease the interest rate, has requested to companies to not sell either one share, has promised more liquidity and has obliged banks to extend the loan. This situation was sustained by the central bank of China. But the crisis is contagious: also Hong Kong, Tokyo and Seoul have decreased.

2.2. CAN THE PRICE CHANGES BE FORECASTED?

Various and numerous trading strategies are systematically developed and applied in order to make money in the market. In this section, we try to analyse if these strategies work and if it possible to forecast if we will tend to trade successfully. In order to be sure that we will make money, we have to be able to predict if the price of the instrument that we want sell or buy increases or decreases. Of course, we must have information about it. Nevertheless, in order to forecast if the price grows up or declines and so make money, we have to know if it has trend or not.

In this section, we analyse if the price trend can be forecasted.

The major theory is that the price follows a random walk. The idea of random walk is often associated with the idea of market efficiency, as analysed in the previous section.

This idea comes from the Bachelier's studies of 1900. Many economists studied the model of random walk for the price. Many researches and academics have analysed and studied if the price changes follow a random walk or if the prices follow a trend or pattern.

2.2.1. The Random Walk Theory

"I have compared the results of observation with those of theory to show that the market, unwittingly, obeys a law which governs it, the law of probability."
Louis Bachelier

Bachelier sustained the idea of a "random walk" in 1900, and then by Fama who defines what does market efficiency mean. Many other have supported this theory.

In order to ascertain in quantitative terms that the model of efficient market is real, it is correct to affirm that the equation of Fama $\Phi m(t-1)=\Phi(t-1)$ consider also the concept of join probability, that it does not seem observable so much that can affirm that a link between the price distribution at time P_1,t..,Pn, t and join probability function exists, predicting that the distribution of prices is determined directly by market forces.

Bachelier constructed a model in which he considered the bond market as a balanced play in sense that it was possible to obtain positive or negative outcome with the same probability (50% and 50%).

Moreover he sustained that the fluctuations of price ex ante because no one could know with certainty all information because the prices follow a random walk, i.e. a walk that does not depend on past event but only on new information come in the market. The price change does not have any memory. From this affirmation, it can be deduced that the price changes would form a series of random variables independent and identically distributed, as by placing in a diagram the variations of the price of a security as a function of a reference period time, like a month or a year, it can see a graphical configuration similar to bell in which the numerous variations but of low intensity are positioned in the middle of the graph, while the variations of greater intensity but that occur with a very low frequency are in the extreme parts of the graph itself. The graphic configuration identified by the French mathematician became known by the term Normal or Gaussian distribution by the German physicist Gauss who first adopted it (Figure 6).

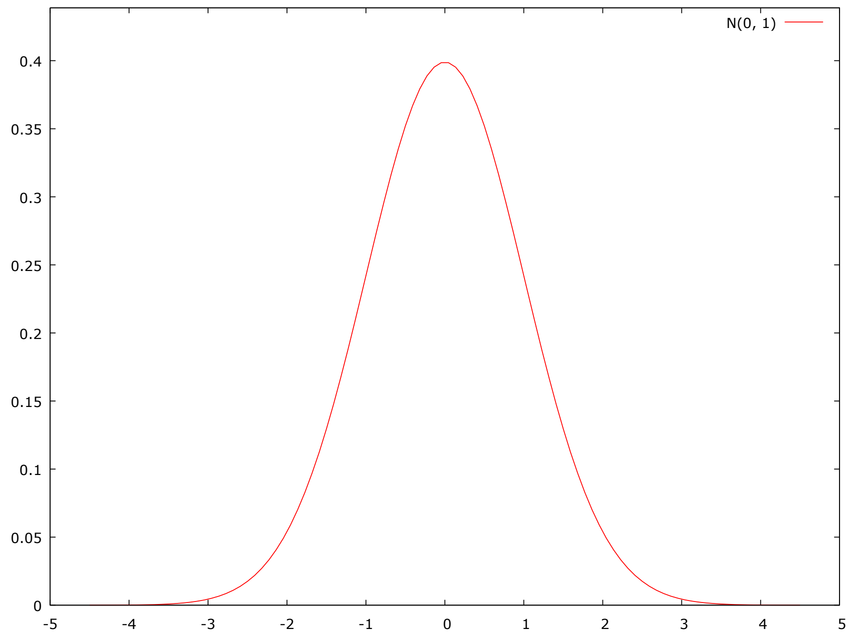

Figure 6. The Normal distribution.
Source: author’s elaboration.

In order to understand the real essence of random walk theory, it is fair to delineate what random walk is (Figure 7).

Figure 7. Representation of random walk.
Source: http://stockcharts.com/school/doku.php?id=chart_school:overview:random_walk_theory

Indeed, from the analytic point of view, in the random walk model the returns are independent and they are distributed identically. They are defined as

$\ln\frac{(Pt,j)}{(Pj,t-1)}$.

The random walk is a stochastic process and we can give three different definitions.

- *Random walk 1: Independent and identically distributed increments*

The first version of the random walk hypothesis is the independent and identically distributed (IID) increments. Indeed, it hypothesizes that all increments are independent and they have the same distribution with the same mean and variance. The process described is the following:

$$X_t = X_{t-1} + \varepsilon_t,\ \varepsilon_t \sim IID(0, \sigma^2)$$

The increments are:

$$r_t = X_t - X_{t-1} = \varepsilon_t, \qquad \varepsilon_t \sim IID(0, \sigma^2)$$

Where X is the process, ε_t is distributed with mean 0 and variance σ^2, and r_t is the increment sequence. These assumptions give a good and correct view about the random walk process, nevertheless this definition is often too strong and theoretical.

The distribution of the ε_t increments is normality.

It is equivalent to the discrete version of Brownian motion, sampled at equal-spaced intervals.

$$X_t = X_{t-1} + \varepsilon_t, \overrightarrow{\imath\imath d}\, N(0, \sigma^2)$$

- *Random walk 2: Independent increments*

The second type of random walk is independent increments.
It assumes all increments are independent but they can be have different distributions. This type in more general than the first because this definition comprehends unconditional heteroscedasticity in the increments. In other words, time-variation fluctuation is permitted in any of the form since the increments are independent. Independent increments are a strong feature that means that also the non-linear functions of increments are uncorrelated:

$$Cov(f(r_h), g(r_k)) = 0 \; for \; any \; f, g \; and \; disjoint \; h, k$$

- *Random walk 3: Uncorrelated increments*

The third type is the most general definition of random walk because it implies uncorrelated increments. In this case, for every pair of distinct increments, we obtain:
$Cov(r_h, r_k) = 0$
Nevertheless, the functions of these increments may not be 0. For example, $Cov(r_h^2, r_k^2) \neq 0$.
This is the weakest definition of random walk hypothesis.
All three definitions of random walk have the same conditional mean and variance:

$$E[X_t|X_0] = X_0 + \mu t$$
$$Var[X_t|X_0] = \sigma^2 t$$

Conditional on the initial value X_0, the conditional mean and variance are both linear with time. So, the random walk process is non-stationary because of unbounded and increasing variance.
In the following work, we analyze the evidence about the third definition of random walk.
Moreover, in the random walk process, the shocks have the same weights and so they are permanent. Indeed, if we recursively substitute $X_{t,}$ we obtain
$X_t = X_0 + \sum_{i=1}^{t} \varepsilon_i$.

The random walk is integrated process I (1), what means that the first difference is a stationary process. Indeed, if we constructed the first difference, we obtain
$\Delta X_t = \varepsilon_t$ Where ε_t=W *f* N~ (0, σ^2)
This means that the price changes are unpredictable. They have no memory of the past, so it cannot possible use the past changes and the past trend to predict the future pattern. Moreover the successive price changes are independent with the past ones. So, the price changes

fluctuate in a random way with the proprieties of Brownian Motion that is a stochastic process.

Fama defined independence in this way : “In statistical terms, independence means that the probability distribution for the price change during time period t is independent of the sequence of the price changes during previous time periods. That is, knowledge of sequence of price changes leading up to time period t is of no help in assessing the probability distribution for the price change during the period t^2.”

$Pr(x_t|x=x_{t-1},x_{t-2,}\ldots)=Pr(x_t=x)$.

The aim of an investor is to consider the random walk model as long as it is not useful to, in order to increase profits, know the past trend of the price fluctuations. He believed that the independence assumption was a good and adequate representation of the real world since “the actual degree of dependence in the series of price changes is not sufficient to allow the past history of the series to be used to predict the future in a way which makes expected profits greater than they would be under a naïve buy and hold model”, according to Fama (1970).

We assume that at any point of time, a fundamental value of each security is present and it depends on at any time we assume that an intrinsic value of security exists and it depends on the earnings prospect of the company which in turn related to economic and political factors. As we have seen in the first part, the market value does not represent the fundamental value and it is not very well know. Moreover, it changes over time due to news.

Fama (1965) has tested empirically if the stock price behavior follows a random walk. This base on two assumptions: the successive price changes are independent and the price changes conform to probability distribution.

The first assumption is proved through serial correlation model, runs analysis and Alexander’s filter technique and the independence assumption of the random walk model is a good description of reality. The two variables that provide the truth of independence are the presence of chartists and analysts. The first acts in the market and competes each other reading the charts and analyzing if there are any dependencies in the series of price fluctuations. The second compete in order to predict the price changes examining financial data, economic and political events.

There are many studies that investigate and tested if the fluctuations of price are random walks.

Burton Malkiel is a strong supporter of this theory because he believes that the prices fluctuations follow random walk process.

2.2.1.1. The broader definition of market efficiency

Malkiel (2007) considers that the fluctuations of price are unpredictable. For this reason, investors and speculators cannot be able to outperform the market. He believed that it was better to buy and hold an index fund instead of use fundamental or technical analysis. He defines as: “taken to its logical extreme, it means that a blindfolded monkey throwing darts at a newspaper's financial pages could select a portfolio that would do just as well as one carefully selected by the experts.”

The random walk theory asserts that stock prices are efficient because they incorporate and reflect all available information. Immediately, prices modify and adjust according to the new information. Indeed, prices move only when new information comes and the information is random and unpredictable.
Malkiel (2007) wrote: “The logic of the random walk idea is that if the flow of information is unimpeded and information is immediately reflected in stock prices, then tomorrow’s price change will reflect only tomorrow’s news and will be independent of the price changes today. But news is by definition unpredictable and, thus, resulting price changes must be unpredictable and random.”
He gives two theories about the investment. The first is fundamental analysis and the second is technical analysis. As regard fundamental analysis he affirms that the stocks have a fundamental value that can be detected through the “Firm Foundation Theory”. The investors after making valuations and estimation examining the volume, the financial data, the dividend, earnings and other variables, determine when it is necessary to sell or buy.
He supports fundamental analysis because he thinks that it is an advantage even if the available information reflects so quickly into the prices so that the traders cannot use it to make money. Indeed, for example, an investor can select stocks with determined features as low P/E, high growth or other. Nevertheless, it can work in the short run but not in long run. Obviously there are some evidences in which value stocks can beat the growth stock or vice-

versa but it is not an inefficiency of market, but it can be that some stocks are riskier than other so the more returns compensate the more risk. [43]

The second theory, called "Castle in the Air Theory" hypothesizes that successful trading depends on behavioral finance. Indeed, who act in the market stabilize if the market is "bull" or "bear". The estimations do not matter so much because the financial instrument is worth how the investors want to pay for it.

He criticizes the technical analysis and considers that "the technical analysis is most akin to astrology. It does not give investors a dependable way to beat the market."
He believes that if irregularities and inefficiencies of the market exist, they are very small that the transaction costs can avoid the profit for the investor.
He also rejects the idea that the prices follow a trend. It is possible that there is a periodical trend but it does not work in the long term.

A random walk means that the future steps or directions cannot be forecasted on the basis of past patterns. In particular, if we apply this term to the stock market, we want explain that short-run fluctuations in stock prices cannot be foreseen. Whatever analyses that deal with investment advisory services, earnings predictions, and other chart patterns or complicated models are inefficient.

Malkiel (2003) gives a *broader definition* of market efficient. He believes that the capital markets are far more efficient and far less predictable.
If we use a broader definition of efficient, in this mean capital markets can be efficient although there can be some mistakes in estimation as occurred during historical events described above. He wrote (2003): "Markets can be efficient even if many market participants are quite irrational. Markets can be efficient even if stock prices exhibit greater volatility than can apparently be explained by fundamentals such as earnings and dividends. Many of us economists who believe in efficiency do so because we view markets as amazingly successful devices for reflecting new information rapidly and, for the most part, accurately. Above all, we believe that financial markets are efficient because they don't allow investors to earn above-average risk-adjusted returns."

[43] Malkiel considered also the P/E ratio, that it is defined as the difference between assets of firm and liabilities divided by the number of shares outstanding. It can be used also to forecast the future returns. If the price-to-book is low, it is considered a symbol of the "value" in equity securities and is also consistent with the view of behaviorists that investors tend to overpay for "growth" stocks that subsequently fail to live up to expectations.

Indeed, many “anomalies” and statistically significant predictable patterns have discovered by some researches in the literature. However, these trends and inefficiencies are not robust and they exist according to determined sample periods, and some of the trends discovered by fundamental valuation measures of individual stocks can show better benchmarks to quantify risk. Moreover, these patterns can last only in the short period not in the long term. He studied the market efficient through these anomalies: Short-term Momentum Including Under reaction to New Information, Long-run Return Reversals, Predictable Patterns Based on Valuation Parameters, Predicting Future Returns from Initial Dividend Yields, Predicting Market Returns from Initial Price-earnings Multiples, Cross-Sectional Predictable Patterns Based on Firm Characteristics and Valuation Parameters (The Size Effect, “Value” Stocks, The Equity Risk Premium Puzzle).

2.2.1.2. Empirical studies on random walk theory

Malkiel (2007) studied empirically the market efficiency in the Chinese market. The results are difficult to interpret and they are conflicting and ambiguous because more studies have used data from the pre-2006 period, in which the capitalization was small and in the Chinese market there are various shares (for examples there are the H-share that are very different from the A-share market that is largely restricted to local residents). The findings show that the A-share market is not a weak-form efficient, indeed the random-walk hypothesis is strongly rejected, and many non-parametric tests also exhibit the inefficiency. Instead, the findings show that the H-share market has not been efficient in the past, (in the 1990s and during the SARS epidemic in 2003) but in more recent years it has become more weak-form efficient over time.

He examines the three definitions of efficiency in different ways. First, he analyzed how important news announcements are included into stock prices without delay.
Secondly, he studied the prices of stocks that are listed in various markets as on the Shanghai stock exchange, in Hong Kong and in New York. Moreover he determines if “the Law of One Price” is valid or violated. Finally, he asks” Do professional investors tend to outperform broad-based index funds? The more inefficient the market, the more likely it is that professional investors, especially those with useful connections, will earn higher risk-adjusted returns than index-fund investors.”

Other authors who studied the Chinese market are Charles and Darné (2013) who analysed the random walk hypothesis for the Shanghai and Shenzhen stock markets. They study this also for two kinds of shares called shares A and B, utilizing daily data over the period 1992–2007. The methodology used is the with new multiple variance ratio tests[44].

Moreover, the study deals with the effect on Chinese stock market efficiency after the changes in the relationship between the banks and the stock market and the change e B-share market when it includes domestic investors. In particular, the findings bring to affirm that Class A-shares are more efficient than Class B-shares. The difference is due to the liquidity, market capitalization and information asymmetry that are relevant in the determination of the weak-form efficiency. Class B-shares for Chinese stock exchanges are not a random walk hypothesis and hence, they are significantly inefficient. Nevertheless they get efficient when the banks re-enter in the stock market. Indeed, when traders invest into B-shares affected positively the market efficiency. [45]

The findings that the prices follow a random walk depend also on features of the market. For example, Dat Bue Lock (2007) finds that the weekly fluctuations prices of the Taiwan Composite Stock Index follow a random walk. In order to find this, he applies the Lo and MacKinlay variance ratio for the values from 1990 to 2006. Nevertheless, he uses the same test for the values between 1971 and 1989 and the findings show a strong rejection of the random walk. This is maybe due to the fact that the market at this period was very young. Indeed, in the 1970s and the 1980s, the trade values, volumes and total market capitalization were very small; after that, the market begins to increase very fast. The author concluded: "It is therefore reasonable to conjecture that the subsequent increase in the degree of scrutiny the market is subjected to as it matured has made the market more random in terms of price movements".

Kim and Shamsuddin (2008) study whether a group of some Asian stock market returns (Hong Kong, Indonesia, Japan, Korea, Malaysia, Philippines, Taiwan, Thailand and Singapore) follow a martingale process because the martingale features is meaningful in order to determine the market efficiency in the weak form. They use daily and weekly price indices

[44] These tests, which are robust to heteroscedasticity, are the Whang-Kim's (2003) subsampling test and Kim's (2006) bootstrap test, which do not rely asymptotic approximations, as well as the Chow-Denning (1993) test.

[45] Shares are traded in the local currency, and directed to domestic investors; instead the shares B are subscribed and traded in foreign currencies, either the US dollars in the SSE or the HK dollars in the SZE. Since February 2001, as regard the shares B the policy of open them to domestic Chinese investors holding US or HK dollars. This provoked a more trading of B-shares and the shares B become more integrated to A-share and the international stock markets. The average volume in Class A is huger than the average volume traded in Class B, hence the Class A are more liquid. Moreover, the investors in A shares are individuals, whereas the investors in Class B shares are large foreign institutional investors.

from 1990 to 2005. The findings show that the market efficiency changes according to the level of equity market development. Hong Kong, Japan, Korea, Singapore, Taiwan characterized that are developed or advanced emerging market exhibit weak-form efficiency, while Indonesia, Malaysia, Philippines that are the secondary emerging markets show the market inefficiency. In particular, the Singaporean and Thai markets show a market efficient after the Asian crisis in 1997.

Okpara (2010) tested if the stock market prices follow a random walk in particular in the Nigeria Market.

The author finds that the Nigerian stock market is efficient in the weak form and this implied that price follows a random walk process. This means that all information available in the past is enclosed in the current price. It will be not advantageous choose stocks in according to information about recent pattern in stock prices because if the price of stocks has grown up or decreased, it will not give a good information in order to know if the price of stock would rise or go down in the future.

Before Okpara, Samuels and Yacout[46] in 1981 tested if there were correlations in the weekly prices of share in 21 companies listed in the market. The results support the thesis of random walk but this outcome was biased because they considered only about 2/10 of the all companies quoted. In order to test this, they use a capitalization-weighted index of all quoted stocks.

Olowe (1999)[47] believed that the market would be weak form efficiency if the stock returns are uncorrelated and this means that the prices follow a random walk process.

$$R_j = \frac{D_{jt} + (P_{jt} - P_{jt-1})}{P_{jt-1}} * 100$$

Where P_{jt} is the stock market price, D_{jt} is yearly dividend per share and R_j is return for security j. It can be use another formula to test if this stock market is efficient. Kokah, Amoo and Joseph-Raji (2007)[48] have calculated the return in this way:

$$R_t = \ln \frac{P_{jt}}{P_{jt-1}}$$

Where:

Ln = natural logarithm

[46] Cited in Okpara (2010).
[47] Cited in Okpara (2010).
[48] Cited in Okpara (2010).

Moreover, Okpara used the non-parametric test[49], the Run test and a more scientific test (autocorrelation that implies correlograms and the Ljung-Box) for a high order serial correlation.

The model of random walk implies that the independent residuals and a unit root, which indicates that observations of the stock prices fluctuate around a constant mean, with constant variance and they are probabilistically independent. The Autocorrelation Function (ACF) is the method to analyze the independent hypothesis. It exhibits the trend of autocorrelations present in the time-series and how the current values of the series are related to various lags of the past data.

It determines if the serial correlation coefficients meaningfully varies from zero.

The autocorrelation function is connected to the correlogram[50] when there is only an estimate (in this case, return) and the partial autocorrelation function. The correlogram made up of a number of values, one for each order of the lag length analyzed, which quantify the correlation between the lag and the current observation. The partial autocorrelation function is analogous to the correlogram apart from it observe the correlation between a particular lag and the current value after the impacts of the other lags.

To sum up, many authors have studied if the fluctuations of price follow a random walk process through different methodology: correlation, variance ratio, runs tests and unit root tests. In particular they have tested if the price changes have at least a features of random walk mentioned above.

Nevertheless, other authors believe that the price variations do not follow a random walk and now we pass to describe the non-random walk theory.

[49] A run test is composed by a series of values that grow up or a series of values that decrease. The length of the run is the total number of variables. A plus means a positive change of price and a minus the opposite case. This model does not consider the distribution.

[50]

$$C_i = \frac{\frac{1}{T}\sum_{t=1}^{T-k}(R_{t+k} - R^*)(R_t - R_t^*)^\wedge 2}{\frac{T}{t=1}\sum_{t=1}^{T}(R_t - R^*)^\wedge 2}$$

2.2.2. The "Non Random Walk" Theory

"Those who cannot remember the past
are condemned to repeat it." G. Santayana

When Fama formulated his theory, it has been offered a theory of financial economics relating to investment portfolio management, starting from the essence of EMH. Markowitz was the promoter of the theory of portfolio and, using the concept of rational investor and risk aversion by investors, presented the Modern Portfolio Theory known as the theory of the efficient frontier. According to the traditional approach in accordance with the Modern portfolio theory (MPT), his portfolio theory is expressed as a function of the demand for financial assets depending on their risk and return given the offer of activities. He tries to understand why investors do not allocate the entire savings in a single activity by distributing the assets in more assets. It is a mathematician model that is actually based on only two variables, i.e. the expected return and the volatility or variance (standard deviation) of random variables in which the investor will choose the portfolio that will maximize the expected return or, which is the same, will minimize the risk.

In the same period, two Nobel Prize winners, Modigliani and Miller proposed their model for estimation of securities, starting from the assumption of the efficient frontier, as well as the perfect spread of information on the financial markets realizing the model that most of all is taught in classes of financial economics, the Capital Asset Pricing Model.
The theory of the efficiency of the Classical school was subsequently criticized by several mathematicians and economists belonging to a current diametrically opposed in the Neoclassical. Among them, Mathematician Benoit Mandelbrot and Franco-Polish Edgar Peters who had the ability to break down each one individually assumptions underlying the EMH.

According to Mandelbrot and Peters, they do not really exist investors homogeneous, equal between them in the selection of securities and information, as well as there are no investors with the same function of risk or with equal time horizons. The reality of the markets now increasingly integrated is different from the theory proposed by Neoclassical; for example, investors differentiate between hold investors or speculators, they can be emotional or not. They have a different financial behavior and so they will also require models and theories divergent. From this statement it will understand how the financial markets, particularly the stock market, can be comparable to a chaotic environment and non-linear or perfect model.

The characteristic of the normality of the price curve, supported by Bachelier and Fama, it was widely criticized by Mandelbrot and other economists, who were able to observe that the markets have price changes that varies jumping abruptly and creating large gaps in days very volatile, which do not respect the uniformity of natural laws, since they are not a compound particles, but places frequented by human individuals who in fact are inaccurate in their actions.

According to the results achieved, the alleged relationship of normality of returns is eliminated due to the presence of events such as the collapse of the New York Stock Exchange in 1987, the collapse the economies of South East Asia in 1997 and the Dot Com Bubble.

2.2.2.1. Mandelbrot and the Fractal Theory

Mandelbrot (2003) believes that the tails of distributions are *Fat Tails* and the price movements are not independent or Brownian, but they are influenced of past events, which could alter the future prices of securities. He thinks that the markets are much riskier and that it is composed by many investors with different investment temporal horizons, act in a similar manner against the risk, which should be corrected according to the time horizon in compliance with the investor.

The characteristic of temporal similarity will attribute to the financial market a fractal matrix, which has been defined by Edgar Peters (1994) as Fractal Market Hypothesis. This feature of similarity, if it is compromised by financial and real variables, it could transform conditions stability of the securities market in situations of non-stability and high volatility, thus changing the time horizon of investors.

Mandelbrot and Peters, in their studies on measures fractals markets, have obtained results about for example the presence of cycles of different length of time in the time series of certain financial instruments, through which it may be useful to consider them for the construction of an investment strategies based on the repeatability of events. The repeatability factor, that the fractal theory incorporated in the concept of autocorrelation or persistence of long-term and it affects the values of securities, was analyzed by Mandelbrot and Peters thanks to a series of statistical tests have shown that the dependence of long-term and eclipsed the assumption of independence of random series.

Mandelbrot identified in some time series of prices commodities, a feature *long-dependence* between the price changes because factors that cause price fluctuations today, they will act a chaotic and wild influencing stock prices in the future, causing increases more than proportional to the days passed and more violent than fluctuations conceivable with the classical methods.

The second result obtained by Peters and Mandelbrot regards the presence of *chaos* or sudden changes in price trends monitored, that they gave as outcome of the investigation the presence in the markets of a risk measure of volatility, signifying an excessive risk markets beyond that normally quantified by Fama, French Marshall and Markowitz unmeasurable, from a certain point of view with conventional measures or Euclidean.

Measurements taken from the study conducted by Peters thanks to the use of the exponent Hurst (a measure of this dependence in the historical data related to securities considered in the study) has highlighted that the currency market, the bond market that the stock market in general, do not follow a path random as claimed by the classical school, represented by Brownian motion with Hurst coefficient of 0.5, but it routes with values of the coefficient of Hurst very different from 0.5 so that some shares of the listed companies in the main stock markets have a characteristic of anti-persistence having a coefficient of Hurst less than 0.5 and they have a very high volatility compared to normal where it is detected H=0.5. Moreover they are characterized by a long-term memory digressive, which goes diminishing in intensity with the pass of time.

Shares or other financial instruments considered by Peters, are instead included in the list with Hurst coefficient greater than 0.5. In this circumstance, the securities despite the presence of a dependence in the long term price series with persistence in the series, has a very low risk compared to price series both with H equal to 0.5 than H less than 0.5, unlike the case anti-persistence.

According to Mandelbrot, product prices depend not only on the costs incurred to realize them or transport them, but of their value. "The value" is represented, in market trends, with a diagram bell. The diagram salt, more or less quickly, sometimes there are inflection, that is, areas of stagnation, and then falls. It can also happen that it occurs the so-called turbulence, unpredictable surges of the value, in a direction (growth) or the other (decrease). In general turbulence are defined by economists as exogenous effects, that means external factors unrelated to the market itself. For example, weather conditions affect crops and crops affect prices or even the distribution of resources in the world (oil, water) supply and this influences the prices. From these simple examples, exogenous conditions unpredictable can happen and can be so remote from neglect predictability, such as a natural disaster.

The question is why the price of such a share, or the value of a currency, changes when an event occurs outside the market? Moreover, is the disorder of the markets really unpredictable? If the probability of an event is infinitesimal, is it fair to neglect it? According to fractal theory, the answers to these questions are no.

The term fractal, coined by Mandelbrot, derived from the Latin *fractus*, meaning broken. In order to understand better, it is necessary to imagine a figure, a snow flake for example, it plays to infinity, always the same shape but smaller and smaller in size. In this way the fractal is used in the description of reality. So the key feature of the figures is the fractal *self-similarity*: if the details are observed at different scales, there is always a certain resemblance to the original fractal. Fractal geometry is a means to identify these configurations, to analyze and manipulate and can be used as a tool of analysis and synthesis. Through fractals, rules are precise and the results are predictable. This contrasts with traditional science that instead includes aspects of nature and irregular events not similar as chaos theory.

Sometimes the reality exceeds the chaos theory in the sense that the unexpected occurs such as the stock market crash in 1929 or the ominous financial events of August 1998. According to the standard models, i.e. models designed by the traditional economy, the sequence of these events was so improbable as to be impossible. Technically it was called "outlier", i.e. very far from the normal expected value in world equities. It can happen. The financial markets are risky, as everyone knows, but a thorough study of the risk, according to the applicators of fractal theory, may offer a new understanding and you can expect to have a quantitative control. The objective is therefore to study the risk, although the same Mandelbrot admits that nothing can be accurately forecast. It is true that observing the behavior of those who play the stock market there is something illogical. Behold the phenomenon of the stock exchange prices are very variable, the movements have an irregular tendency. Those who bet on these trends to amass wealth, generally lose out because the changes are accounted for as no order: prices rise then without warning, this trend will stop and you can even set up the opposite trend.

In order to apply the fractal methodology to the market, we try to reduce the scale of observation and observe the phenomenon. Irregular Trends are grouped by size: the big changes come in quick succession followed by sequences of small changes. The behavior of the stock market is therefore a fractal structure. Similarly it is possible to proceed in the description of "bubbles" of investment, i.e. the dilation of a value. Bubbles, though they may seem calamitous, are common both in general market indices (e.g. Dow Jones) as in the individual activities. Despite this, the traditional business models consider bubbles as deviation, caused for example by a greedy speculator. Mandelbrot asks: why do not we consider as the combined result of many discontinuity? Or why the traditional finance assumes that the financial system is a linear machine and continues though he admits the existence of the bubbles?

Mandelbrot drew the concept of fractal dimension from the Hausdorff, who first devoted attention to the subject. According to Mandelbrot, a set F is cataloged as the fractal, if the Hausdorff dimension, H (f), is strictly greater than the topographical size.

The topological dimension DT is always represented by a whole natural number not exceeding three. And the size commonly understood as Euclidean. For a point DT = 0, for a line DT = 1, for the plane DT = 2 and for three-dimensional space DT = 3. This dimension, for fractal objects, does not coincide with the size Euclidean DE. In the studies of fractal there are three size classes: Euclidean dimension DE, DT topological and fractal DF.

For the construction of the carton of a financial chart, Mandelbrot served with simple steps to demonstrate how fractals can be used with purposes forecasting in the context of the securities markets, identifying the future trend in prices and describing the range of adaptability to different fractals scales and time series.

Given a set of financial data as a set F, we can say that it has fractal characteristics if:

1. F has a structure "end"; this means that for every scale chosen, the image detail remains invariant.

2. F must have irregularities in order to define it fractal and it cannot be analyzed with the dictates of Euclidean geometry.

3. The fractal dimension of F is usually greater than its dimension topological and not whole.

4. F frequently present approximate or Stochastic forms of self-similarity.

Dubovikov *et alia* (2003) built a new approach as regard the fractal analysis proposed by Mandelbrot. To compute the fractal dimension, they present the sequence of the minimal covers linked to a decreasing scale δ. This brings about new fractal characteristics: the dimension of minimal covers D_μ, the variation index μ related to D_μ, and the new multifractal spectrum $\zeta(q)$ defined on the basis of μ. In order to consider μ as a local fractal feature, they did numerical computations performed for the financial series of companies that composed the Dow Jones Industrial Index. The computations exhibit that the minimal scale $\tau_{\mu,}$ which is necessary to quantify μ in accuracy way, is almost two orders smaller than an analogous scale for the Hurst index H. Moreover the findings show that $\mu(\tau)$ is linked to the stability of underlying processes. In particular, if μ>0,5, the process is stable; if μ<0,5, then the process is unstable.

The index of fractality is defined as F = DHB – DT, where D_{HB} is the HausdorI-Besicovich dimension and D_T is the topological dimension that is minimal number of coordinates which determine the position of a point on the set. Linked to DT, they add a metric dimension D which represents the relation of the natural measure of the set to the unit of length. If they increase (decrease) the unit length in b times, hence the measure will decrease (increase) in b^D times.

In the practice, they enclosed a compact fractals into Euclidean space so that DHB=DH. Hence, it refers to the latter as the fractal dimension D. Thus, the definition of the index of fractality can be rewritten as F = D – DT. F=μ if we substitute this with $\mu = D_\mu - 1$.

In the case of Financial series, these local fluctuations can be the response of a stock price to the external information. Thus, the authors explains:" the observed correlation between $\mu(t)$ and the stability of a stock price may be reviewed as the correlation between large-scale fluctuation and small-scale one."

In financial market a feedback emerges between the price expectations of investors (real or potential) and the price: the actions of investors represent their expectations, accelerate (brake) the motion of a price in some direction, which in turn accelerates (brakes) the expectations. If the feedback is positive there is trend. If the feedback is negative, there is flat. In any case, it may be interpreted as the intensity of a feedback. If the feedback disappears, hence $\lambda = 0$. In this particular case, the fluctuations of a stock price, at any time, are caused only by an external force (information) at that time. In this case, it is correct to apply the stochastic model of a Brownian motion originally proposed by Bachelier but they found that for real price time series there is a $\lambda \neq 0$ ($\mu \neq 0.5$). This means that the modification of a price is provoked also by an internal state delineated by the feedback intensity. The changes of the function λ(or $\mu(t)$) are caused by the activity of speculators who buy when the trends rise and they sell when the trends go down.

Ladislav Kristoufek (2013) studied if the forecast of the fractal markets hypothesis is valid as regard the dominance of specific investment horizons during the turbulent. His results show that Global Finance Crisis can be described very well by the fractal markets hypothesis and, in particular, Kristoufek (2013) wrote "Global Financial Crisis can be very well characterized by the dominance of short investment horizons which is well in hand with the fractal markets hypothesis. Misbalance between short and long investment horizons thus created a tension between supply and demand, leading to decreased liquidity which has been repeatedly shown to lead to occurrence of extreme events."

2.2.2.2. The variance ratio of Lo and MacKinlay and empirical researches about non-random theory

When price changes follow a random walk process, the volatility of returns must grow up one-for-one with the return horizon. For example the volatility of two-week returns must be two times the volatility of one period. So, in order to test if price changes follow a random walk process, it can be useful compare the volatility of two-week returns with twice the volatility of one-week returns. If they are similar, fluctuations price follow a random walk. Lo and MacKinlay (1988) implement a statistical in variance ratio in order to test it.

They employ the variance ratio statistic to two broad-based weekly indexes of U.S. equity returns equal and value weighted indexes of all securities traded on the New York and American Stock Exchanges derived from the University of Chicago's Center for Research in Securities Prices (CRSP) daily stock returns database. Lo and MacKinlay decide to build weekly returns from the daily database because more recent data have a meaningful power and they represent better the current reality and since their test is based on variances, the sample size provokes impacts, and weekly data are good sample to maximize sample size and minimize effects of market frictions, such as the bid/ask spread.

They found that the series do not follow the RWH: variances increase faster than linearly with the return horizon.

So, as we have seen before, if random walk implies that it cannot forecast stocks returns, the rejection means that they are forecastable.

But this test is based on historical data so the past performance is not an assurance to future profitable trading and the impact caused by trading costs is not considered. If we do not consider the trading cost, it is impossible to understand the real significance of the rejection of random walk theory because they have a relevant weight.

Indeed, on the long-term investment horizon, the impact on transaction costs is higher. There are so many models and methods in order to contain and measure transaction costs that apply high frequency data, economic models of price impact, and advanced optimization techniques. These models can add value. Moreover , the creation of new financial instruments can decrease transaction costs, e.g., swaps, options, and other derivative securities, can add value.

In an efficient market, in order to gain profits, it is necessary to have a competitive advantage.

We have to underline that in efficient financial markets are characterized by financial technology. Nowadays the barriers to enter are not so higher even if the degree of competition is very higher, and for most financial technologies it cannot be possible to patent. These new features imply that financial markets can be more efficient but of course they are not perfectly efficient because anomalies can be exists.

Lo believes that in the financial markets there are both random and non-random models. Prices sometimes follow a trend and respond to indicators or other signals. Instead, price can ignore trend or indicators and follow unpredictable ways.

Lo compares the research of above-average returns to a firm that tries to sustain its competitive advantage. Indeed, in order to remain above the competition, the company has to continue to progress and innovate. Moreover, the traders, investors and other actors in the market have to maintain their flexibility and innovation to outperform the market.

Lo (1991) examines another point of stock market prices: the long-term memory. Time series with long-term memory show that they have a not usually high degree of persistence. This means that the observations in the past are non-insignificant correlated with observations in the future, “even as the time span between the two observations increases.” The long-term memory is a feature that is well known in the natural sciences e.g. hydrology, meteorology, and geophysics, and some have asserted that also economic time series have this characteristic.

Lo (1991) implements a test for long-term memory that is robust to short-term correlations of the sort uncovered by Lo and MacKinlay (1988), and he finds that, even if there is an earlier evidence support the contrary, there is trivial indication for long-term memory in stock market prices. So, he concludes :“Departures from the RWH can be fully explained by conventional models of short-term dependence.”

The subject on trading activity in financial markets is very analyzed and studied. More authors try to find the winner strategy to outperform the market. In order to analyze the market, many use volume. As measure of volume, many utilize the total number of shares traded on the NYSE. Other authors calculate, in order to obtain the volume, the aggregate turnover that is the total number of shares traded divided by the total number of shares outstanding. The relations more common to try to identify a possible pattern of price is: price and volume, volatility and volume, Individual turnover and number of trading days.

Lo and Wang (2000) calculate the total number of shares of a financial instrument j traded at time t, that they consider volume in this way:

$X_{jt} = \frac{1}{2}\sum_{i=1}^{I} \mid S_{jt}^{i} - S_{jt-1}^{i} \mid,$

For each investor i, S_{jt}^{i} is the number of shares of stock j that he holds at date t. Let

$P_t \equiv [P_{1t} \dots P_{Jt}]^\wedge T$ and $S_t \equiv [S_{1t} \dots S_{Jt}]^\wedge T$ denote the vector of stock prices and shares held in a portfolio and A^T is the transpose of a vector or matrix A.

The return on stock j at time t is $R_{jt} \equiv (P_{jt} - P_{jt-1} + D_{jt})/P_{jt-1}$

Denote X_{jt} the total number of shares of security j traded at time t.

The authors base their studies on turnover because "it is the most natural measure and it yields the sharpest empirical implications".

The turnover is defined $\tau_{jt} \equiv \frac{X_{jt}}{Nj}$ where X_{jt} is the share volume of security j at time t and Nj is the total number of shares outstanding of stock *j*. The turnover of value-weighted and equal-weighted

$\tau_t^{VW} \equiv \sum_{j=1}^{J} \omega_{jt}^{VW} \tau_{jt}$ and $\tau_t^{EW} \equiv \frac{1}{J}\sum_{j=1}^{J} \tau_{jt}$ where $\omega_{jt}^{VW} \equiv N_j P_{jt}/(\sum_j N_j P_{jt})\ for\ j = 1, \dots, J.$

Asymmetric information, idiosyncratic risks, transaction costs and other anomalies of the market are meaningful in order to determine the level and variability of trading activity, hence the authors examine the implications of mutual fund separation.

The two-fund separation implies all actors in the market invest in the same mutual funds: there are a riskless asset and a stock fund. The last one is the market portfolio that is (measured in shares outstanding) is a vector $S_t^i = h_t^i S^M = h_t^i \begin{matrix} 1 \\ \dots \\ 1 \end{matrix}$ where h is the share of the market portfolio held by investor i (and the sum is equal to 1 for all t).[51]

[51] Statistics for regressors:
$\hat{\alpha}_{\tau,j}$ is the intercept coefficient from the times series regression of stock j's turnover on the value weighted market turnover.
$\hat{\beta}_{\tau,j}$ slope coefficient from the time-series regression of stock j's turnover on the value-weighted market turnover.
$\hat{\sigma}_{\epsilon,\tau,j}$ is the residual standard deviation of the time series regression of stock j's turnover on the value-weighted market turnover.

The main aim of Darrat and Zhong (2000) is to analyze, utilizing the new daily data, if the stock price changes of the Shanghai and Shenzhen Exchanges follow a random-walk process and in this way it can be considered efficient. They studied this using two different models the common variance-ratio test of Lo and MacKinlay (1988) and a model-comparison test that contrasts *ex post* forecasts from a random-walk (NAIVE) model with those gained from other alternative models.

The findings from the variance-ratio test, reject strongly the hypothesis of random walk process in both Chinese markets.

Also the results from Artificial Neural Network supported the predicting theory of the stock market.

The findings from variance ratio tests using the new daily stock price data of China's two official stock exchanges (Shanghai and Shenzhen) show a strong tendency for positive autocorrelation, which means the potential for predictability.

In order to study if the price fluctuations follow a random walk, the authors use another approach in order to test it. It consists to compare the *ex post* forecasts from the NAIVE model.

The random-walk hypothesis is not accepted if the NAIVE model does not predict alternative models. They use this model-comparison approach and create *ex post* (one week-ahead) forecasts of Chinese stock prices from four different forecasting models: NAIVE, ARIMA, GARCH, and ANN. They compare the *ex post* predicting ability of these models on the basis of alternative evaluation criteria (RMSE, MAE, and Theil's U). Moreover, they construct tests in order to assess statistical superiority among rival forecasting models. The findings strongly reject the random-walk hypothesis in both Chinese stock markets and they discover that there is strong evidence that supports the ANN approach over other models.

Ravi Dhar (2001) has studied how different investors want to act in the market and so, what are the different expectations with respect to the future price fluctuations. He analyzes the contrarians who to buy and sell and traders who follow the momentum strategy who are willing to buy or sell. The reference price (monthly low and high prices) strongly influenced contrarian traders; instead, for the others happen the opposite. All categories do not want trade with the losers, but the most reluctant are contrarian sellers who attend for price reversals.

These differences in behavior are very meaningful in asset pricing. After, various agent-based models have found that the momentum and contrarians traders cause price fluctuations that show features of empirical returns series. The authors found that noise trader risk in the market may be limited. Indeed, momentum and contrarian traders have diametrically opposite expectations and their trades in the financial market induce to destabilize and restore forces in the market. Thanks to these forces, the prices of financial instruments do not differ from the fundamental value and the amount of noise trader risk is limited.

Moreover, the presence of momentum and contrarian traders can explain the cause of existence of high trading volume and large price movements, even if there is not any meaningful news. The internal dynamic of momentum and contrarian traders may eventually provoke the anomalies and irregularities in the financial market. It is necessary to consider the factors that are created from trading behavior and factors created by internal risk (called market created risk).

Both psychological and non-psychological variables, e.g. asymmetric information and different interpretation of information can explain trend tracking behavior among investors. Non-psychological factors may also be responsible for the observed disposition effect. The authors finished: “A recent paper by Ranguelova (2000) finds that the disposition effect is present primarily in large cap stocks and surprisingly, in the lower decile stocks, the propensity to sell losers is higher than the propensity to sell winners”.

Pavlenko (2008) thinks that the mean reversion theory can be applied to the stock price because traders observe with attention the recent pattern in returns. He observed that the stock has a positive return as the effect after positive information, it is very probably that the stock continue to produce profit.

Generally, the market, after the communication of good news, overreacts. So, the fundamental traders that measure the intrinsic value of a stock discover that the stocks are overpriced and so they want to sell them. In this way, the price falls down. For this reason, the theory of mean reversion is accepted.

He asserts that “The larger magnitudes of prices fluctuations due to market overreaction causes misallocation of funds.”

During the years, other authors have explained the mean reversion theory.

According to Cecchetti *et al.* (1990) and Fama and French (1998)[52], fluctuations in risk tolerance and riskiness of a stock for a given riskless interest rate will modify the interest rate of borrowing for the firm, thus the modification of the stock price provokes mean reversion.

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[52] Cited in Pavlenko (2008).

Alternatively, given a level of risk for a stock, modifications in a riskless interest rate produce price fluctuations. Given adjustments in interest rate, stock prices may also exhibit mean reverting trend, but in different way with respect to the situation of stock market overreaction.

The modifications in interest rate provoke mean reversion in prices, but they do not determine market inefficiency. Poterba and Summers (1988)[53] assert that the change in interest rates should be very huge and meaningful to originate mean reversion trends.

The mean reversion determines the predictability of returns in the future. Hence it automatically exclude the hypothesis of market efficiency.

In more recent years, the procedures applied in order to test the mean reversion were more powerful.

According to Pavlenko (2008), Balvers, Wu and Gilliland (2000) utilize panel data for 18 developed countries' stock indices with sample period from 1969 to 1996 to give more power to the test. The test shows strong evidence in favor of mean-reversion.

Chaudhuri and Wu (2004)[54] study monthly data for 17 emerging capital markets starting January 1985 to April 2002 and reject the hypothesis of random walk in favor the hypothesis of mean reversion. They discover the half-life of mean-reversion to be about 30 months, which is close to findings from developed countries.

Gropp (2004) assumes the stationary difference between fundamental values, as Balvers, Wu and Gilliland (2000) and Chauhudri and Wu (2004)[55], but he uses the fundamental values of portfolios. Also Gropp does not give any explanation and reason for which he adopted this assumption.

Pavlenko (2008) affirms: "Together all the studies in the field present mixed evidence about mean reversion. Those concentrated on individual stock returns usually lack power to reject random walk in favor of mean reversion. More recent studies that employ panel tests provide more convincing evidence of presence of mean reverting components. But they concentrate mostly on cross country analysis, checking for mean reversion between countries' stock indices, whether markets under study are developed or emerging. Also, there is lack of theoretical backing for the methodology applied in these studies."

The study of his work is to analyze if in Ukrainian stock market the prices follow a mean reversion theory. He uses different methods to examine this. As the first, he utilizes ADF test to this equation stock by stock.

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[53] Cited Pavlenko (2008).
[54] Cited Pavlenko (2008).
[55] Cited Pavlenko (2008).

$$R^i_{t+1} - R^r_{t+1} = \alpha^i + \lambda\left(P^i_t - P^r_t\right) + \omega^i_{t+1}$$

where $R^i_{t+1} = (P^i_{t+1} - P^i_t)$.

Nevertheless, this test has low power in order to reject null hypothesis of mean reversion. It was able only to demonstrate the evidence of mean reversion hypothesis for two stocks out of 31.

La Spada *et al.* (2008) believe that, even if prices are not a perfect random walk, this is a good approximation: "While there may be some structure in the drift term, so that occasionally clever arbitrageurs can predict and exploit small deviations from randomness, basically the direction of price movements is very close to random. "They think that the volatility do not follow a random walk. Indeed, their work analyze this term. What produces fluctuation in volatility is difficult to stabilize. As we have seen before, the volatility can be modified by new information, but new information is hard to quantify. This confirms by studies on longer time scale, instead in study with a short time scale show a weak correlation between volatility and new information.

A recent study has shown that the volatility is very correlated to the size of individual price changes, and this is weakly correlated with the size of transactions and with the transaction frequency. The transaction signs (plus for buyer and minus for sellers) have a long memory and this caused that the signs of transaction can be forecasted. If a buyer makes a transaction, the price goes up and so the seller makes another action to push the price down. This can mean that prices should be predictable, but it is in contrast with the market efficiency. There is another relationship between transactions and prices. They study prices changes as steps in generalized random walk. Generalized random walk means that there is the possibility that there is a correlation between the transactions (signs of step) and their size. They start from assumption that prices changes are permanent and they construct a model that forecast the expected volatility "in terms of properties of the generalized random walk, such as the number of steps, the average step size, the variance of the step sizes, the imbalances between positive and negative steps, and sums of the autocorrelation functions for step signs and sizes. "

These findings point out that, thanks to an understated long range interaction between signs of returns and their sizes, the volatility is decreased by almost a half even if the return signs do not have long-memory properties. They think that this correlation is linked to the interaction between the transaction signs and returns. Nevertheless, since the transactions have long memory and this causes that it is possible to forecast their signs, "the returns must compensate so that they are not equally predictable." It can happen if the price impacts are temporary that means that when transactions occur, prices fluctuate but this change decline slowly with time. Or, if price fluctuations have a permanent component, but this component is modified according to the predictability of transaction signs: if the probability is high that a future transaction is to be a buy, the size of sell returns is much smaller than the size of buy returns. They conclude that "In either case it suggests a reduction of volatility relative to what one would expect under an unconditional permanent impact model such as the one we have developed here."

Bahadur (2009) studied the Nepalese Stock Market using daily information from 2003 to 2009 of the general NEPSE index and seven different sector-wise indices. He implemented different methodologies to test the series. He used the unit root tests (ADF, KPPS and PP), the autocorrelation function, the variance ratio and he tried to fit a garch model for the volatility.
He used the returns calculated as

$$R_t = \ln P_t - \ln P_{t-1}$$

The results reject the hypothesis of random walk. There is a relevant and meaningful correlation (such as 0,21 and 0,48) and in the runs test he reject the null Hypothesis of random order because the p-values are zero. He moreover apply the unit root test but the outcome is in contrast with the random walk. Also the variance ratio (in this case is different than one) and Garch model induce to affirm the non efficiency of the Nepalese Stock Market.
Hiremath (2014) analyzed the Stock market returns in India from 1997 to 2010 of 14 indices traded on the National stock exchange (NSE) and Bombay stock exchange (BSE). He implemented the autocorrelation test, the runs test and the variance ratio of Lo and MacKinlay.
The autocorrelation exhibits a non-significant value. The results show that there is no correlation in the returns. Hence we can accept the hypothesis of random walk.
Nevertheless, the variance ratio results greater than one in some case and in other less than one. In all situation it is different from one so the random walk hypothesis is not accepted.
He used also the variance ratio that takes into account the heteroscedasticity in the data analyzed. Also in this case the random walk hypothesis is rejected.
Finally, the runs test and BDS test also exclude that the price changes follow a random walk because the p-value are close to zero.

Abbas (2014) examined the daily stock returns on Damascus Securities Exchange from 2009 to 2014. He applied the variance ratio, autocorrelation, BDS and runs tests.

As we have mentioned above, he used the same formula to calculate the returns from the prices.

After analyzing the statistics of data and discovering that the returns are not normal distributed, he implemented the tests.

He found a huge correlation (0,68 the maximum value) and the variance ratio for each period selected is less than one. This outcome strongly reject the hypothesis that the price changes follow a random walk.

This theory is confirmed also by the non-parametric tests: the runs test and BDS test have p-values very close to zero, so this induce to do not accept the null hypothesis of random walk.

All tests done exhibit a contrast with the market efficient.

PART III.

"Practice should always be based on a sound knowledge of theory."
Leonardo da Vinci

In the first part we have examined the market structure and players. In the second part we have investigated the concept of market efficiency, from the beginning up to nowadays.
Can a trading strategy outperform the market or are price fluctuations randomly distributed?

In the second part we have addressed the two major theories: random walk theory and non-random walk theory. In order to check the relationship between efficiency and predictability in price changes, we examined several theoretical and empirical studies.

In this third part we apply and compare the main methodologies, empirically used by various authors. Our goal has been to verify the coherence, or alternatively, to highlight the differences and the contradictions among the different methodologies in order to check the weak efficiency of the market.
Ftse Mib and Stoxx Europe 600 Index daily prices, from January 4, 1999 to February 11, 2016[56], have been chosen.
Finally, we comment and sum up the results.

3.1. METHODOLOGY

Market efficiency has been extensively studied and investigated in the literature. As already underlined[57], there are the following definitions:

1. Weak: the market is efficient when it reflects all market information;
2. Semi-strong: the market is efficient if it reflects all public market information;
3. Strong: the market is efficient if it reflects all public and private information.

In order to evaluate efficiency level, specific tests are available:
Weak market: *statistical tests* check the stationarity, the correlation, the volatility changes, which distribution best fits the data and predictability in price changes. The aim is to

[56] We implement them thanks to the econometric software Gretl and a little part with MATLAB and Stata.
[57] See part II.

understand if the prices follow a random walk process. Other tests, the *trading tests*, analyze the trading strategy considering the transaction costs and the abnormal returns.

Semi-strong: *event tests* investigate how a security value changes after an event. The aim is at seeing that an investor can not earn above average returns.

Strong: particular tests focus on *group of investors* that have relevant and meaningful information: insiders, exchange specialists, analysts and institutional money managers.

Here we study the weak form of market efficiency. As many authors highlighted, the second and the third form are theoretical only: it is very difficult to have such type of markets in the real world.

As we have seen in the second part, there are many statistical tests for random walks have been implemented in the literature.

In order to better understand the logic behind every test, we recall here the most important features of random walk.

The process is the following:

$$X_t = X_{t-1} + \varepsilon_t,\ \varepsilon_t \sim IID(0, \sigma^2)$$

The increments are[58]:

$$r_t = X_t - X_{t-1} = \varepsilon_t, \qquad \varepsilon_t \sim IID(0, \sigma^2)$$

where X_t is the process, ε_t is distributed with mean 0 and variance, and r_t is the increment sequence.

The random walk is a non-stationary process[59], i.e. the mean and the variance depends on time:

$$E[X_t|X_0] = X_0 + \mu t$$
$$Var[X_t|X_0] = \sigma^2 t$$

Nevertheless, if we make the first difference, we obtain a stationary process.

For testing non-stationary feature, we use the unit root tests.

[58] We recall that there are three type of random walk:

1. Random walk with IID increments (they follow a normal distribution)
2. Random walk with independent and uncorrelated increments (different distribution from normal)
3. Random walk with uncorrelated increments (it is admitted the correlation in the nonlinear relation such as in the squared values)

[59] The non-stationarity implies that the process have a unit root: $X_t = aX_{t-1} + \varepsilon_t$ where a is equal to 1.

3.1.1. The Unit Root Tests

To investigated if each variable of time series is integrated and has a unit root, we can use: the Augmented Dickey-Fuller Test (ADF), the Philips-Perron test (PP), the Kwaiatkowski, Philips, Schmidt and Shin test (KPSS) and the Zivot Andrews test. The existence of unit root indicates that the time series in not stationary and it is a random walk.
The equation for the unit root test is the following:

$$R_t = \alpha + \rho R_{t-1} + \varepsilon_t$$

where ε_t is the error term with zero mean and constant variance. If ρ is equal to 1 the unit root exists and the series are random walk. In particular, the null hypothesis H_0 is ρ=1 against the H_1= ρ<1. The null hypothesis of a unit root is rejected if the test statistic is more negative than the critical value. The KPSS employs a parametric method to search for the autocorrelation; it hypothesizes that the observed time series can be divided into the sum of a deterministic trend, a random walk with zero variance and a stationary error term. It tests the null hypothesis of trend stationarity linked to the hypothesis that the variance of the random walk equals zero.

The data used are characterized by clustering volatility and structural breaks[60]. If we use ADF test, the outcome could be biased. So, we add two other tests: Zivot-Andrews and Philips-Perron tests.

3.1.1.1. Philips and Perron test

The PP test includes an alternative and nonparametric method for testing a unit root, by estimating the non-augmented Dickey Fuller equation and changing the test statistic. In this way, its asymptotic distribution is unaffected by serial correlation. Phillips and Perron (1988) have implemented an unit root test that differs from the ADF test in the serial correlation and in the heteroscedasticity of the errors. In particular, the ADF test adopts a parametric autoregression to approximate the ARMA structure of the errors in the test regression, where the PP test considers any serial correlation in the test regression and it considers the heteroskedastic errors. The test is:

$\boldsymbol{\Delta y_t = \beta' D_t + \pi y_{t-1} + u_t}$ where $\boldsymbol{u_t}$ **is I (0)** and it can be heteroskedastic

[60] They are unexpected changes in the times series.

So, this test directly modifies the test statistic $t_{\pi=0}$ and $T\hat{\pi}$ in this way:

$$Z_t = \left(\frac{\hat{\sigma}^2}{\hat{\lambda}^2}\right)^{1/2} * t_{\pi=0} - \frac{1}{2}\left(\frac{\hat{\lambda}^2 - \hat{\sigma}^2}{\hat{\lambda}^2}\right) * \left(\frac{T * SE(\hat{\pi})}{\hat{\sigma}^2}\right)$$

$$Z_\pi = T_{\hat{\pi}} - \frac{1}{2} * \frac{T^2 * SE(\hat{\pi})}{\hat{\sigma}^2}(\hat{\lambda}^2 - \hat{\sigma}^2)$$

The null hypothesis is when $\pi = 0$; in this case we get a process without unit root and the PP has the same asymptotic distributions as the ADF t-statistic and normalized bias statistics. The advantage of using the PP test is in its robustness to general forms of heteroscedasticity in the error term u_t. Moreover, it does not require to specify a lag length.

3.1.1.2. Zivot-Andrews

A common problem using the conventional unit root tests is they ignore the presence of structural breaks. If we assume time of the break as an exogenous phenomenon, Perron has proved that the power to reject a unit root decreases when the stationary alternative is true and a structural break is not considered. Zivot and Andrews have implemented a variation of Perron's original test where the exact time of the break-point is unknown. Perron, instead, uses a data dependent algorithm to proxy, in order to find the break points. Zivot and Andrews have defined three models to test for a unit root: (1) model A permits a one-time change in the level of the series; (2) model B allows for a one-time change in the slope of the trend function, and (3) model C combines one-time changes in the level and the slope of the trend function of the series.

So, in order to test for a unit root against the alternative of a one-time structural break, Zivot and Andrews utilize the following regression equations:

$$x_t = \alpha_0 + \alpha_1 DU_t + d(DTB)_t + \beta t + \rho x_{t-1} + \sum_{i=1}^{p} \phi_i \Delta x_{t-1} + e_t$$

$$x_t = \alpha_0 + \gamma DT_t^* + \beta t + \rho x_{t-1} + \sum_{i=1}^{p} \phi_i \Delta x_{t-1} + e_t$$

$$x_t = \alpha_0 + \alpha_1 DU_t + d(DTB)_t + \gamma DT_t + \beta t + \rho x_{t-1} + \sum_{i=1}^{p} \phi_i \Delta x_{t-1} + e_t$$

where DU_t is a dummy variable for a mean shift occurring at each possible break-date (TB) while DT_t is corresponding trend shift variable. In more specific terms:

$$DU_t = \begin{cases} 1 \ldots\ldots\ldots.\,.\ldots\ldots if\ t > TB \\ 0 \ldots otherwise \end{cases}$$

$$DT_t = \begin{cases} t - TB \ldots\ldots\ldots\ldots. if\ t > TB \\ 0 \ \ldots\ldots\ldots\ldots\ldots\ldots\ otherwise \end{cases}$$

The null hypothesis is: α=0 in all the three models. This means that the series {yt} contains a unit root with a drift that eliminates the hypothesis of any structural break, while the alternative hypothesis α<0 i.e. that the series is a stationary process with a one-time break that happens at an unknown point in time.

The Zivot and Andrews test considers every point as a potential break-date (TB) and it implements a regression for every possible break-date sequentially. Of all possible break-points (TB), the system chooses, as break-date (TB), the date which minimizes the one-sided t-statistic for testing αˆ (= α −1) =1. Its appropriate use is when data are very volatile and when by bubbles, crashes and crisis affect the period to be analyzed.

3.1.2. The normal distribution of increments.

The first definition of random walk requires the increments have to be independent and identically distributed. In order to check these characteristics, we implement the following techniques:

a. The theoretical normal distribution of returns versus the real distribution of returns; Calculation of summary statistics, focusing on mean, standard deviation, kurtosis[61] and skewness[62];

[61] $\alpha_4 = E\left(\frac{x-\mu}{\sigma}\right)^4$

[62] $\alpha_3 = E\left(\frac{x-\mu}{\sigma}\right)^3$

b. the Q-Q plot of returns[63];

c. Run of Normality tests:

a. Doornik-Hansen test

It is based on transformations of skewness and kurtosis much closer to standard normal than the raw moment measures. Under the normality null hypothesis, the test statistic is distributed as chi-squared with 2 k degrees of freedom.

b. Shapiro-Wilk test

It compares two alternative estimators of variance σ^2 : a non-parametric estimator, based on a linear combination of order statistic of a normal random variable in the numerator, and in the denominator the usual parametric estimator of the sample variance.

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

where x_i is the i-th smallest value (the rank) of the sample, $\bar{x}$ is the arithmetic mean of the sample and a is a constant.

c. Lilliefors test

After calculating the sample mean and sample variance, it compares the maximum difference between the empirical distribution function and the cumulative distribution function (CDF) of the normal distribution, with the mean and variance before estimated. Finally, it measures if the maximum difference is large enough to be statistically significant. Under this output, the null hypothesis of normality can be rejected.

d. Jarque-Bera test

This test checks for the normality of the data, measuring the kurtosis and the skewness.

$JB = \frac{n-k+1}{6}\left(S^2 + \frac{1}{4}(C-3)\right)^2$ where S is the sample skewness and C is the sample kurtosis.

[63] It is a graphical method that compares used to compare the distribution of the data with the normal distribution. It is called Q-Q because it plots the quantiles of the two distributions. In the x ax there is the quantile of a normal distribution, instead in y ax there is the quantiles of the data distribution. If the two distribution are similar (i.e. if the data distribution is normal), the points in the Q–Q plot will be located and stay on the line $y = x$.

3.1.3. Correlation and autocorrelation functions

As the first definition of random walk does not fit appropriately the reality because it requires very specific conditions such as the independent and identically distributed increments, we investigate the third definition that requires uncorrelated increments only.

In general, the correlation between two random variables X and Y is measured by the ρ coefficient:

$$\rho_{X,Y} = \frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}} = \frac{E[(X-\mu_x)(Y-\mu_y)]}{\sqrt{E(X-\mu_x)^2 E(Y-\mu_y)^2}}$$

Where μ_x and μ_y are the mean of X and Y, respectively.

This coefficient quantifies the strength of linear dependence between the two variables. The coefficient ρ takes value from -1 to 1. If $\rho_{X,Y}$ is equal to 0, the two variables are not correlated, the opposite if $\rho_{X,Y}$ is equal to 1. Moreover, if both X and Y are independent, they are not correlated. [64]

Autocorrelation function

When considering the linear dependence between r_t and its past values r_{t-i}, in a weakly stationary series of returns, the concept of correlation is linked to autocorrelation.

The correlation coefficient between r_t and r_{t-l} is denominated the lag-l. The coefficient of autocorrelation is ρ_l and it is defined as:

$$\rho_l = \frac{Cov(r_t, r_{t-l})}{\sqrt{Var(r_t)Var(r_{t-l})}} = \frac{Cov(r_t, r_{t-l})}{Var(r_t)} = \frac{\gamma_l}{\gamma_0}$$

3.1.4. Correlation in the squared series

Here we check the correlation in the squared series since the third type of random walk admits this correlation.

If it is found in the time series, we are dealing with a clustering volatility phenomenon. Clustering volatility occurs when large changes tend to be followed by large changes or small

[64] Be careful: the independency implies the non-correlation. The opposite is not true.

changes tend to be followed by small changes. Another way to confirm clustering volatility phenomenon is the Engle test to look for the arch effect.

3.1.4.1. The Engle Test

Uncorrelated returns in a time series can dependent from a dynamic conditional variance process. Indeed, a time series can have autocorrelation in the squared series or conditional heteroscedasticity. This is called *autoregressive conditional heteroscedastic* (ARCH) effect. Engle's ARCH test is a Lagrange multiplier test to check the significance and the presence of this ARCH effect.

Please consider this time series: $y_t = \mu_t + \varepsilon_t$

where μ_t is the conditional mean of the process and ε_t is an innovation process with mean zero and they are created as $\varepsilon_t = \sigma_t z_t$ and z_t is an independent and identically distributed process with mean 0 and variance 1.

Hence, $E(\varepsilon_t \varepsilon_{t+h}) = 0$ for all lags $h \neq 0$ and the innovations are uncorrelated.

If H_t is the history of the process at time t, the conditional variance of y_t is

$$Var(y_t|H_{t-1}) = Var(\varepsilon_t|H_{t-1}) = \sigma_{2t}$$

Conditional heteroscedasticity, in the variance process, is equal to autocorrelation in the squared innovation process.

The residual series are $e_t = y_t - \mu_t$.

The alternative hypothesis for Engle’s ARCH test is autocorrelation in the squared residuals, given by the regression $H_a: e_{2t} = \alpha_0 + \alpha_1 e_{2t-1} + \cdots + \alpha_m e_{2t-m} + u_{t,}$

where u_t is a white noise error process.

The null hypothesis, instead, is $H_0: \alpha_0 = \alpha_1 = \cdots = \alpha_m = 0$.

In order to capture the arch effect, we can fit a GARCH model.

3.1.4.2. The GARCH Model

These models consider a time variant conditional variance and nonlinearities in the generating mechanism.

In the GARCH (1,1) forecasts of time varying variance are connected to the lagged variance of the asset. When, at time t, returns go down or go up unexpectedly, this causes an increment in the expected variability at the time t+1. The models in more specific term, the GARCH (1,1) is:

$$h_t = \omega + \alpha_l \varepsilon_{t-1}^2 + \beta_l h_{t-1}$$

where h_t is the variance and it is a function of the intercept ω, α that is a shock from prior period and β that represents the variance from last period. The mean equation is:

$$R_t = \mu + \theta R_{t-1} + \varepsilon_t$$

if (α+β) <1 the GARCH (1,1) model is weakly stationary; if (α+β) = 1, it exhibits high persistence in volatility clustering; this provokes inefficiency on the market.

In order to better fit the data with the model, it is possible to apply different distribution. In this work we have used the normal distribution, the t-Student distribution[65], the GED[66], the Skewed t and the skewed GED distribution. (Figure 8, 9 and 10).

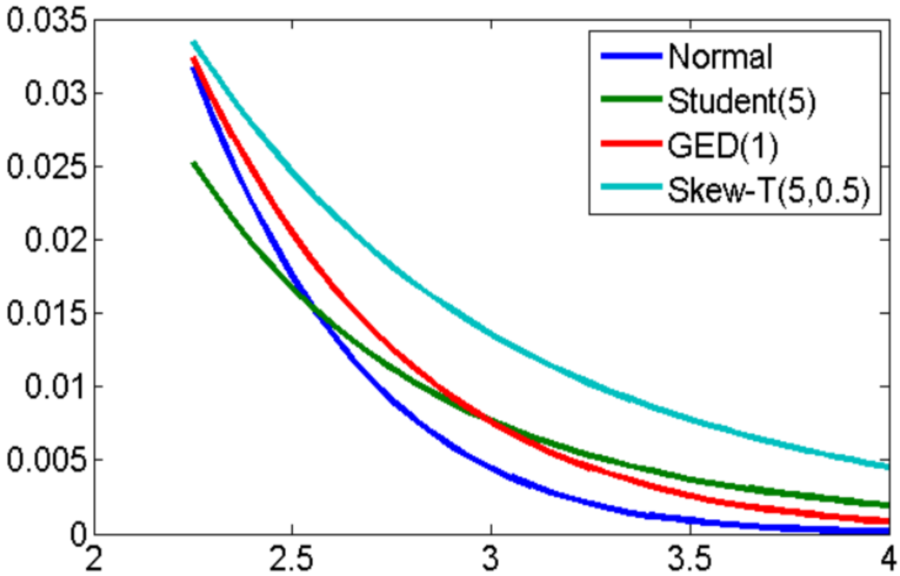


Figure 8. Normal, t-Student, GED and Skew-T distributions.
Source: author's elaboration.

[65] The t-Student distribution has heavier tails than the normal distribution. They are called "fat". It depends on *v* that measures the degree of freedom. It has a variance equal to $\frac{v}{v-2}$. The standardized version of this distribution is when the variance is equal to 1. The Skew t-Student depends on two parameters: *v* and the asymmetric coefficient. If the last term is equal to zero, it is a t-Student distribution.

[66] It is a parametric continuous distribution that adds one parameter called β to the normal distribution. If the β is equal 2, the distribution is normal. This distribution fits appropriately the tails that are heavier than normal (when β<2) or lighter than normal (when β>2).

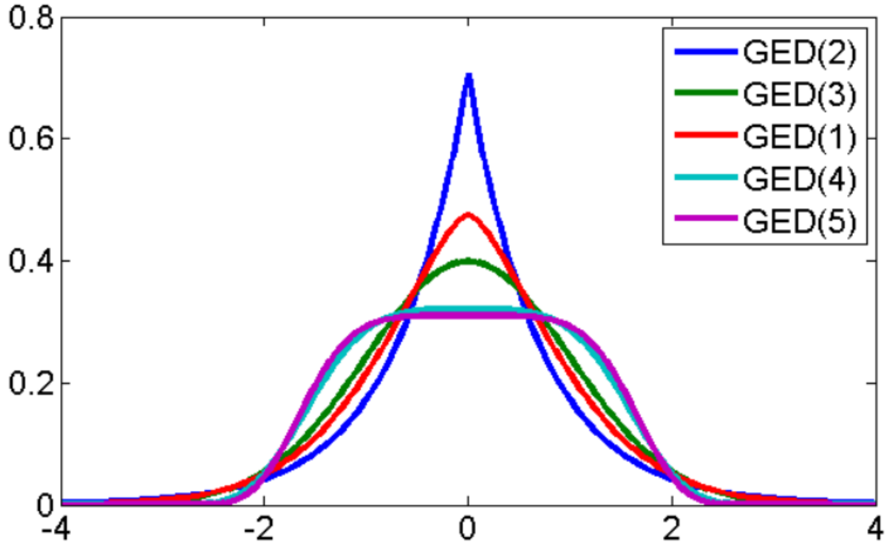


Figure 9. Different GED distributions.
Source: author's elaboration.

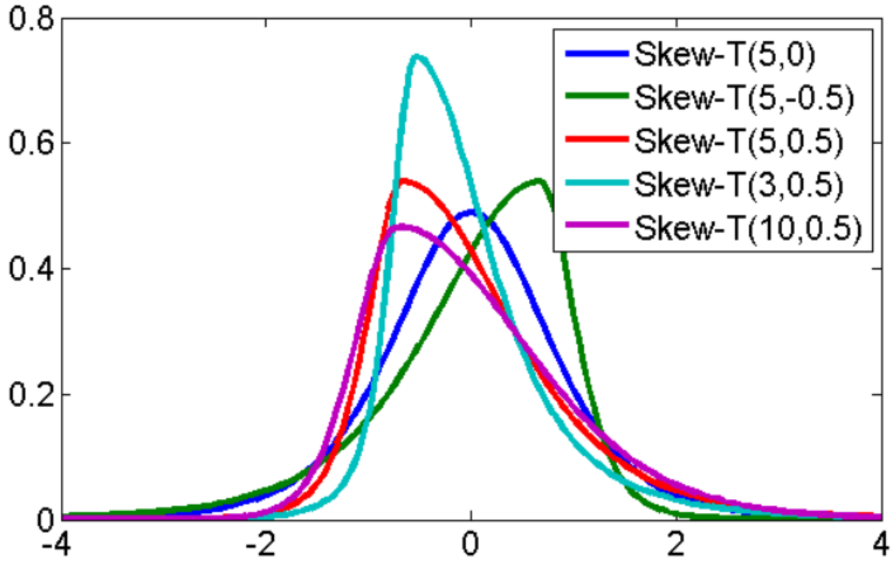


Figure 10. Different Sk-T distribution.
Source: author's elaboration.

3.1.5. The variance ratio test

In the second part, we have described the Lo and Mackinlay theories in which they support the non-random walk theory. Taking into account a very important property of random walk, they considered random walk increments as linear function of time variable. They used the variance ratio. Variance ratio test, examines the predictability of time series data by comparing variances of differences of the data (returns) calculated over different intervals. If we assume the series follows a random walk process, the variance of a q-th differenced variable should be q times as large as the first-differenced variable. When prices follow a random walk process, the volatility of returns must grow up one-for-one with the return horizon (e.g. the volatility of two-week returns must be two times the volatility of one period).

In more general terms:

$$Var(R_t - R_{t-q}) = qVar(R_t - R_{t-1})$$

Then the variance ratio is defined as:

$$VR(q) = \frac{\frac{1}{q}Var(R_t - R_{t-q})}{Var(R_t - R_{t-1})} = \frac{Var[R_t(q)]}{q.Var[R_t]} = 1 + 2\sum_{k}^{q-1}(1 - \frac{k}{q})\rho(k)$$

The null hypothesis: VR(q)=1 for all q means prices follow a random walk process.

- If VR(q)≠1 the random walk null hypothesis is not accepted. [67]
- If VR(q)>1, the series *tend to move in trend* where changes in one direction are often followed by changes in the same direction.
- If VR(q)<1, the series exhibits some degree of mean reversion. The mean reversion theory suggests that prices and returns eventually move back towards the mean or average. This mean or average can be the historical average of the price or return.

Because of heteroscedasticity, the result is not always reliable. The series could show a random walk behavior even if VR(q)≠1.

To overcome this difficulty, Lo and MacKinlay implemented a new version of the test robust to variances changes. Even in the presence of heteroscedasticity, as the number of observations increase without bound, the variance ratio must still approach unity, and the variance of the sum of uncorrelated increments must still equal the sum of the variances. So, in presence of heteroscedasticity, the test statistic is the following:

$$\Psi(q) = \frac{\sqrt{nq}(\overline{VR}(q) - 1)}{\sqrt{\hat{\theta}(q)}} \sim_a N(0,1)$$

[67] The t statistic changes according the type of random walk analyzed. In this work, we analyze the third type of random walk. So, the test used is modified for the series that is characterized by heteroscedasticity.

where $\hat{\theta}(q)$ is the heteroscedasticity-consistent estimator of θ(q) that is the asymptotic variance of the $\overline{VR}(q)$.

3.1.6. The Hurst Coefficient

We have extensively described Mandelbrot theory in the second part. Here we concentrate our attention on his method to quantify the long term memory in the returns: the Hurst coefficient[68].

In order to standardize this measure, Hurst constructed a non-dimensional index dividing the range by the standard deviation of the observed variables: rescaled range analysis R/S. [69]

Given a time series with t observations, we calculate the cumulated deviation of observations from their average, during a certain period of time N:

$$X_{t,n} = S; t\ (and\ t - MN)$$

where: $X_{t,n}$ is the cumulated deviation of period N; t is the observation t; MN is the average of the observations in the period N.

Then we pass to calculate the range of this cumulative difference between the maximum value and the minimum value that it assumes:

$$RN = MAX\left(X_{t,n}\right) - MIN(X_{t,n})$$

At this point RN is divided by the standard deviation (S) of t in the period N in order to standardize the measurement.

Hurst found that R/S could be estimated using the following equation ("Empirical Hurst's Law"):

$$\frac{R}{S} = (a * N)^H$$

where: H is the Hurst exponent; a is a constant; R/S is the rescaled range.

---

[68]The name Hurst comes from Harold Edwin Hurst (1880–1978). Hurst worked in the field of hydrology. He constructed a project of a dam on the River Nile in Egypt. His task was to study a system of checking the amount of water contained in the reservoir so that it was never too much or too little.
The main factor that influences the level of water in a dam is undoubtedly the amount of rainfall and, it follows a random walk. Hurst decided to test if the level of water in the dam, measured in successive time periods, followed or not a random walk. To do this, he developed a new statistical tool called "Hurst exponent (H)", which, according to the author, is able to distinguish a random series from a non-random even if the random series is not normally distributed. Hurst measured the way the level of the lake floated around its mean with the passing of time. It should be expected that the range of this fluctuation depends on the length of the time period used for the measurement. If the series is random, the range should grow with the square root of time.

[69] See also CONT (2005), CAJUEIRO *et al* (2008), NAWROCKI (1995) and RASHEED *et al* (2004).

Moreover, we can consider also the logarithms:

$$\ln(R/S) = H * \ln N + \ln a$$

H can be estimated by regressing the $\ln(R/S)$ against the $\ln N$. Mandelbrot has shown that H can assume a value between zero and one. If H=0.5 analyzed the series follows a random walk. In other words, the range increases with the square root of time, N. There is no statistical dependence of long period. However, when H is different from 0,5 observations are not independent of each other. The most recent events have a greater impact than those far away, but they have still residual influence. To sum up:

- H=0.5, indicates that the analyzed series follows a random walk. The events are not related to each other. The underlying probability distribution may be the normal one.
- 0<H<0.5 we have a system where the series tend to revert to the mean. The strength of this "anti-persistency" in the series is as greater as H approaches zero
- 0.5<H<1 implies persistency in the analyzed series. This means that if the trend has been positive in the last period, is likely to be positive in the subsequent period and vice versa. The level of this persistence is as greater as H approaches the value 1[70].

3.1.7. The non parametric test: Runs Test

This non-parametric test[71], can be used to decide if a data set comes from a random process. A *run* is defined as a series of increasing values or a series of decreasing values. The number of increasing, or decreasing, values is the length of the run. The first step in the runs test is to count the number of runs in the given data sequence. This number is compared with the *expected number* of runs. If the number is the same, the successive fluctuations are independent and in a random order (i.e. the null hypothesis is E(runs)=μ). The total expected number of runs is normally distributed with this mean:

$$\mu = \frac{N(N+1) - \sum_{i=1}^{3} n_i^2}{N}$$

and this standard deviation:

[70] These phenomena follow a trend over time that can be described as a stochastic process "distorted", later called Fractional Brownian Motion (FBM) by Mandelbrot.

[71] The terms non parametric means that they do not quantify parameters. They search for the causal order in the data.

$$\sigma_\mu = [\frac{\sum_{i=1}^{3}[\sum_{i=1}^{3} n_i^2 + N(N+1)] - 2N(\sum_{i=1}^{3} n_i^3 - N^3)}{N^2(N-1)}]^\wedge(1/2)$$

where n_i is the number of runs of type i.

3.2. DATA

In order to implement the tests to control the weakly market efficiency we analyze two indexes: the Stoxx Europe 600 and the Ftse Mib.

The reason why we consider Stoxx Europe 600 is for detecting if the european market, characterized by the most strong and solid economies (e.g. France, Germany and United Kindom), can be efficient or inefficient. This represents the overall european economic situation.
Next, we analyze Italy Ftse Mib efficency/inefficency focus in order to compare the two scenarios.

The time interval is January 4, 1999 to February 11, 2016. We select from January 1999 because the Euro became in effect at this date. In this way, we can have an homogeneous comparison of Europe and Italy. We have collected 4464 daily observations, from Bloomberg, considering the closing prices; [72] [73] this long time period can guarantee an unbiased and robust analysis.
In the financial analysis the two most important variables are: prices and returns. While the price is not always meaningful in itself, it is used to calculate the returns. So our analysis focuses more on returns than on prices. The two main reasons are the following:

1. returns have interesting statistical properties, such as the stationarity and ergodicity.
2. returns represent the investment opportunity, as they measure the financial activity profitability.

The following formula links returns to prices:

[72] For monthly data we collect 205 observations.
[73] Moreover we use also the monthly data to analyze the volatility clustering.

$$R_t = \ln P_t - \ln P_{t-1}$$

R_t is called compounded return or logreturn of an asset.[74]

Moreover in a random walk process the returns are the increments and have to be uncorrelated.

Now, we describe the analysis in order to test if markets are efficient.

We analyze also the monthly data to highlight the differences (in particular as regard the volatility) from the daily data.

[74] The advantages of continuously compounded returns come into play when we take into account multiperiod returns because the continuously compounded multiperiod return is simply equal to the sum of continuously compounded single-period returns.

3.2.1. The Stoxx Europe 600 Index

Description and Composition.

The STOXX Europe 600 Index comes from the STOXX Europe Total Market Index (TMI) and is a subset of the STOXX Global 1800 Index. With a fixed number of 600 components, the STOXX Europe 600 Index includes large, mid and small capitalization companies across 18 countries of the European region: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. It is composed of 18 Supersectors according to the ICB industry classification and it represents the exposure to a certain sector in terms of free-float market capitalization. The index is free-float market capitalization-weighted. The prices are in EUR. In order to represent the market appropriately, all constituents of each supersector index are subject to a 30% capping for the largest company and a 15% capping for the second-largest company.

We choose this type of index because it represents the overall economy in the Europe. The sectors are:

1. Automobilists and parts
2. Banks
3. Basic resources
4. Chemicals
5. Construction and material
6. Food and beverage
7. Financial services
8. Health care
9. Industrial goods and services
10. Insurance
11. Media
12. Oil and gas
13. Personal goods
14. Retail
15. Technology
16. Telecommunications
17. Travel and leisure
18. Utilities

The weight of the most ten super-sector is shown in the Figure 11 and the Country weighting in the Figure 12. Nestlé, Novartis and Roche represent 2%-3% of the index. In the Figure 13 there are the weights of the top 10 components.

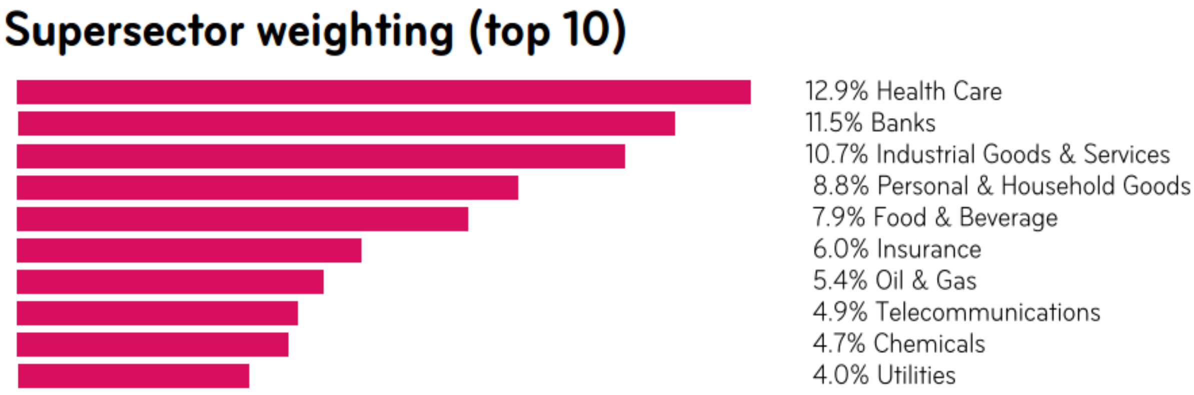


Figure 11. The supersector weighting in Stoxx Europe 600 Index.
Source: https://www.stoxx.com/document/Bookmarks/CurrentFactsheets/SXXGR.pdf

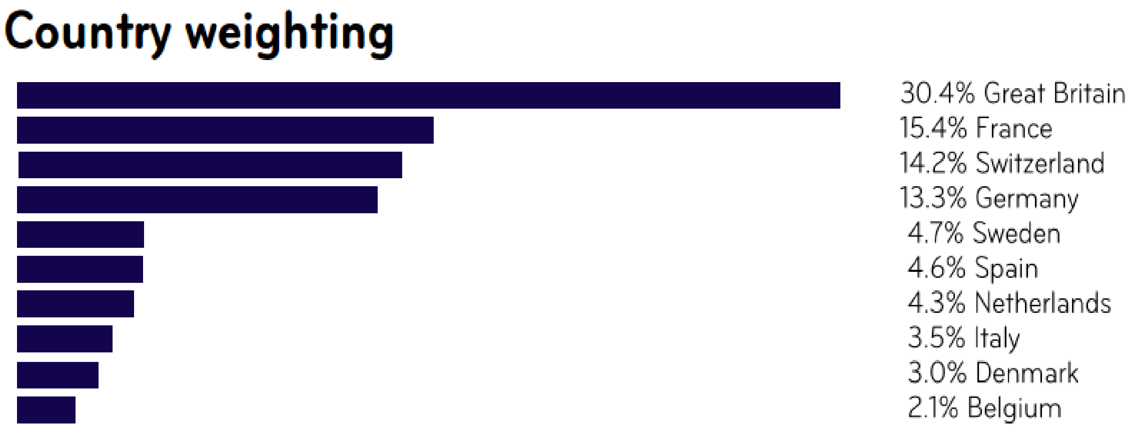


Figure 12. The country weighting in the Stoxx Europe 600 Index.
Source: https://www.stoxx.com/document/Bookmarks/CurrentFactsheets/SXXGR.pdf

Top 10 Components[5]

Company	Supersector	Country	Weight (%)
NESTLE	Food & Beverage	CH	2.93
NOVARTIS	Health Care	CH	2.39
ROCHE HLDG P	Health Care	CH	2.36
HSBC	Banks	GB	1.64
TOTAL	Oil & Gas	FR	1.43
BRITISH AMERICAN TOBACCO	Personal & Household Goods	GB	1.33
NOVO NORDISK B	Health Care	DK	1.28
GLAXOSMITHKLINE	Health Care	GB	1.24
SANOFI	Health Care	FR	1.23
ROYAL DUTCH SHELL A	Oil & Gas	GB	1.18

[5] Based on the composition as of Feb. 29, 2016

Figure 13. The Top 10 Components in the Stoxx Europe 600 Index (based the composition as of Jan. 29, 2016). Source:https://www.stoxx.com/document/Bookmarks/CurrentFactsheets/SXXGR.pdf

In order to test the market efficiency, we start describing and analyzing some descriptive statitistics of data.

Figure 14 shows the daily closing prices from 1999 to 2016.

Figure 14. Daily prices of Stoxx Europe 600 Index from January 1, 1999 to 11 February, 2016. Source: author's elaboration.

Figure 15 shows the returns, for the same period.

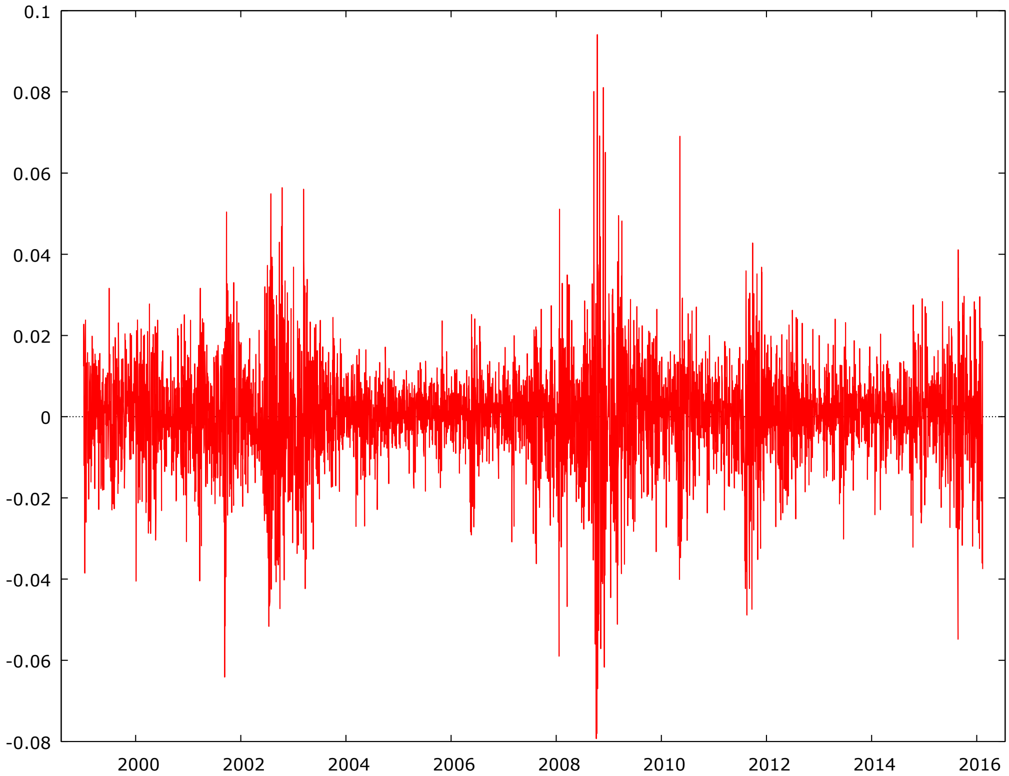


Figure 15. Daily returns of Stoxx Europe 600 Index from January 2, 1999 to February 11, 2016.
Source: Author's Elaboration.

At a first glance, a sort of regularity in the amplitude of fluctuations appears. The series present the phenomenon called *volatility clustering*. This means that large changes tend to be followed by large changes and small changes tend to be followed by small changes, of either sign. From the prices graph and the returns graph we can recognize the two most downturns: in the 2002 and in the 2009. Especially, the year 2009 is characterized by a high volatility in which large changes are followed by large changes.

The first down peak can be referred to the past Argentinian crisis of 2001, and the "dot.com" bubble, as described in the second part. Probably, these downturns moved to Europe because of European investments in the Argentinian markets and in the technology sectors. When these bubbles burst, the European market sunk.

The second collapse was stronger. In particular, this event was due to the financial crisis, also explained in the second part. This situation it brought the European financial market in crisis. The index was very low during March 2009; it reached its lowest point on March 9, 2009.

Then, the index recovered but it was hit by another downturn. In the 2012 the index decreased. It can be explained by another crisis in Europe: the sovereign debt crisis. The European countries supported high debt in order to recover from the financial crisis.

The European debt crisis is a crisis that lasts for several years. Indeed, many European states such as Greece, Portugal, Ireland, Spain and Cyprus were not capable to refinance or pay their government debt, without the support of the other European countries or institutions such as IMF[75] or ECB[76].

The specified causes are several. In most countries, private debts were originated from a property bubble. The bubble moved to sovereign debt as a consequence of banking system bailouts and government acts, to respond to the slow European economies after this bubble. Because of Eurozone has a currency union (the euro) without fiscal union (there are different methods to impose taxes and there are different pension rules) this situation restricted the actions of European leaders.

In order to recover from this crisis, leading European nations supported other countries through financial measures e.g. the European Financial Stability Facility (EFSF) and the European Stability Mechanism (ESM). The ECB kept low the interest rate and furnished cheap loans, in order to recover from the crisis. On September 6, 2012, the ECB announced free unlimited support for Eurozone, calming the financial markets. The ECB program consisted in a sovereign state bailout EFSF/ESM and the Outright Monetary Transaction (OMT).

3.2.1.1. Are the returns normally distributed?

In the figure 16 we plot the returns distribution in order to test whether the data are normally distributed. As we can note, the variables do not fit with the normal distribution. The Q-Q plot in the figure 17 also confirms it. The dots do not lie on the line: in the left side, the red line, that represents the quantile returns, is below the blue line and in the right side it is above. These two plots induce us to analyze a specific feature: the leptokurtosis. It means that the distribution that fits appropriately has a fat tails, i.e. tails are heavier than normal distribution. Indeed, the most data are located on the tails. We confirm this phenomenon calculating some statistics in the next page.

[75] International Monetary Fund.
[76] European Central Bank.

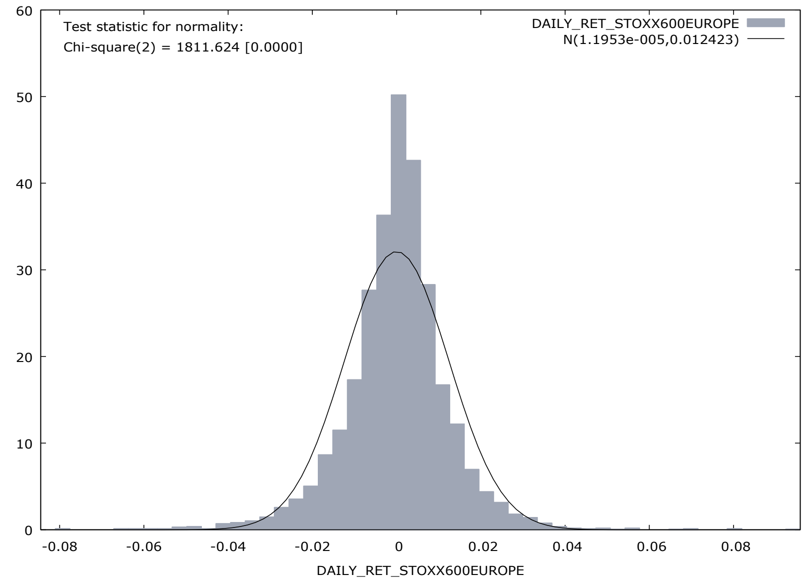


Figure 16. The returns distribution of Stoxx Europe 600 Index.
Source: Author's elaboration.

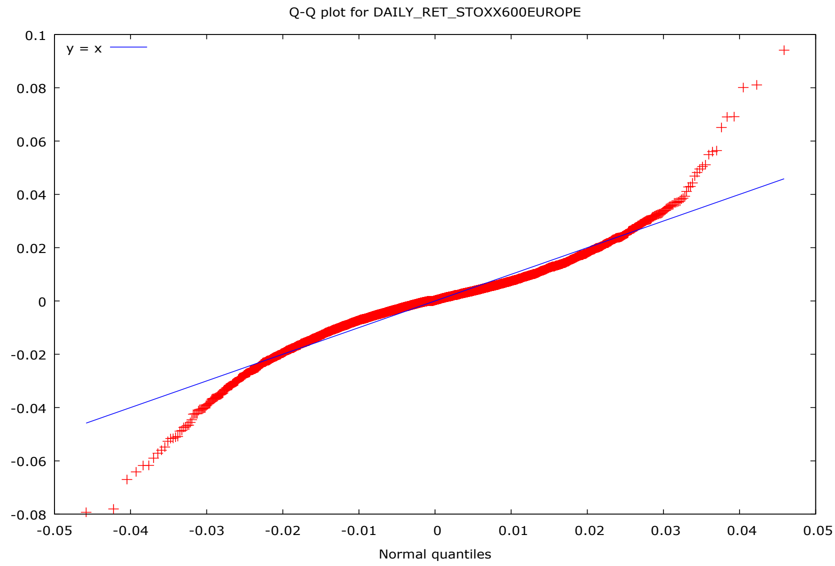


Figure 17. The Q-Q plot of returns of Stoxx Europe 600 Index.
Source: Author's elaboration.

We present the summary statistics of the returns collected.

Mean	**1.1953e-005**
Median	0.00027389
Minimum	-0.079297
Maximum	0.094100
Standard deviation	**0.012423**
C.V.	1039.3
Skewness	**-0.14710**
Ex. kurtosis	**5.0495**
5% percentile	-0.020174
95% percentile	0.018807
Interquartile range	0.012032
Missing obs.	1

We focus our attention on the mean, standard deviation, skewness and kurtosis. If the returns were normally distributed, the mean, the skewness and the kurtosis would be zero and the standard deviation would be 1.

If the kurtosis is more than 3, there is the phenomenon of leptokurtosis. So, we confirm the hypothesis made in the previous plots.

In order to support the idea that the returns are not distributed as a normal distribution, we implement four tests, to check the normality:

```
Test for normality of ret_dailySTOXX600:

 Doornik-Hansen test = 1811.62, with p-value 0

 Shapiro-Wilk W = 0.942899, with p-value 1.82154e-038

 Lilliefors test = 0.0719216, with p-value ~= 0

 Jarque-Bera test = 4757.47, with p-value 0
```

These results confirm the previous analysis: in all tests the p-value is zero and this brings to reject the null hypothesis of normality.

Hence we conclude that the returns, despite the traditional theory, do not normally distribute.

This is in contrast with the first definition of random walk and classical theory, but this is consistent with the second and the third type, because they do not require the normal distribution for the increments. Indeed, they admit another type of distribution.

3.2.1.2. Does the process have a unit root?

In order to check the presence of unit root, we implement the ADF, KPPS, PPerron and Zivot-Andrews tests on prices and the returns. If the data follow a random walk, the prices will have a unit root and the returns will not have. Here, there are the results:

```
Augmented Dickey-Fuller test for l_STOXX600EUROPE
including 0 lags of (1-L)l_STOXX600EUROPE
(max was 90, criterion BIC)
sample size 4463
unit-root null hypothesis: a = 1

  test with constant
  model: (1-L)y = b0 + (a-1)*y(-1) + e
  estimated value of (a - 1): -0.0018649
  test statistic: tau_c(1) = -2.03616
  p-value 0.2714
  1st-order autocorrelation coeff. for e: -0.004

  with constant and trend
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + e
  estimated value of (a - 1): -0.00188503
```

```
  test statistic: tau_ct(1) = -2.05144
  p-value 0.5722
  1st-order autocorrelation coeff. for e: -0.004

  with constant and quadratic trend
  model: (1-L)y = b0 + b1*t + b2*t^2 + (a-1)*y(-1) + e
  estimated value of (a - 1): -0.00232391
  test statistic: tau_ctt(1) = -2.27615
  p-value 0.691
  1st-order autocorrelation coeff. for e: -0.004
```

KPSS test for l_STOXX600EUROPE (including trend)

```
T = 4464
Lag truncation parameter = 90
Test statistic = 0.324206

                   10%      5%      1%
Critical values: 0.119   0.148   0.218
P-value < .01
```

Zivot-Andrews unit root test for STOXX600

```
Allowing for break in intercept

Lag selection via TTest: lags of D.STOXX600 included = 6

Minimum t-statistic -2.369 at 2334 (obs 2334)

Critical values: 1%: -5.34 5%: -4.80 10%: -4.58
```

Phillips-Perron test for unit root

```
                                                   Number of obs   =      4463
                                                   Newey-West lags =         9
```

	Test Statistic	---------- Interpolated Dickey-Fuller --------- 1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-6.862	-20.700	-14.100	-11.300
Z(t)	-1.851	-3.430	-2.860	-2.570

```
MacKinnon approximate p-value for Z(t) = 0.3553
```

All these tests confirm that the process, regarding the prices, has a unit root. Indeed, the p-value of ADF test are high so we are able to accept the null hypothesis of unit root. In the KPPS, instead, the p- value is low but the null hypothesis is different: no presence of unit root. So, we can reject the null hypothesis of stationarity.

Finally, the Zivot-Andrews and PPerron tests that consider the structural breaks, give the same results: the t-statistic is lower than the critical value, so we can accept the null hypothesis of presence of unit root.

We implement the same analysis on the returns to observe if the series, after a differenciation, become a stationary process. Here, we present the results.

```
Augmented Dickey-Fuller test for DAILY_RET_STOXX600EUROPE
including 4 lags of (1-L)DAILY_RET_STOXX600EUROPE
(max was 90, criterion BIC)
sample size 4458
unit-root null hypothesis: a = 1

  test with constant
  model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -1.11646
  test statistic: tau_c(1) = -32.1851
  asymptotic p-value 3.194e-044
  1st-order autocorrelation coeff. for e: -0.002
  lagged differences: F(4, 4452) = 9.560 [0.0000]

  with constant and trend
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -1.11651
  test statistic: tau_ct(1) = -32.1819
  asymptotic p-value 4.412e-124
  1st-order autocorrelation coeff. for e: -0.002
  lagged differences: F(4, 4451) = 9.560 [0.0000]

  with constant and quadratic trend
  model: (1-L)y = b0 + b1*t + b2*t^2 + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -1.11651
  test statistic: tau_ctt(1) = -32.1781
  asymptotic p-value 0
  1st-order autocorrelation coeff. for e: -0.002
  lagged differences: F(4, 4450) = 9.558 [0.0000]

KPSS test for DAILY_RET_STOXX600EUROPE (including trend)

T = 4463
Lag truncation parameter = 90
Test statistic = 0.0603664

                   10%      5%      1%
Critical values: 0.119   0.148   0.218
P-value > .10


Zivot-Andrews unit root test for  retstoxx600

Allowing for break in intercept

Lag selection via TTest: lags of D.retstoxx600 included = 7

Minimum t-statistic -24.432 at 2657  (obs 2657)

Critical values: 1%: -5.34 5%: -4.80 10%: -4.58


Phillips-Perron test for unit root                Number of obs   =      4462
                                                  Newey-West lags =         9
```

```
                             ---------- Interpolated Dickey-Fuller ---------
                 Test         1% Critical       5% Critical      10% Critical
               Statistic          Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)        -4169.231          -20.700           -14.100           -11.300
 Z(t)            -67.254           -3.430            -2.860            -2.570
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

The results exhibit the stationarity of the returns: the p-value in the ADF, Phillips-Perron and Zivot Andrews tests is very close to zero, so we are able to reject the null hypothesis of presence of unit root.

In the KPPS we have a high p-value so we can accept the null hypothesis of stationarity.

The output is congruent with the hypotheses of random walk. In a random walk process, the prices have a unit root and the returns do not have.

3.2.1.3. Are the returns correlated?

As we have already underlined, in the reality the variables are seldom independent even if they can be uncorrellated. Next step is to check for the correlation: if the increments are not correlated, we can affirm that the market is weakly efficient.

In order to analyze the correlation, we use acf (autocorrelation) and pacf (partial autocorrelation) of returns. (Figure 18).

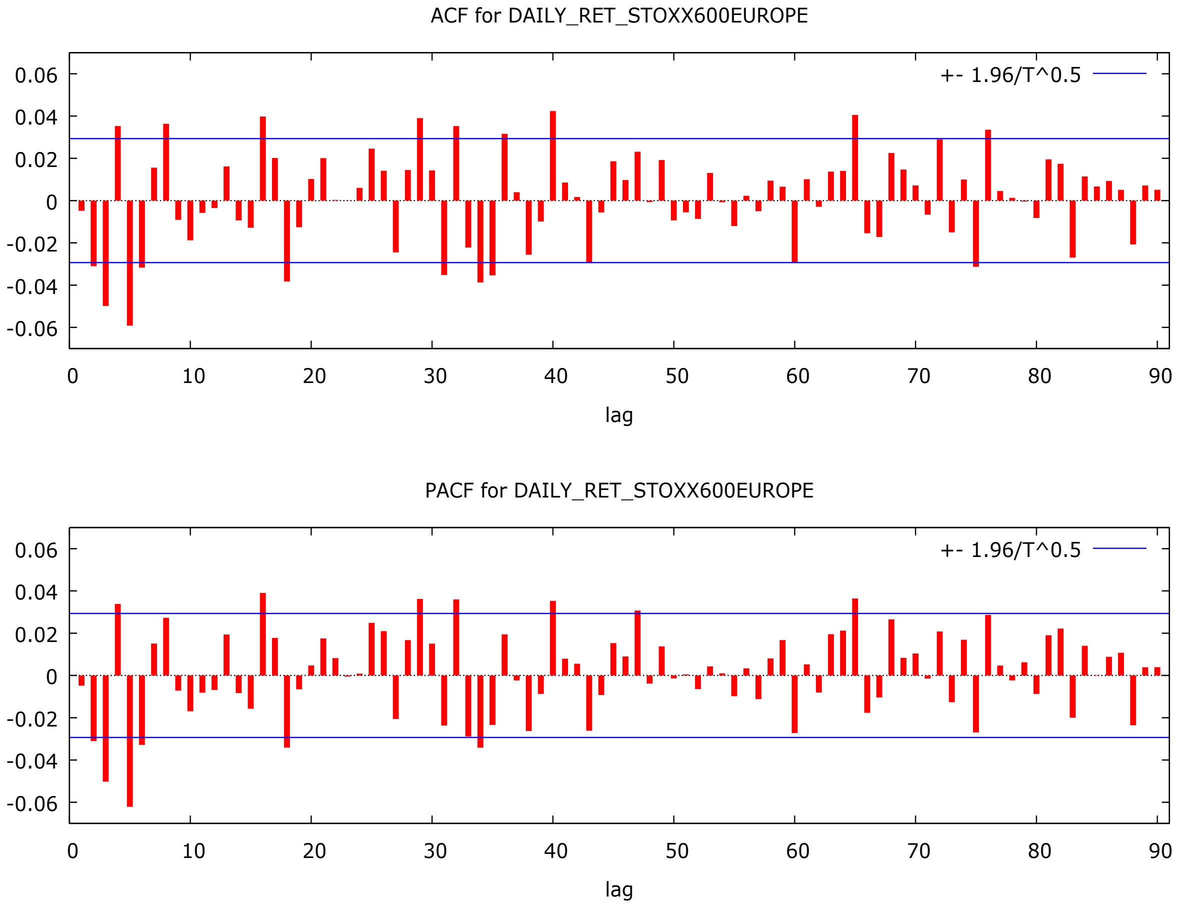


Figure 18. Acf and Pacf of daily returns of Stoxx Europe 600 Index from January 4, 1999 to February 11, 2016. Source: Author's elaboration.

The plot indicates that there is not a significant and relevant correlation as almost all the red bars are inside the blue lines (confidence intervals). Even if in the third, fourth and fifth lag, the correlations (red lines) are outside their value. It is not significant in order to identify a correlation.[77]

3.2.1.4. Is the squared series correlated?

As we have noted, the time span considered is a difficult and critical period, full of downturns, upturns, bubbles, crashes and crisis. So, these years are characterized by very high volatility. If we look at the returns plot, we observe that large changes are followed by large changes or small changes are followed by small changes. This phenomenon is called clustering volatility.

This phenomenon can be explained by some models we will address later, such as arch and garch models, so it is also called arch effect.

[77] The blue lines are the confidence intervals. They are so narrow because the time span is large.

This arch effect can also be detected using the Engle test and the acf and pacf to looking for the correlation in the squared returns.

The Engle test has been implemented in the Matlab. The results indicate that the arch effect is present. This means that there is a sort of correlation in the volatility.

```
>> e = data - mean(data);
[h,p,fStat,crit] = archtest(e,'Lags',2)
h =  1     p =0    fStat = 486.0613   crit = 5.9915
>> h = archtest(data)   h = 1
```

The p-value and the h indicate that we are able to reject the null hypothesis (no presence of arch effect). Hence there is arch effect.

Another way to confirm the clustering volatility is to do the acf and pacf of the squared returns, as we can see in the figure 19.

Differently from the correlation of the returns, previously analyzed, we affirm that the correlation is present and it is meaningful. Indeed all bars are outside the blue lines and the value of correlation is very high. We have all values above 0,1 and for the first lag the correlation reaches also the 0,4.

So, it is possible to capture this effect using the GARCH models.

Before to fit these models, we have to underline that the arch effect strongly depends on the frequency of the data collected. Indeed, if we use the monthly data, we can see that the correlation in the squared returns diminishes. It persists but it is lower than the correlation in the daily data. Correlation appears in first three lags only, with the maximum value of 0,22 (in daily squared returns the correlation is 0,4). If we implement the Engle test in Matlab, we are able to reject the null hypothesis of no presence of arch effect, because the p-value is equal to 0 and the h is equal to one. (Figure 20).

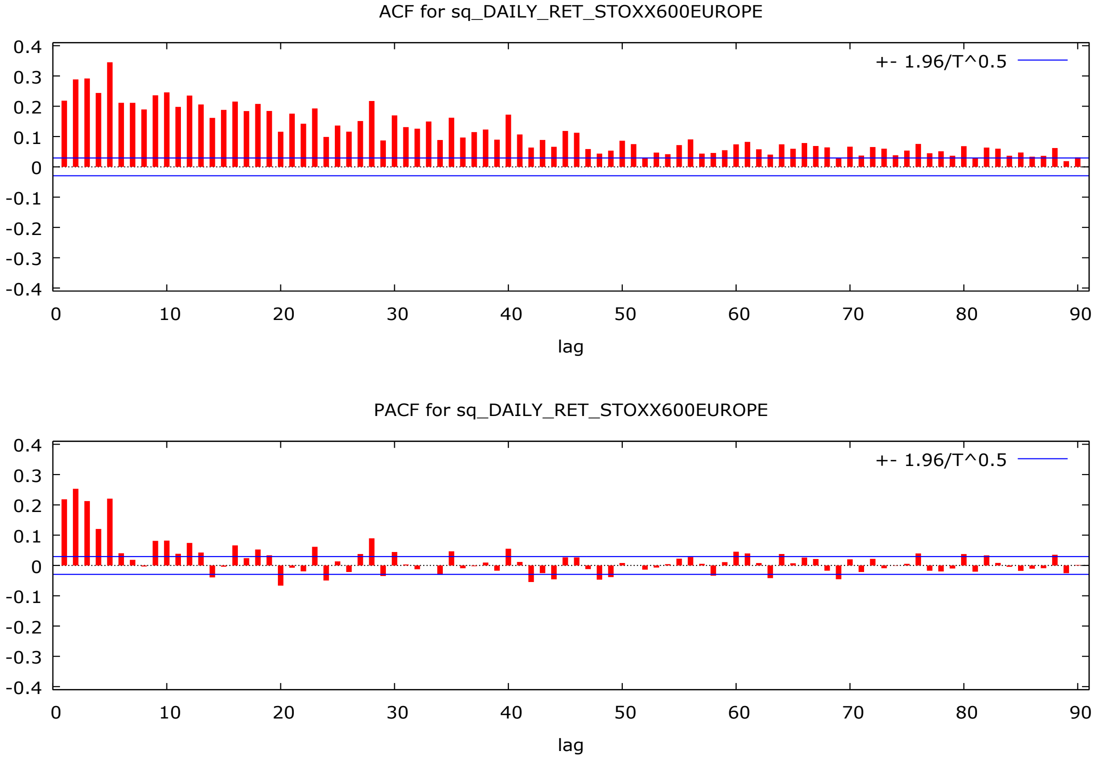


Figure 19. Acf and Pacf of daily squared returns of Stoxx Europe 600 Index.
Source: Author's elaboration.

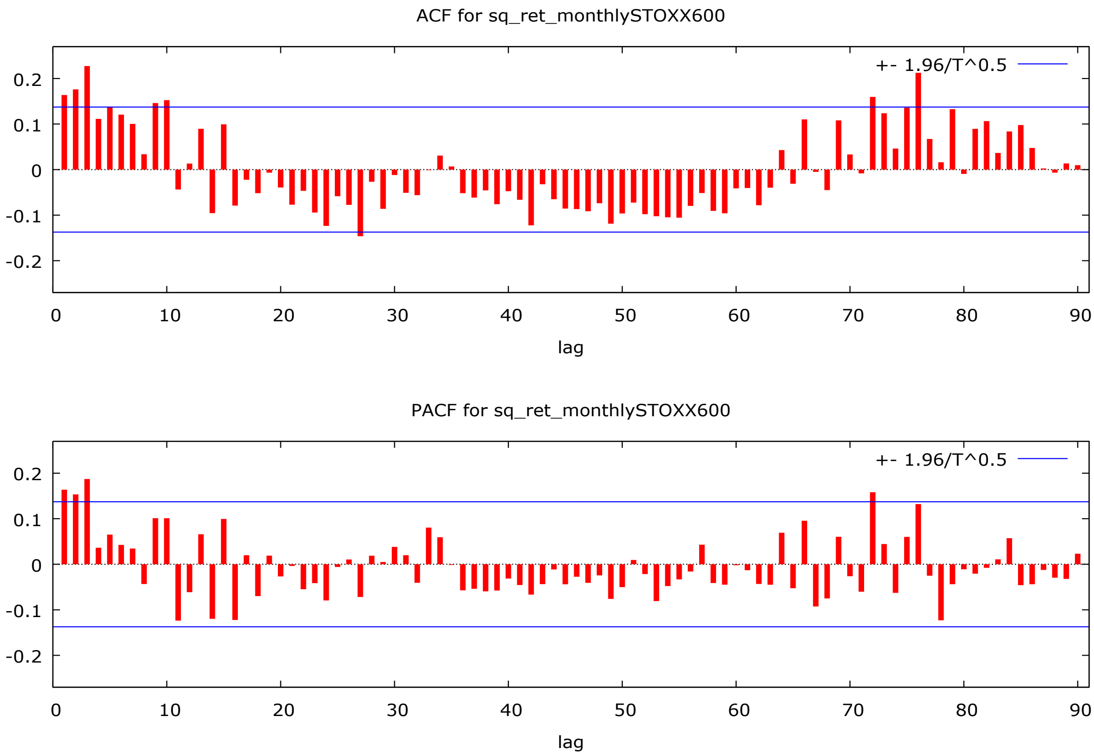


Figure 20. Acf and Pacf of monthly squared returns of Stoxx Europe 600 Index.
Source: Author's elaboration.

3.2.1.5. Variance ratio

We use this test to see if the increments have a constant volatility: if the data follow a random walk process, the volatility of increments should grow up one-for-one with the return horizon. For example, the volatility of two-week returns should be two times the volatility of one period.

Indeed, the variance ratio would be 1 in a random walk process. Here there are results of the calculation of variance ratio for q=2, 4, 8 and 16. As we have underlined in the section "methodology", this test is constructed to the random walk with heteroscedasticity.

We calculated variance ratio in Matlab and Stata, the outcome is the same in all the calculations. The small difference is due to rounding. The variance ratio is, in all cases, different from 1: 0.512957 (q=2), 0.240395 (q=4), 0.119989 (q=8) and 0.0599299 (q=16). Moreover all p-values are very close to zero and the h is equal to one, so we are able to reject the null hypothesis of random walk.

Stata outputs:

```
Lo-MacKinlay modified overlapping Variance Ratio statistic for retstoxx600
[2 - 4464 ]
q          N          VR          R_s        p>|z|
-------------------------------------------------
2        4447      0.512     -32.5060    0.0000
4        4447      0.239     -27.0995    0.0000
8        4447      0.120     -19.8134    0.0000
16       4447      0.060     -14.2134    0.0000
```

Matlab outputs:

```
q= 2 4 8 16
Variace ratio  = 0.5130    0.2404    0.1200    0.0599
h = 1     1     1     1
pValue =1.0e-15 * 0.0000    0.0000    0.0000    0.1293
```

Here the variance ratio assumes a value different from one, because it also depends on the correlation.[78] The value is equal to one when correlation is equal to zero. We have seen that, this series is not correlated even if it presents a little bit of correlation (no meaningful). As a correlation=0 is never found, the variance ratio can be different form 1.

[78] See the formula in the methodology part.

3.1.2.6. The GARCH model

In order to capture the arch effect, we try to fit a GARCH model. To check the goodness of this model we apply some diagnostics. The diagnostic tests should be computed on the standardized residuals[79].

The diagnostics are:

- Autocorrelation test: the rejection of the null hypothesis (i.e. no correlation) suggests a misspecification of the conditional expected value.
- Normality test: the rejection of the null hypothesis of normality indicates the choice of another distribution for the errors or the choice of the robust option in estimation.
- Autocorrelation test of the squared standardized residuals ${\tilde{u}_t}^2$ useful to check if the chosen GARCH models are able to eliminate the ARCH effect. The rejection the null hypothesis (i.e. no more ARCH effect) signifies a misspecification of the heteroscedasticity model.

We selected several GARCH models in order to capture the arch effect and to fit the data. In these models all coefficients are significant. The p-values are close to zero, so we are able to reject the null hypothesis of coefficients equal to zero.

We present all models in the Appendix; here, as example, we present the first model, according to the BIC criterion[80].

1. GARCH (1,1) with Sk-GED distribution
2. GARCH (1,1) with Sk-t Student distribution
3. GARCH (1,2) with Sk-t Student distribution
4. GARCH (1,1) with GED distribution
5. GARCH (1,2) with GED distribution
6. GARCH (1,2) with t Student distribution
7. GARCH (2,1) with Sk-GED distribution

[79] The standardized residuals ($\tilde{u}_t$) are the residuals ($\hat{u}_t$) divided by the conditional variance estimates $({\hat{\sigma}^2}_t)$: $\tilde{u}_t = \frac{\hat{u}_t}{\sqrt{{\hat{\sigma}^2}_t}}$

[80] The Bayesian information criterion (BIC) or Schwarz criterion (also SBC, SBIC) is a criterion in order to select the model selection among a finite set of models. The best model is the model with the lowest BIC. This criterion is based on the likelihood function.

```
Model: GARCH(1,1) [Bollerslev] (Skewed GED)
Dependent variable: DAILY_RET_STOXX600EUROPE
Sample: 1999-01-05-2016-02-11 (T = 4463), VCV method: Robust

    Conditional mean equation

             coefficient   std. error      z     p-value
  ------------------------------------------------------
  const      0.000420229   0.000135820   3.094   0.0020  ***

    Conditional variance equation

             coefficient   std. error      z       p-value
  ---------------------------------------------------------
  omega      1.57165e-06   3.86936e-07    4.062   4.87e-05  ***
  alpha      0.0970880     0.0113956      8.520   1.60e-017 ***
  beta       0.893352      0.0118087     75.65    0.0000    ***

    Conditional density parameters

             coefficient   std. error     z       p-value
  --------------------------------------------------------
  ni          1.48576      0.0490035    30.32    6.35e-202 ***
  lambda     -0.0936203    0.0181147    -5.168   2.36e-07  ***

      Llik:  14115.86282   AIC: -28219.72563
      BIC:  -28181.30417   HQC: -28206.18174
```

For each model, we have run all the diagnostics: all models have been found to be valid. Indeed, there is not significant and relevant correlation, both in the standardized residual and in the squared standardized residuals. In the first lag the bars are inside the bands. The maximum value of correlation is 0,035 that can be not considered meaningful. Moreover, we verify if the sum of the coefficients is equal to one. If alpha plus beta are greater than one, the volatility is growing without bounds, so this implies that the garch model chosen is not a good alternative. The model selected has the sum of coefficient less than one. With regard to the normality test in the standardized residuals, in all models the p-values are very low and close to zero so we are able to reject the null hypothesis of normality. For this reason, in order to fit the data, we choose models with distribution different from normal e.g. GED, t Student, Sk-GED and Sk-t Student distributions.

As example, we illustrate the diagnostics of the first model GARCH (1,1) with Sk-GED distribution. (Figure 21 and 22).

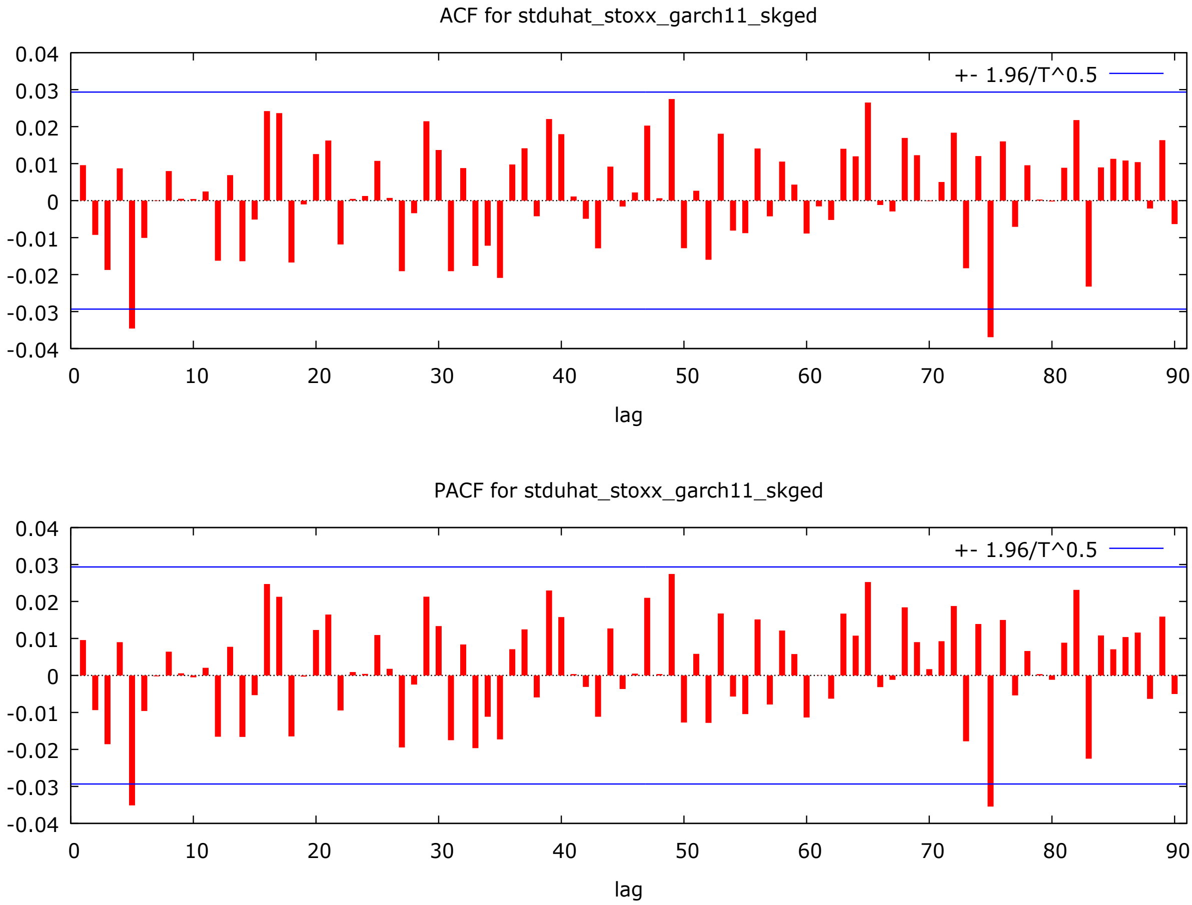


Figure 21. Acf and Pacf of standardized residuals of the model GARCH (1, 1) with Sk-GED distribution. Source: Author's elaboration.

```
Test for normality of stduhat_stoxx_garch11_skged:

 Doornik-Hansen test = 151.063, with p-value 1.57438e-033

 Shapiro-Wilk W = 0.989673, with p-value 1.51567e-017

 Lilliefors test = 0.0406379, with p-value ~= 0

 Jarque-Bera test = 286.817, with p-value 5.22902e-063
```

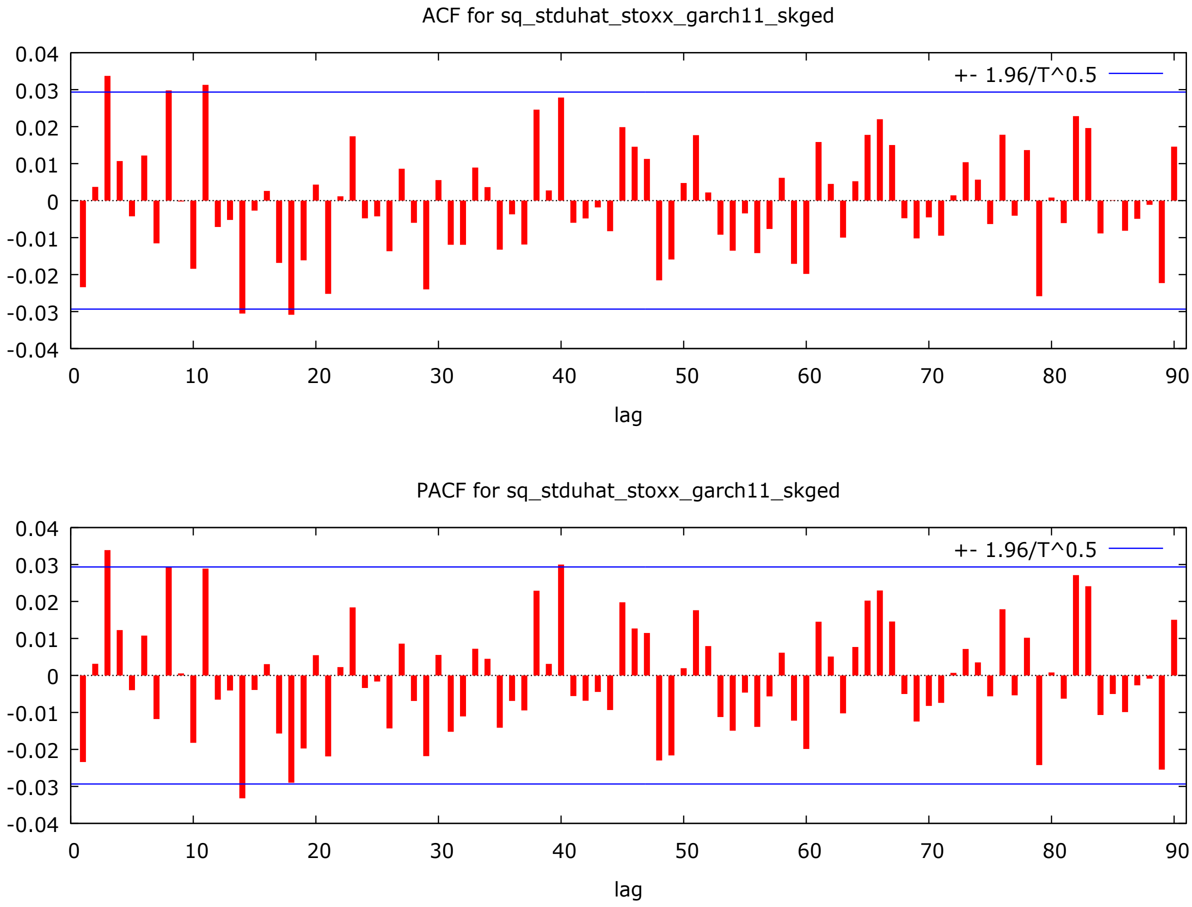


Figure 22. Acf and Pacf of squared standardized residuals in the model GARCH (1, 1) with Sk-GED distribution.
Source: Author’s elaboration.

The diagnostics show that the model is good and appropriate.

In particular, there is not a significant correlation in the standardized residuals. The maximum value is 0,03 that is not meaningful. This means that the conditional expected value is appropriately estimated.

The same result is obtained in the squared residuals, where the maximum correlation is 0,03 that it can be not considered relevant. Hence, the chosen GARCH model is able to diminish and eliminate the arch effect. So the model is appropriate.

3.1.2.7. Is the series long range dependent? The Hurst coefficient and the Lo test

The increments in random walk process are independent and unpredictable, so they lose memory.

Mandelbrot instead, proved that the price changes are predictable, because the financial market has a fractal structure. The returns have a long memory, it can be measured by the Hurst coefficient (H). All changes are due to the past events and the future increments are based on the previous changes. This theory is in contrast with the classical and random walk theory, in which the price changes are not predictable, as we have delineated in the second part of this work. In order to understand if the process is a long range dependent, we calculate the Hurst coefficient, explained above in the methodology. The results are presented in the figure 23 below.

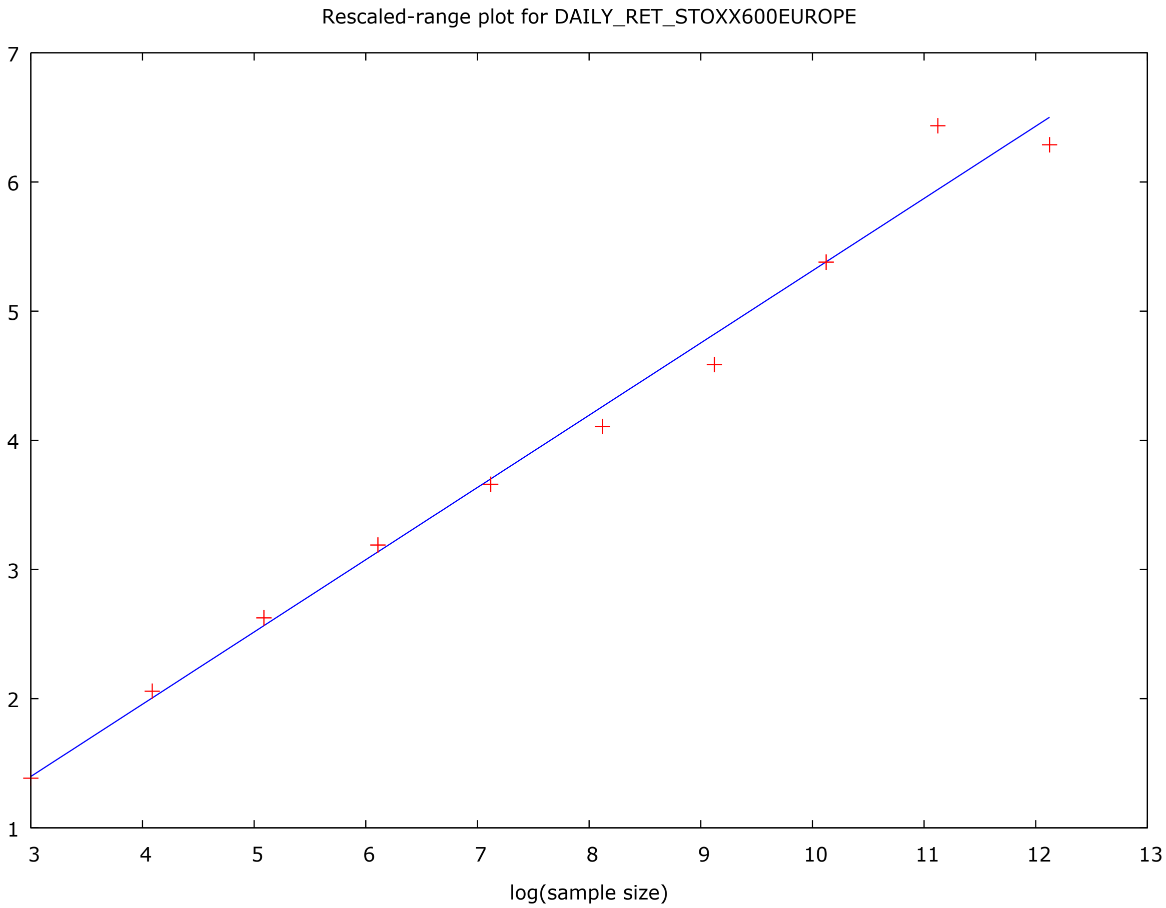


Figure 23. The plot of Hurst coefficient for the daily returns of Stoxx Europe 600 Index.
Source: Author's elaboration

```
Rescaled range figures for DAILY_RET_STOXX600EUROPE
(logs are to base 2)

 Size     RS(avg)   log(Size)     log(RS)
 4463      78.155      12.124      6.2883
 2231      86.565      11.123      6.4357
 1115      41.636      10.123      5.3798
  557      24.035      9.1215      4.5871
  278      17.237      8.1189      4.1075
  139      12.640      7.1189      3.6599
   69      9.1228      6.1085      3.1895
   34      6.1730      5.0875      2.6260
   17      4.1641      4.0875      2.0580
    8      2.6115      3.0000      1.3849

Regression results (n = 10)

                    coeff   std. error
   Intercept     -0.28024      0.19317
       Slope      0.55936     0.023743

Estimated Hurst exponent = 0.559364
```

Moreover, we implement a test created by Lo using the Stata software:

```
Lo Modified R/S test for retstoxx600
Critical values for H0: retstoxx600 is not long-range dependent
90%: [ 0.861, 1.747 ]
95%: [ 0.809, 1.862 ]
99%: [ 0.721, 2.098 ]
Test statistic:     1.17  (0 lags via Andrews criterion)  N = 4463
```

However, when H is different from 0,5, the increments are not independent of each other. Each of them carries within it a “memory” of all the events that preceded it, which is not short-term, but it is a “long memory” which, theoretically, can last forever. The most recent events have a greater impact than those far away, but they have still residual influence.

The value of the Hurst coefficient in the random walk is equal to 0,5. In this case, it is not so far from 0,5: because it is 0,5593. This can mean that there is not a meaningful memory. This is also confirmed by the Lo test implemented in Stata. It exhibits that the process is not long range dependent because the test statistic is inside the critical values. Hence, we are able to accept the null hypothesis that establishes the no long-range dependency.

3.1.2.8. Is the order of the data series random?

In order to conclude our analysis, we implement now a non-parametric test: the run test. The goal is to analyze if the process follows a random behavior and, so, if the returns are independent. The results are the following:

```
Runs test (level)
Number of runs (R) in the variable 'DAILY_RET_STOXX600EUROPE' = 2200
Under the null hypothesis of independence and equal probability of positive
and negative values, R follows N(2232.5, 33.3991)
z-score = -0.97308, with two-tailed p-value 0.330514
. runtest retstoxx600, mean
 N(retstoxx600 <= .0000119526388074) = 2192
 N(retstoxx600 >  .0000119526388074) = 2271
                 obs = 4463
             N(runs) = 2200
                  z  = -.95
            Prob>|z| = .34
```

The p-value is 0,330514, so we can accept the null hypothesis: the order of the variables is random.

This output is congruent with the random walk hypothesis. In this specific case, the hypothesis of random walk is accepted. This may be related to the Stoxx Europe 600 Index, composed of 600 companies from the main countries in all over the Europe composition.

The Stoxx 600 Index includes different sectors, without having a specific sector that can affect the index.

To sum up: after describing the data and we have tested the if the returns are normally distributed. Q-Q plot, returns distribution, statistics and normality tests show the data do not follow the normal distribution. This output stands in contrast with the classical theory and the first definition of random walk, but it is congruent with the second and third definition.

Another way to check price changes unpredictability is to look for the presence of unit root. A set of tests has discovered unit root in the series of prices and not in its differentiation (the series of returns), according to the random walk process. We have also investigated the correlation in the returns: results exhibit no correlation. This conforms to the third definition of random walk. In this part of the analysis, we have identified a volatility clustering: large changes are followed by large changes, and small changes are followed by small changes. Then we have tried to capture this effect using GARCH models: the chosen models fit appropriately.

We implement the variance ratio that considers volatility clustering phenomenon, as volatility clustering is a common knowledge among economists, as the variance ratio is lower than 1 hypothesis of random walk hypothesis is rejected.

Finally, we quantified the Hurst coefficient for the returns series in order to investigate the long range dependence. The coefficient value does not differ too much from the value calculated in the random walk. Lo test also confirmed it.
In addition, we have used a non-parametric test: the runs test. The outcome shows the order of variables is random, without any dependency.
Hence, we can affirm that, under the most restrictive idea of random walk, Stoxx Europe 600Index cannot be considered weakly efficient, because this condition is theoretical only, as many authors have explained. If we relax the definition of random walk, we can sustain the hypothesis of weakly efficiency, because the examined data have the features of the random walk of the third type; even if the variance ratio rejects the null hypothesis of random walk. This rejection can be due to the fact that the correlation is present even if it does not have a significant value.

3.2.2. The Ftse Mib

Description and Composition

The Ftse Mib is considered as the primary benchmark index for the Italian equity market. It represents approximately 80% of the domestic market capitalization. This index is composed of highly liquid leading Italian companies. In particular, it quantifies the performance of 40 Italian equities seeking to replicate the broad sector weights of the Italian stock market.

The Index is composed of the stocks traded on Borsa Italiana (BIt) main equity market. The Index is a market cap-weighted index, regulating the constituents according to float.

The constituents in alphabetic order are: Anima Holding Spa Anima Holding Spa, Atlantia Spa, Azimut Holding SPA, Banca Mediolanum, Banca Monte dei Paschi di Siena S.p.A., Banco Popolare Società Cooperativa Scarl, Banca popolare dell'Emilia Romagna Società Cooperativa, Buzzi Unicem, CNH Industrial NV, Davide Campari-Milano Spa, Enel Green Power Spa, ENEL Ente Nazionale per L'Energ Elet Spa, Eni Spa, EXOR Spa, Fiat Chrysler Automobiles NV, Finmeccanica Spa, Assicurazioni Generali, Intesa Sanpaolo, Italcementi Spa, Luxottica Group Spa, Mediobanca Spa, Moncler Spa, Mediaset, Banca Popolare di Milano BPM Bipiemme, Prysmian Spa, Poste Italiane Spa, Ferrari N.V., Salvatore Ferragamo Spa, Saipem Spa, Snam Spa, STMicroelectronics NV, Tenaris SA, Telecom Italia Spa, Tod's

Spa, Terna Spa, Unione di Banche Italiane Spa, UniCredit Spa, Unipol Gruppo Finanziario Spa, UnipolSai Spa and YOOX NETAPORTER.

The ICB Super-sectors included in the Ftse Mib are in the figure 24 and the top ten constituents of Ftse Mib are in the figure 25. The sector that has the more weight is banks with 23,35% that is a very high percentage. In the second position there is utilities sector, with 20,54% and as third position oil and gas, with 13,71%. The data are updated in March 31, 2016.

ICB Supersector Breakdown

ICB Code	ICB Supersector	No. of Cons	Net MCap (EURm)	Wgt %
0500	Oil & Gas	2	34,790	13.71
1700	Basic Resources	1	5,171	2.04
2300	Construction & Materials	2	3,094	1.22
2700	Industrial Goods & Services	4	25,690	10.13
3300	Automobiles & Parts	2	11,046	4.35
3500	Food & Beverage	1	2,484	0.98
3700	Personal & Household Goods	3	11,646	4.59
5300	Retail	1	1,609	0.63
5500	Media	1	2,720	1.07
6500	Telecommunications	1	9,259	3.65
7500	Utilities	5	52,097	20.54
8300	Banks	8	59,229	23.35
8500	Insurance	5	25,042	9.87
8700	Financial Services	3	6,730	2.65
9500	Technology	1	3,064	1.21
Totals		**40**	**253,671**	**100.00**

Figure 24. The ICB Supersector Breakdown of Ftse Mib.
Source: www.ftse.com

Top 10 Constituents

Constituent	ICB Sector	Net MCap (EURm)	Wgt %
Eni	Oil & Gas Producers	32,762	12.92
Intesa Sanpaolo	Banks	29,301	11.55
Enel	Electricity	26,758	10.55
Generali	Nonlife Insurance	16,427	6.48
Unicredit	Banks	15,511	6.11
Snam	Gas Water & Multiutilities	13,478	5.31
Atlantia	Industrial Transportation	11,631	4.59
Telecom Italia	Fixed Line Telecommunications	9,259	3.65
Luxottica Group	Personal Goods	8,620	3.40
Terna	Electricity	7,157	2.82
Totals		**170,903**	**67.37**

Figure 25. The top 10 constituents of Ftse Mib.
Source: www.ftse.com

We start our analysis describing the data: daily prices from January 4, 1999 to February 11, 2016.[81]

In the figure 26, we show the prices of Ftse Mib Index.

Figure 26. Daily Prices of Ftse Mib Index from January 4, 1999 to February 11, 2016.
Source: Author's elaboration.

As we can note at first glance, there are two downturns: in the 2001 and in the 2009. These two peaks can be related to the same events we have analyzed in the Stoxx 600 Index: the Argentinian crisis, the "Dot-com" bubble in the 2001 and the financial crisis in the 2008. This chart differs from of Stoxx 600 chart: in the Stoxx 600 chart, prices increase after the financial crisis. In Ftse Mib Index, after the financial crisis, the Daily Prices had a quite weak recovery. This may related to the sovereign debt crisis. In the case of Stoxx600, the recovery could be related to the strong economies in Germany, United Kingdom and France.

On March 6, 2000, Ftse Mib closed at its highest point. After the bursting of the speculative bubble in the technology sector (internet bubble), on March 2003, the index sank to a lowest point. From spring 2003, Ftse Mib began to rise again, until May, 2007.

During the international financial crisis, originated by the US subprime crisis in the summer of 2007, the Ftse Mib began to decline again. On June 2008 it fall down and the volatility of index increased. On October, 2008, the index continued to decrease reaching its lowest point on March-May, 2009.

[81] We explained the reasons above.

The index increased on May, 2010 due, probably, to the decision of establishing the European Stability Mechanism. From the spring 2009, the index recovered. The euro crisis in 2010 and the weakening of the world economy, from 2011, led to a significant drop in FTSE MIB. On September 2011, the index sunk. The announcement of new bond purchase programs of the European Central Bank and the Fed induced a recovery of prices in the stock market. The monetary stimulus has played an important role in the formation of prices, given the contraction of the Italian economy and the situation of the companies.

3.2.2.1. Are the returns normally distributed?

The returns are represented in the figure 27. We can note the phenomenon of volatility clustering. The volatility is very high in the 2001 and in the years after the financial crisis. As we have analyzed, this time period was characterized by downturns. Indeed, large changes are followed by large changes or small changes followed by small changes.
Respect to the figure of returns of Stoxx Europe 600, this exhibits a higher volatility.

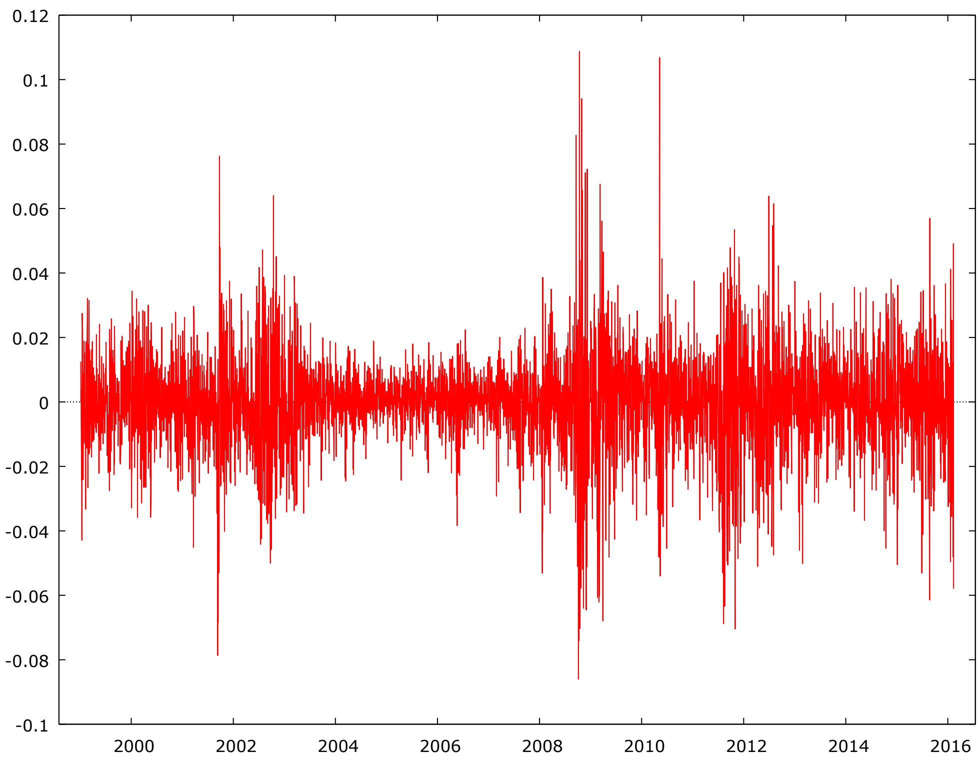


Figure 27. Daily returns of Ftse Mib from January 5, 1999 to February 11, 2016.
Source: Author's elaboration.

In order to test if the returns follow a normal distribution, we calculate some statistics, tests for normality, the Q-Q plot (figure 28) and the plot distribution of returns (figure 29).

```
Summary statistics for ret_daily_FTSEMIB:
Mean                         -0.00019526
  Median                       5.2292e-005
  Minimum                        -0.085991
  Maximum                          0.10874
  Standard deviation              0.015197
  C.V.                              77.828
  Skewness                        -0.10619
  Ex. kurtosis                      4.1974
  5% percentile                  -0.025105
  95% percentile                  0.023194
  Interquartile range             0.014947
  Missing obs.                           1
```

```
Test for normality of ret_daily_FTSEMIB:

 Doornik-Hansen test = 1405.34, with p-value 6.83318e-306

 Shapiro-Wilk W = 0.951145, with p-value 3.35217e-036

 Lilliefors test = 0.0736714, with p-value ~= 0

 Jarque-Bera test = 3284.66, with p-value 0
```

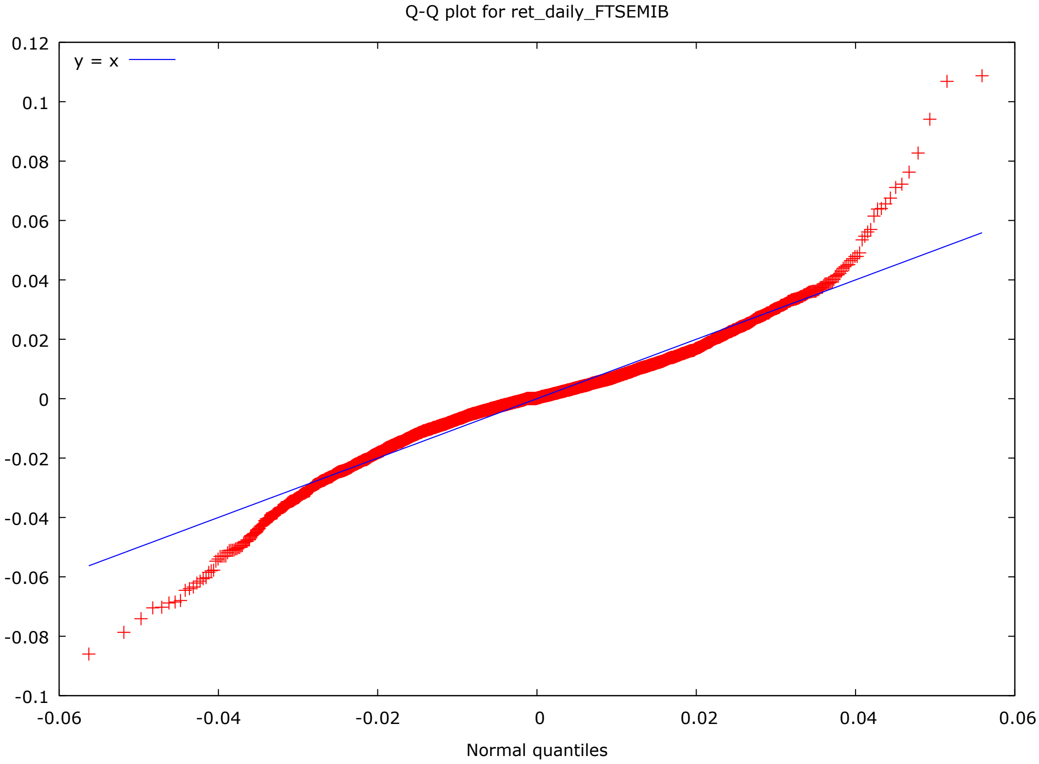


Figure 28. The Q-Q plot of daily returns of Ftse Mib Index.
Source: Author's elaboration.

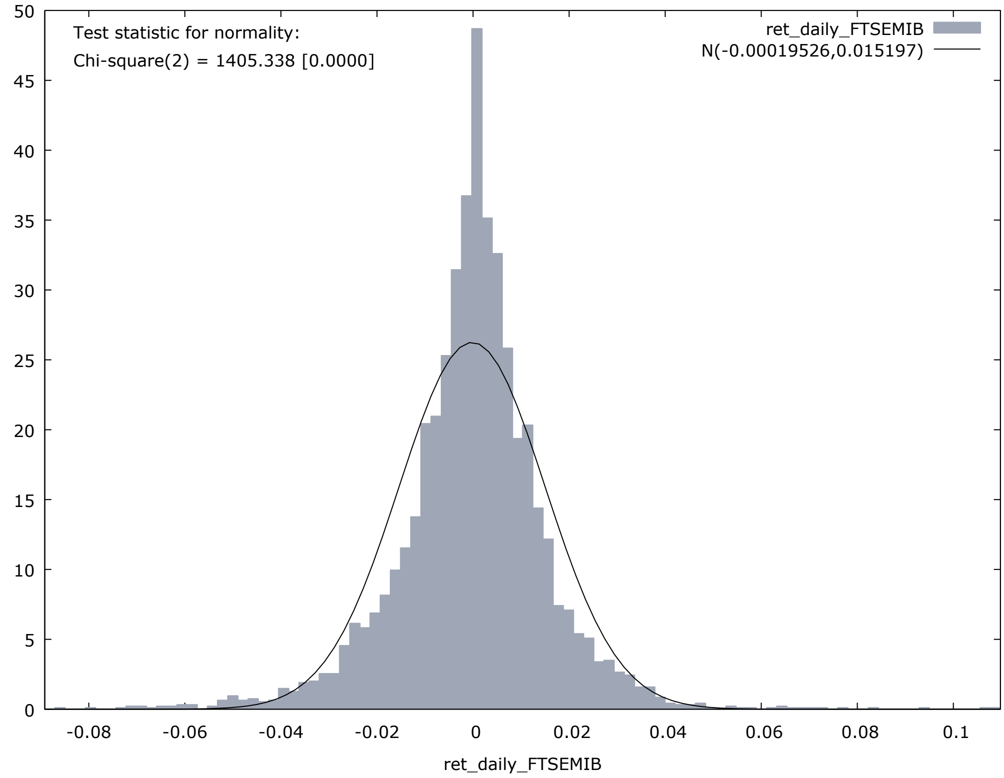


Figure 29. The distribution of daily returns of Ftse Mib Index.
Source: Author's elaboration.

All these methods confirm that the returns do not follow a normal distribution. From the summary statistics, we note: if the returns were distributed as normal, the mean, the kurtosis and the skewness would be zero and the standard deviation would be one. In this case instead, mean is close to zero, standard deviation is 0,015, the skewness is -0,10619 and the kurtosis is 4,1974.

These data show: the distribution is asymmetric (-0,10619), it has a fat tails (kurtosis>3) and it is sharper than a normal distribution. As for Stoxx Europe 600 Index, also here the normal distribution is not appropriate to represent the returns; it tends to underestimate the probability of extreme events[82]. The presence of leptokurtosis is also compatible and linked to the hypothesis of the dependency of variance over time. This will be addressed after, in the test of autocorrelation for the squared returns.

Leptokurtosis appears also in the Q-Q plot in the figure 28. The red line does not fit completely with the blue line. The red line (starting from the left side) is above the blue line and then moves below. This means we are dealing with fat tails.

[82]The tendency to look heavier tails than the normal distribution is defined by the term leptokurtosis. The leptokurtic distributions have the peculiarity to assign a higher probability to events far removed from the average value of the distribution.

This is also confirmed in the return distribution plot in figure 29. Here the black line reproduces the normal distribution that does not fit the data appropriately. The returns cross the black line in the fat and in the extremes.
Finally, the Doornik-Hansen, Shapiro-Wilk, Lilliefors and Jarque-Bera tests strongly confirm the description of returns distribution delineated so far. The null hypothesis of these tests is normality. As all p-values are near to zero, we can reject the null hypothesis of normality.

To sum up, we have found the returns are not normal distributed as Mandelbrot proved in his studies. This, however, does not mean that the market is inefficient and the prices do not follow a random walk. This part focuses on the random walk of the second and third types, more relaxing definitions than the first: In these definitions, other distributions, different than normal, are admitted.

3.2.2.2. Does the series have a unit root?

In order to analyze the presence of unit root, we implement the unit root tests on the prices and on the returns. If the random walk hypothesis is verified, the prices have a unit root and the returns do not have it.
For the analysis, we use the Dickey Fuller augmented, KPSS, Phillips-Perron and the Zivot-Andrews tests. In particular, the last one is more reliable as this test is constructed for the data with structural breaks and high volatility.

We show the results below:

```
Augmented Dickey-Fuller test for l_FTSEMIB
including 0 lags of (1-L)l_FTSEMIB
(max was 90, criterion BIC)
sample size 4463
unit-root null hypothesis: a = 1

  test with constant
  model: (1-L)y = b0 + (a-1)*y(-1) + e
  estimated value of (a - 1): -0.000887709
  test statistic: tau_c(1) = -1.31256
  p-value 0.6259
  1st-order autocorrelation coeff. for e: -0.022

  with constant and trend
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + e
  estimated value of (a - 1): -0.00221762
  test statistic: tau_ct(1) = -2.2226
  p-value 0.4762
  1st-order autocorrelation coeff. for e: -0.021

  with constant and quadratic trend
```

```
  model: (1-L)y = b0 + b1*t + b2*t^2 + (a-1)*y(-1) + e
  estimated value of (a - 1): -0.00221835
  test statistic: tau_ctt(1) = -2.22292
  p-value 0.718
  1st-order autocorrelation coeff. for e: -0.021
```

```
KPSS test for l_FTSEMIB (including trend)

T = 4464
Lag truncation parameter = 90
Test statistic = 0.269251

                   10%      5%      1%
Critical values: 0.119   0.148   0.218
P-value < .01
```

```
Zivot-Andrews unit root test for  FTSE

Allowing for break in intercept

Lag selection via TTest: lags of D.FTSE included = 8

Minimum t-statistic -2.934 at 2348  (obs 2348)

Critical values: 1%: -5.34 5%: -4.80 10%: -4.58
```

```
Phillips-Perron test for unit root                Number of obs   =      4463

                                                  Newey-West lags =         9

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)           -3.382           -20.700           -14.100           -11.300
 Z(t)             -1.249            -3.430            -2.860            -2.570
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.6524
```

The tests give the same results, indicating the prices are non-stationary.

The p-values of Zivot-Andrews test, the Adf test and Phillips-Perron test are very high. This implies we can to accept the null hypothesis of the presence of unit root.

The null hypothesis of KPPS is no presence of unit root: for this reason the p-value is near zero: so we can reject the null hypothesis.

As regard the series returns, the results are the following:

```
Augmented Dickey-Fuller test for DAILY_RET_FTSEMIB
including 0 lags of (1-L)DAILY_RET_FTSEMIB
(max was 80, criterion BIC)
```

```
sample size 4462
unit-root null hypothesis: a = 1

  test with constant
  model: (1-L)y = b0 + (a-1)*y(-1) + e
  estimated value of (a - 1): -1.02238
  test statistic: tau_c(1) = -68.1895
  p-value 0.0001
  1st-order autocorrelation coeff. for e: -0.000

  with constant and trend
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + e
  estimated value of (a - 1): -1.02239
  test statistic: tau_ct(1) = -68.1827
  p-value 4.067e-015
  1st-order autocorrelation coeff. for e: -0.000

  with constant and quadratic trend
  model: (1-L)y = b0 + b1*t + b2*t^2 + (a-1)*y(-1) + e
  estimated value of (a - 1): -1.02239
  test statistic: tau_ctt(1) = -68.1749
  p-value 0
  1st-order autocorrelation coeff. for e: -0.000
```

KPSS test for DAILY_RET_FTSEMIB (including trend)

```
T = 4463
Lag truncation parameter = 80
Test statistic = 0.0552712

                    10%      5%      1%
Critical values: 0.119   0.148   0.218
P-value > .10
```

Zivot-Andrews unit root test for retftse

```
Allowing for break in intercept

Lag selection via TTest: lags of D.retftse included = 7

Minimum t-statistic -23.241 at 2657  (obs 2657)

Critical values: 1%: -5.34 5%: -4.80 10%: -4.58
```

Phillips-Perron test for unit root

```
                                                   Number of obs   =      4462
                                                   Newey-West lags =         9

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)        -4474.727           -20.700           -14.100           -11.300
 Z(t)            -68.229            -3.430            -2.860            -2.570
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

The results exhibit that the series of returns does not have a unit root: the p-values of Zivot Andrews, Phillips-Perron and ADF are near zero so we are able to reject the null hypothesis of non-stationarity. The p-value in the KPSS test is high; hence we can accept the null hypothesis of stationarity. Through these tests, we have demonstrated that the prices have a unit root and the returns do not have. This output confirms the features of random walk process.

3.2.2.3. Are the returns correlated?

In this part, we are going to test if the returns are correlated or uncorrelated. If they are uncorrelated, they respect the conditions of random walk (of the third type, as the un-correlation does not imply the independence that is required for the random walk of the second type) and we can assert the market is weakly efficient.

In order to test the autocorrelation we implement the ACF and PACF graphs on the return series and the results are shown in the figure 30:

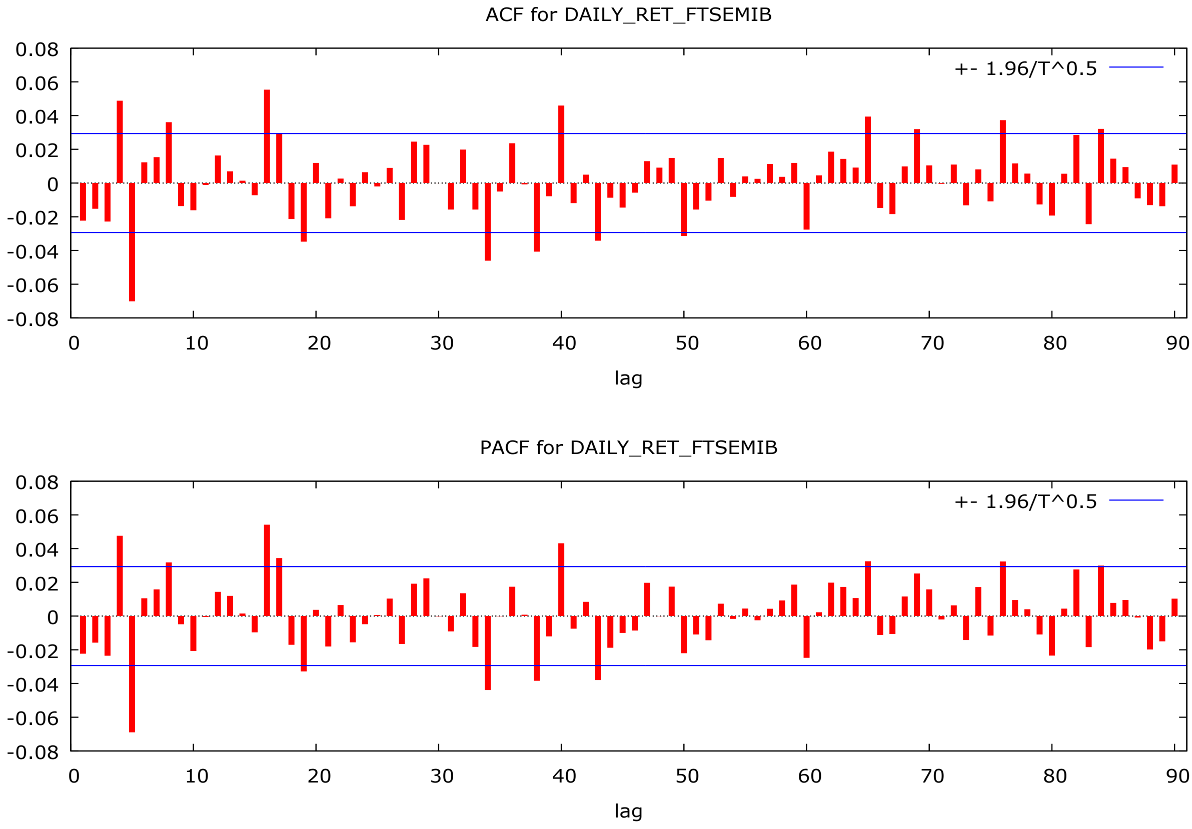


Figure 30. Acf and Pacf of daily returns of Stoxx Europe 600 Index.
Source: Author's elaboration.

The returns do not show any significant correlation. As the maximum value of correlation is a little bit more than -0,06 on fifth lag, this is not considered meaningful correlation.

Hence we can conclude the returns are not correlated and so they satisfy the requirements of the random walk process and the weakly efficiency.

3.2.2.4. Is the squared series correlated?

In the third type of random walk process, the data have to be uncorrelated only, not independent. This means it is possible that the functions of these returns may not be 0, e.g., $Cov(r_h^2, r_k^2) \neq 0$.

In order to confirm this and to examine in more specific terms the phenomenon of volatility clustering , we use the autocorrelation test on the squared returns of Ftse Mib Index. (Figure 31).

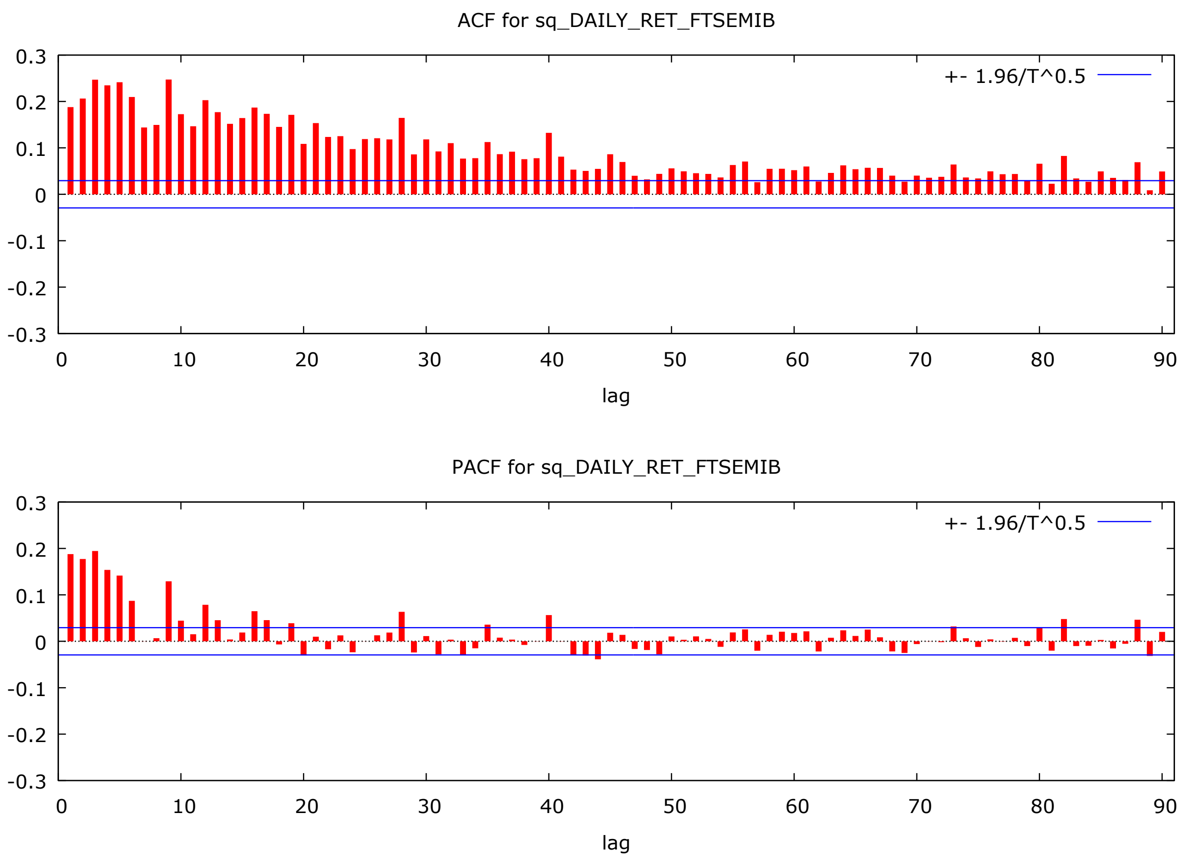


Figure 31. Acf and pacf of squared returns of Ftse Mib Index.
Source: Author's elaboration.

The figure shows a very strong correlation in the series of squared returns. It implies that the volatility is correlated and it depends on the past events. The Arch effect found in the series explains the volatility behavior. This effect can be incorporated in the model GARCH, as we will examine later on.

In order to confirm the presence of Arch effect, we implement, in MATLAB, the Engle test. Here there is the output:

```
e = data - mean(data);
>> [h,p,fStat,crit] = archtest(e,'Lags',2)              h =1
p =0    fStat = 294.4523       crit =5.9915
```

The result (P-value=0 and h=1) means that we are able to reject the null hypothesis of no arch effect. Hence, we confirm our analysis of the presence of arch effect in the series.

As the frequency of data collection affect the ARCH effect and the volatility clustering, we go here a step further, using monthly data. We expect, the ARCH effect becomes weaker.

ACF and PACF of the squared monthly returns of the Index (Fig.32) show that the correlation almost disappears. A significant correlation appears in the second lag as the value is 0.17. Hence, changing the data frequency, the arch effect tends to become weaker and vanishing. Engle test supports this analysis too, as *h*=0. So, we can accept the null hypothesis of no presence of arch effect in the series.

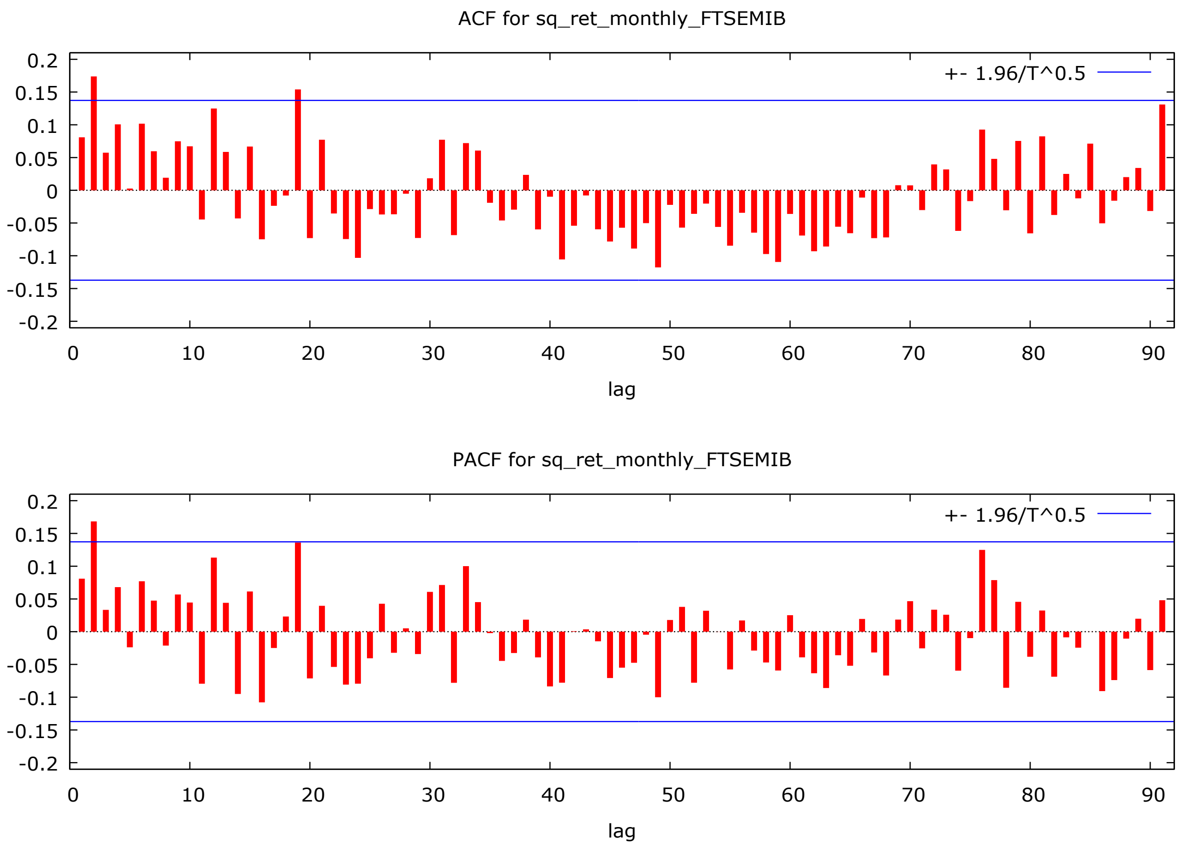


Figure 32. Acf and Pacf of the monthly returns of Ftse Mib Index.
Source: Author’s elaboration.

3.2.2.5. Variance ratio

If the series follows a random walk process, the variance of a *q*-th differenced variable is *q* times as large as the first-differenced variable. When prices follow a random walk process, the volatility of returns must grow up one-for-one with the return horizon. For example, the volatility of two-week returns must be two times the volatility of one period. If the variance ratio is 1, the data follow a random walk process. This test is implemented in Stata and Matlab.
Here Stata output:

```
Lo-MacKinlay modified overlapping Variance Ratio statistic for retftse
[2-4464 ]
q         N         VR          R_s       p>|z|
-------------------------------------------------
2        4447      0.495     -33.6642    0.0000
4        4447      0.231     -27.3852    0.0000
8        4447      0.118     -19.8684    0.0000
16       4447      0.058     -14.2474    0.0000
```

Matlab output :

```
q = 2 4 8 16;
Variance ratio = 0.4962    0.2339    0.1184    0.0582
h = 1     1     1     1
pValue = 1.0e-20 * 0.0000    0.0000    0.0000    0.3571
```

All these two results are similar and take in account the heteroscedasticity. The variance ratios are not equal to one, so the hypothesis of random walk is rejected. The null hypothesis of random walk is also rejected, because the p-values are close to zero and the *h* is equal to one.
In this case, the result can suggest a mean reverting process. Nevertheless VR<1 might be related to a very small correlation, even if correlation value is not significant, since the variance ratio depend also on correlation.

3.2.2.6. The GARCH model

In order to capture the arch effect, we try to fit a GARCH model. Then we apply some diagnostics to check the model viability. The diagnostic tests[83] should be computed on the standardized residuals, as done in the case of Stoxx Europe 600Index.

[83] The same explained in the case of Stoxx600 Europe Index.

The models selected present all significant coefficients. The p-values are very low and close to zero, so we are able to reject the null hypothesis that establishes that the coefficients are zero. In the Appendix we describe all the models; here, as example, we describe the first model according to the BIC criterion[84].The order according to BIC is:

1. GARCH (1,1) with Sk-t Student distribution
2. GARCH (1,1) with GED distribution
3. GARCH (1,2) with GED distribution
4. GARCH (2,1) with Sk-GED distribution

```
Model: GARCH(1,1) [Bollerslev] (Skewed T)
Dependent variable: DAILY_RET_FTSEMIB
Sample: 1999-01-05-2016-02-11 (T = 4463), VCV method: Robust

    Conditional mean equation

               coefficient   std. error      z     p-value
  -----------------------------------------------------------
  const      0.000272163   0.000158754   1.714   0.0865  *

    Conditional variance equation

               coefficient   std. error      z       p-value
  --------------------------------------------------------------
  omega      9.47772e-07   3.49837e-07    2.709   0.0067    ***
  alpha      0.0826007     0.00966573     8.546   1.28e-017 ***
  beta       0.916874      0.00928270    98.77    0.0000    ***

    Conditional density parameters

               coefficient   std. error     z       p-value
  -------------------------------------------------------------
  ni           8.64273     1.06749       8.096   5.67e-016 ***
  lambda      -0.119736    0.0197163    -6.073   1.26e-09  ***

       Llik:  13180.59791   AIC: -26349.19581
       BIC:  -26310.77435   HQC: -26335.65192
```

Here there are the diagnostics of the first model (figure 33):

[84] We show the diagnostics for the first model as example for the other because all these models have more or less the same diagnostics.

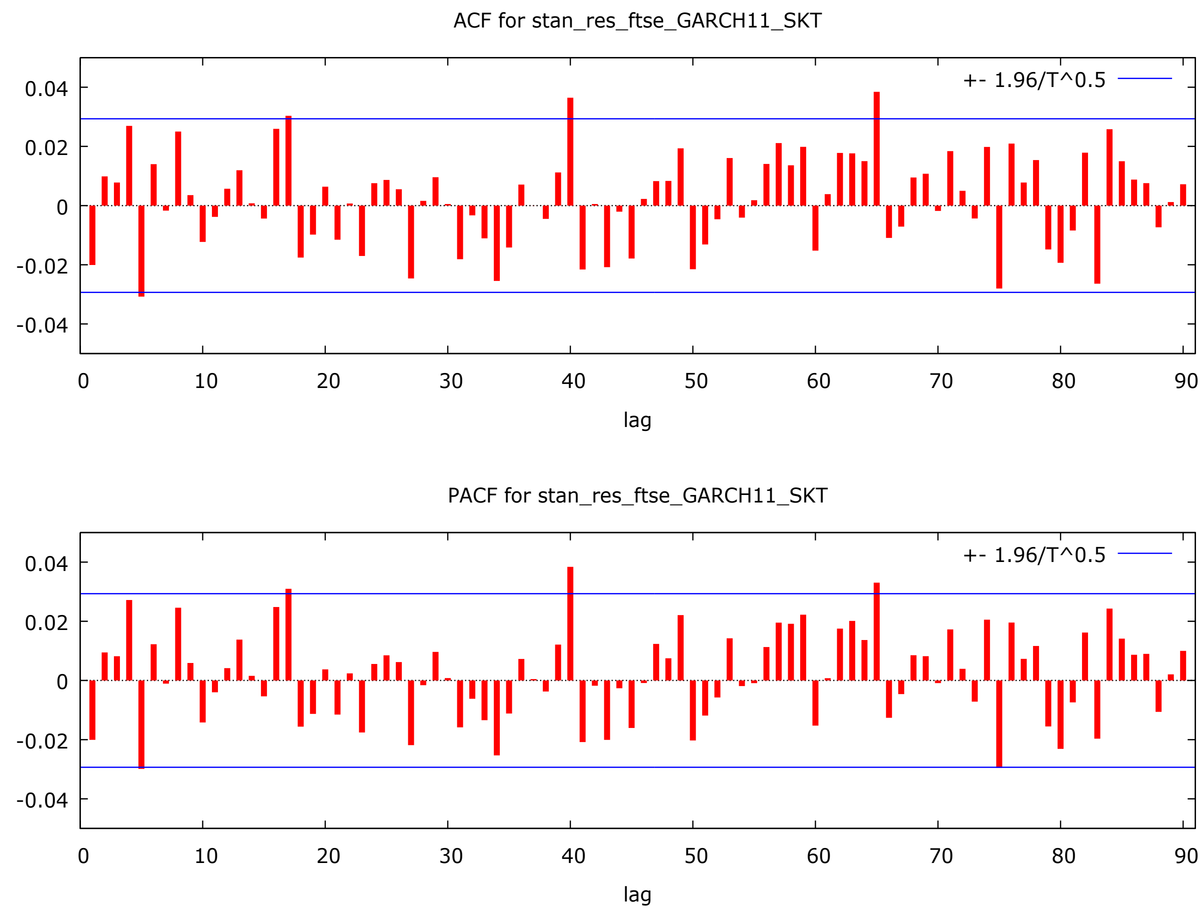


Figure 33. Acf and Pacf of standard residuals of the model GARCH (1, 1) with Skew t-Student distribution. Source: author's elaboration.

```
Test for normality of stand_res_garch11_skt:

 Doornik-Hansen test = 156.199, with p-value 1.20744e-034

 Shapiro-Wilk W = 0.988005, with p-value 4.92914e-019

 Lilliefors test = 0.0467994, with p-value ~= 0

 Jarque-Bera test = 308.947, with p-value 8.18515e-068
```

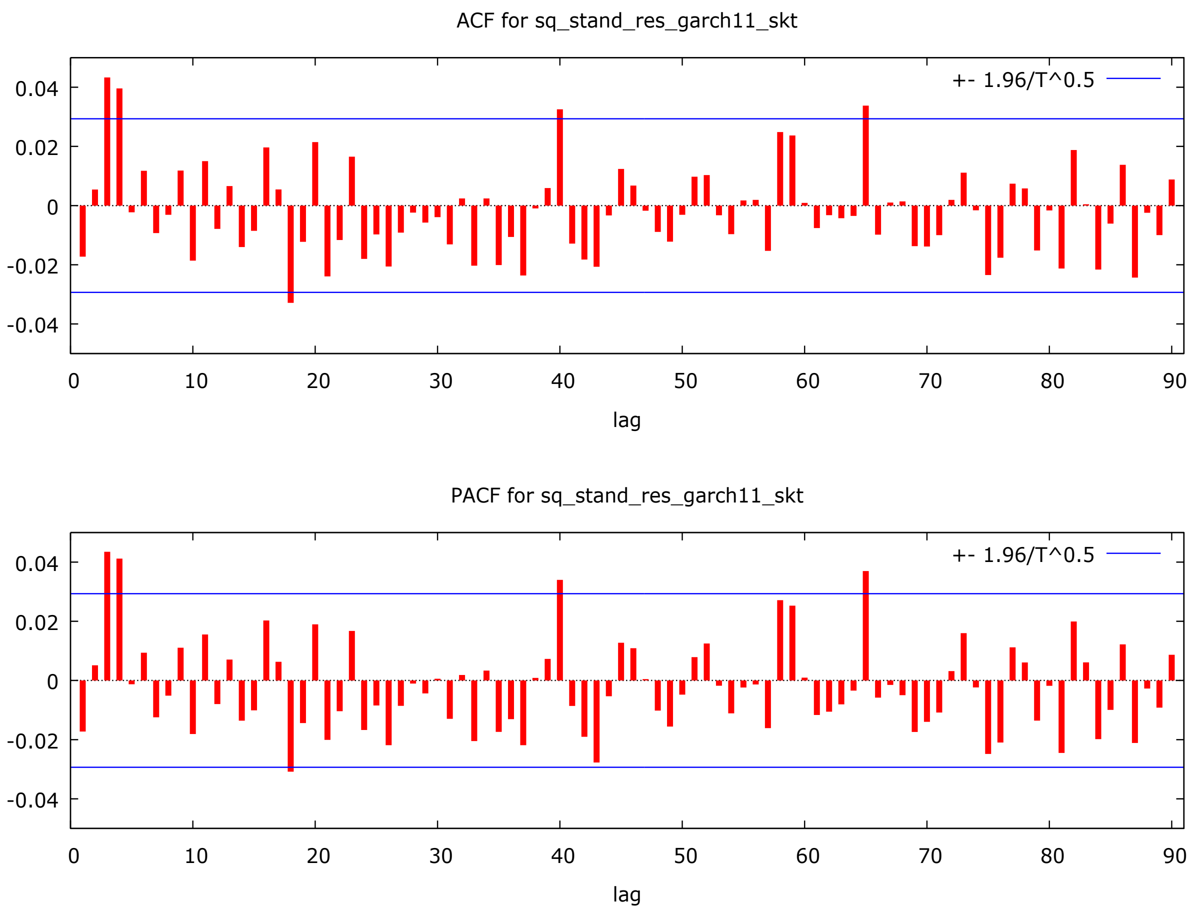


Figure 34. Acf and pacf of the squared standardized residuals of the model GARCH (1,1) with Skew t-Student distribution.
Source: author's elaboration.

All the models have a good diagnostics. There is no autocorrelation in the standardized residuals, so the conditional variance is appropriately identified (Figure 33). The squared standardized residuals are not correlated (Figure 34), hence the Garch model fits the volatility and it entirely incorporates the Arch effect (the maximum correlation is 0,0304 that is a non-significant and meaningful correlation). Moreover, the sum of the coefficients alpha and beta are lower than one: the model could be considered a good test.[85]

With respect to the errors, we selected a distribution different from Normal distribution (such as GED, sk-GED, t Student and Sk-t Student), because the test for normality in the standardized residuals gives p-value very close to zero. We can so reject the null hypothesis of normality.

[85] Recall: if the sum of the coefficients is greater than one the volatility grows up without bound.

3.2.2.7. Is the series long range dependent? The Hurst coefficient and the Lo test

Another method, to establish if the market is efficient and if it follows a random walk, is to understand if the returns series have memory, according to the Mandelbrot's theory. We then calculate if the value of the Hurst coefficient in the (0,1) interval is different from 0.5 (Random Walk case) (Figure 35).

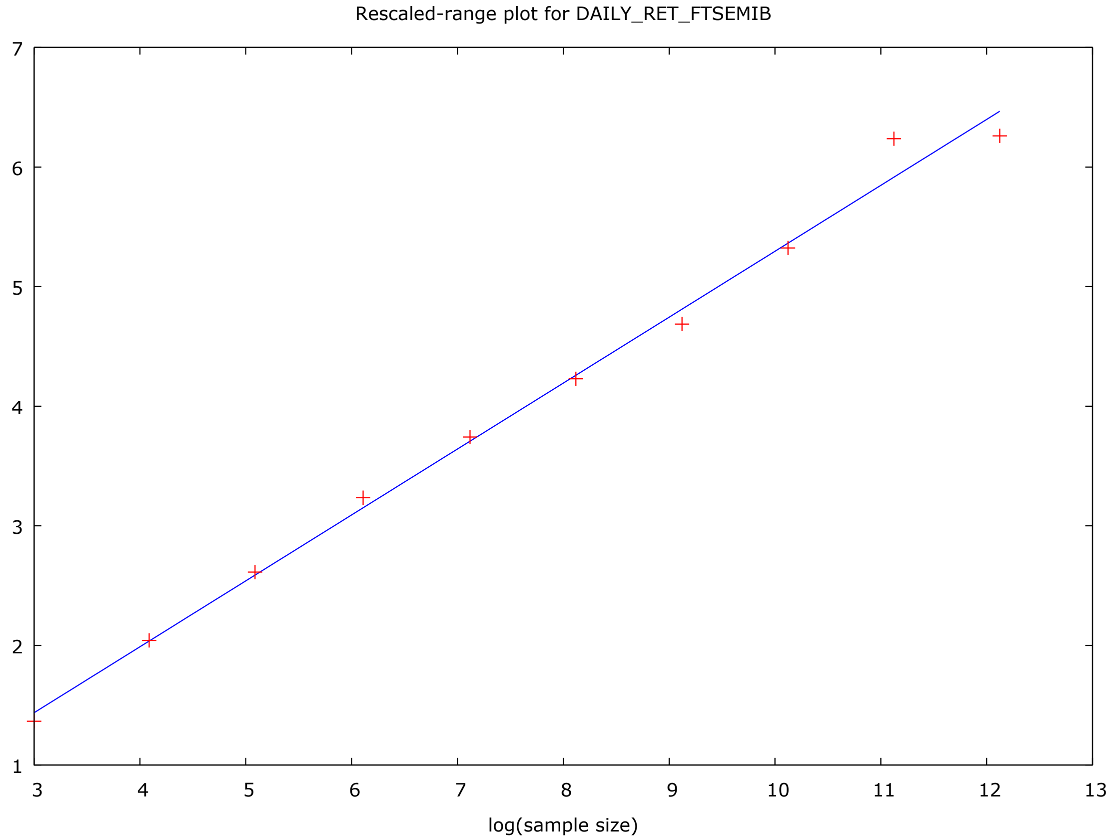


Figure 35. Plot of R/S analysis for daily returns of Ftse Mib Index.
Source: Author's elaboration.

```
Rescaled range figures for DAILY_RET_FTSEMIB
(logs are to base 2)

 Size      RS(avg)   log(Size)     log(RS)
 4463       76.677      12.124      6.2607
 2231       75.421      11.123      6.2369
 1115       40.037      10.123      5.3233
  557       25.758      9.1215      4.6870
  278       18.754      8.1189      4.2291
  139       13.387      7.1189      3.7428
   69       9.4151      6.1085      3.2350
   34       6.1186      5.0875      2.6132
   17       4.1179      4.0875      2.0419
    8       2.5771      3.0000      1.3657


Regression results (n = 10)
```

```
                  coeff   std. error
   Intercept     -0.21653      0.13235
       Slope      0.55123     0.016268
```

Estimated Hurst exponent = 0.551234

In this case, the Hurst coefficient is 0,551234. This is not exactly equal to 0,5 as in the case of random walk, but it is very close to it. Indeed, using **Lo Modified R/S test** we find that the series of returns has no memory, as we accept the series is not long-range dependent(null hypothesis). Here the results:

Lo Modified R/S test for retftse

```
Critical values for H0: retftse is not long-range dependent

90%: [ 0.861, 1.747 ]

95%: [ 0.809, 1.862 ]

99%: [ 0.721, 2.098 ]

Test statistic:     1.15  (0 lags via Andrews criterion)  N = 4463
```

3.2.2.8. Is the order of the data in the series random?

The last method implemented to examine the efficiency of the financial markets is based on a non-parametric test: the runs test. The null hypothesis of this test is that successive fluctuations are independent and in random order.

For the daily returns of Ftse Mib Index, the results are the following:

```
Runs test (level)

Number of runs (R) in the variable 'DAILY_RET_FTSEMIB' = 2354
Under the null hypothesis of independence and equal probability of positive
and negative values, R follows N(2232.5, 33.3991)
z-score = 3.63782, with two-tailed p-value 0.000274953
```

. runtest retftse, mean

```
 N(retftse <= -.000195258805597) = 2082
 N(retftse >  -.000195258805597) = 2381
             obs = 4463
         N(runs) = 2294
              z  = 2.15
        Prob>|z| = .03
```

The p-value is very close to zero, so we can reject the null hypothesis of random walk. In this case, we do not have a confirmation that Ftse Mib Index does not follow the random walk.
As the non-parametric methods do not evaluate all statistical variables, they can be less accurate, even if they are a standard and widely used among the economists. This test measures only if the sequence of the data is random, i.e. if the process can produce independent and identically distributed (i.i.d.) samples.[86]

The result of this test can be related to the composition of the index. The Ftse Mib is composed of 40 Italian companies and a relevant and meaningful part of this index is made up of banking sector. This sector can affect the overall trend of the index and so the sequence of the data cannot be seem random.
As we have underlined, the independence is difficult to find in the actual contest, because the Italian financial market is very correlated to the European and to other countries financial markets.

In general, the results can be considered plausible; they are in line with studies that found the un-correlation in the returns and the phenomenon of volatility clustering.
As we have done for Stoxx Europe 600 Index, we started from the statistical description. Considering the graph distributions and the normality-tests, we highlighted that the returns are not normally distributed; they have a distribution with fat tails (the kurtosis is greater than 3), corresponding to leptokurtosis phenomenon.
We analyzed the presence of unit root in the series, as one of the most important features of random walk. According to the tests, the price series presents a unit root and the returns series is stationary. This agrees with the principles of random walk.
Then, another meaningful feature is the non-correlation of the returns. In the Acf and Pacf graphs, we could assert that the series follows a random walk (third type), because the correlation is not significant. We also used the Acf and Pacf to check the correlation in the squared returns. Here the data are characterized by arch effect, proved also applying the Engle test. Moreover, we try to capture this Arch effect, using the GARCH model. We have found many valid garch models, with different distributions, as t-Student and GED.
Regarding the variance, we have implemented the variance ratio; this test considers also the heteroscedasticity and we found that the data do not follow a random walk process: in fact, if they followed the random walk process, the variance ratio would be one; in this case, instead,

[86]If an observed value in the sequence is influenced by its position in the sequence, or by the observations that precede it, the process is not truly random.

it is less than one. This can imply a mean reverting process due, probably, to the fact that there is a little bit negative correlation, even if not significant.

In order to apply the Mandelbrot theory, we checked the long-range dependency in the returns, calculating the Hurst coefficient with R/S analysis. We discovered a Hurst coefficient equal to 0,55, so the returns do not present a long-range dependency, according to the random walk theory. Finally, we applied a non-parametric test; it analyzes if the data are in random order. In this case, opposite to the Stoxx Europe 600 Index, we reject the null hypothesis of random walk. The run test looks for the independency of the series, which is very difficult to find because it Ftse Mib is composed of 40 companies only and the bank sector covers a huge percentage (approximately 25%) while Stoxx600 is made up of more companies (600) and there is not a so relevant sector.

In current market context, high volatility, the crisis, the unstable situation, it is hard to say if the market is efficient.

In technical terms, in a *weakly market efficient*, prices follow a random walk process, i.e. fluctuations are unpredictable.

The literature considers multiple types of random walk. The first and second definitions are mainly theoretical and cannot be applied to real market situations. The third definition, is more relaxed and can fit a wide range of real market conditions. We analyzed Stoxxx600 Europe and Ftse Mib, under this this third type of random walk.

Our study has found that both indexes are weakly efficient, in the analyzed time frame: January 4, 1999 to February 11, 2016.

CONCLUSIONS

In this work we have tested the Weak Form of Efficient Market Hypothesis, analyzing Stoxx Europe 600 and the Ftse Mib Indexes, for the following time frame: January 4, 1999 to February 11, 2016**.**

After defining the structure of the market and the role of different market players, we have introduced the concept of market efficiency, going in details of this notion. We have also outlined the history, the development and the major scientific contributions to the argument.

Different available mathematical models have been studied, in order to gain a deeper and integrated understanding of the market both in general and empirical terms. Statistical and econometric tests have been applied to the selected time series, in order to determine their efficiency. While every hypothesis and the form of efficiency are not appropriate to describe the current market situation with high volatility, crisis, bubbles and crashes, we have concentrated our attention on the weakly form. As described in the literature, the weakly form is more suitable to this real market: it is considered the first step from where to move on, to see whether markets can work efficiently and, eventually to look for inefficiency components.
As in a weak efficient market price changes are unpredictable and random, mathematics assumes prices follow a random walk process. In this case is not possible to forecast the price movements and so the returns. In order to test random walk process, literature describes several methodologies, approaches and perspectives.

As for each perspective there is a specific test oriented to highlight a certain feature of random walk process[87], we have conducted the following statistical and econometrical analyses:

1) Returns analysis: after calculating the returns of the closing price, we tested if they are independent and normally distributed. We used the following tools: theoretical normal distribution of returns vs. the real distribution of returns, calculation of summary statistics - focusing on mean, standard deviation kurtosis and skewness- and the Q-Q plot of returns.

[87] Three types of random walk exist: the first definition is very theoretical: the increments are independent and identically distributed. In the second the increments are independent and in the third they are uncorrelated. The first and the second types are too theoretical; instead the third is more appropriate and adaptable to the real world. This is the reason why we chose to investigate the third type of random walk.

Normal distribution has been checked using Doornik-Hansen test, Shapiro-Wilk test, Lilliefors test, Jarque-Bera test. We have found, for both indexes, that the returns are not independent and not normally distributed. They exhibit a distribution with fat tails.

2) Unit root tests analysis: to check if prices and returns have a unit root. Following tools have been used: Augmented Dickey-Fuller Test (ADF), the Philips-Perron test (PP), the Kwaiatkowski, Philips, Schmidt and Shin test (KPSS) and the Zivot Andrews test. PP and Zivot Andrews tests are particularly important, as they consider the presence of structural breaks, meaningfull in periods characterized by crisis, bubbles and crashes. We have found prices have a unit root and returns do not, for the both indexes. This output supports random walk hypothesis.

3) Correlation analysis: to check if the returns are correlated. To test this, autocorrelation function has been used. We have found returns of the both indexes do not have a relevant and significant correlation, so the market can be considered weak efficient. This conforms to the third definition of random walk. Moreover, we have identified volatility clustering[88], also named autoregressive conditional heteroscedastic (ARCH) effect. This phenomenon has been detected, looking for autocorrelation in the squared series. ARCH effect has also been confirmed, using another test, Engle's ARCH test. Further, to reduce and capture the volatility clustering, GARCH models, with different probability distributions, have been used. Finally, in order to check if the chosen models fit appropriately, we have run the diagnostics[89]. The models are adequate and serving the purpose.

4) Volatility analysis: we analyzed if the volatility of increments grows up, one-for-one, with the return horizon. To perform this task, Lo and MacKinlay Variance Ratio Test has been used. The output value (<1) suggests to reject random walk hypothesis, for the both indexes.[90]

5) *Long run dependence analysis*: we investigate the long range dependence to check if the returns are independent and unpredictable or they have memory. It can be measured by the Hurst coefficient (H). The coefficient value does not differ too much from the value calculated in the random walk[91], for the both indexes; so the returns have no memory,

[88] Large changes are followed by large changes, and small changes are followed by small changes.
[89] Autocorrelation test (autocorrelation function) and Normality test (Doornik-Hansen test, Shapiro-Wilk test, Lilliefors test, Jarque-Bera test) for the standardized residuals and the Autocorrelation test of the squared standardized residuals.
[90] If the data follow a random walk process, the variance ratio is equal to 1.
[91] The Hurst coefficient value is between 0 and 1. If the data follow a random walk process, the Hurst coefficient is equal to 0,5.

supporting the random walk hypothesis. This result has also been confirmed using Lo test of long range dependency.

6) Non parametric test analysis: to check if returns are random, we have used a non-parametric test: the runs test. This test investigates the order of the data. The outcome shows the order of variables is random, without any dependency, for Stoxx Europe 600and not random process for Ftse Mib. This can be related to the different composition and different sectors combination, in each of the two indexes.

To wrap up, Stoxx Europe 600 and Ftse Mib Index can be considered weakly efficient, as the two analyzed time series exhibit the features of random walk process: prices have a unit root, returns are uncorrelated, Hurst Coefficient indicates no long range dependency. Even if Lo variance ratio test, for both indexes, and the Run Test for Ftse Mib only, seem to reject the random walk hypothesis, the information can be meaningful. We have to find out, and critically investigate, the possible reasons behind, concentrating on an overall analysis approach and not on a singular result only, as literature suggests. In the specific case, reasons could be related to different indexes structure and composition, abnormal volatility in the analyzed period, economical context, the nature of the test, its structure and its specifications.

Appendix

Models and Diagnostics for Stoxx Europe 600

GARCH (1,1) with Skewed T:

```
Dependent variable: DAILY_RET_STOXX600EUROPE
Sample: 1999-01-05-2016-02-11 (T = 4463), VCV method: Robust

    Conditional mean equation

             coefficient   std. error      z      p-value
  ------------------------------------------------------
  const      0.000464733   0.000135507   3.430    0.0006   ***

    Conditional variance equation

             coefficient   std. error      z        p-value
  ---------------------------------------------------------
  omega      1.38335e-06   3.56867e-07    3.876    0.0001     ***
  alpha      0.0972396     0.0112969      8.608    7.46e-018  ***
  beta       0.895633      0.0114766     78.04     0.0000     ***

    Conditional density parameters

             coefficient   std. error     z        p-value
  --------------------------------------------------------
  ni           9.23569     1.22273        7.553   4.24e-014  ***
  lambda      -0.100170    0.0195186     -5.132   2.87e-07   ***

        Llik:   14111.28469        AIC: -28210.56938
        BIC:  -28172.14792         HQC: -28197.02549
```

Diagnostics:

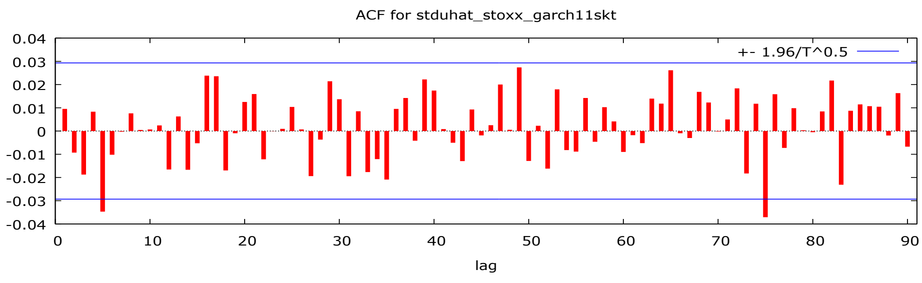
```
Test for normality of stduhat_stoxx_garch11skt:

 Doornik-Hansen test = 154.704, with p-value 2.54962e-034

 Shapiro-Wilk W = 0.989528, with p-value 1.10907e-017

 Lilliefors test = 0.0402639, with p-value ~= 0

Jarque-Bera test = 295.845, with p-value 5.7295e-065
```



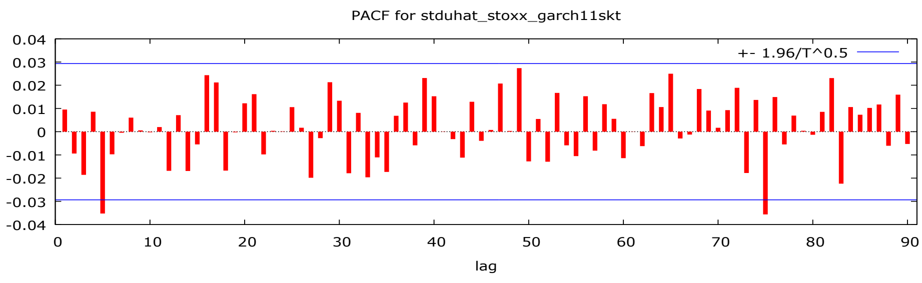


Figure 36. Acf and pacf of the standardized residuals of the model GARCH (1,1) with Skew t-Student distribution.
Source: author's elaboration.

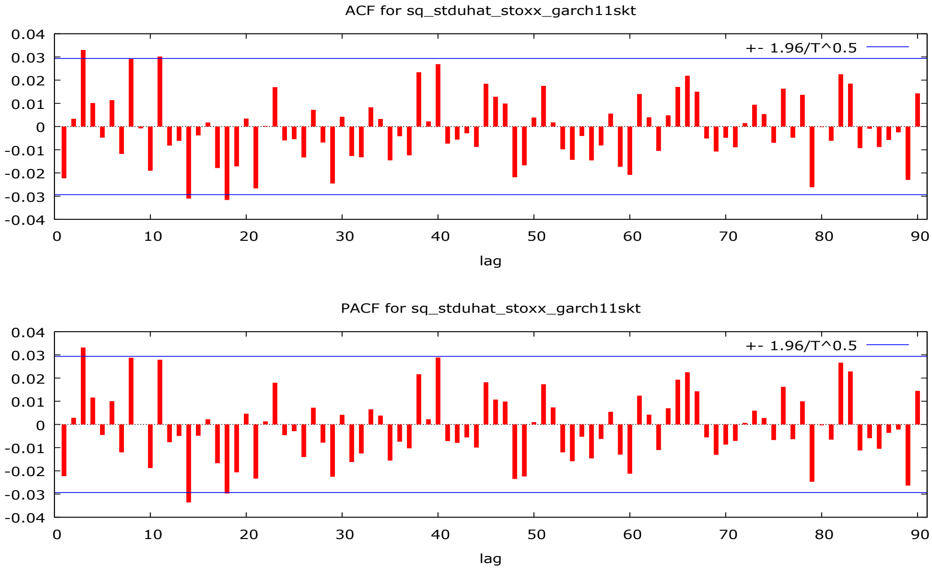


Figure 37. Acf and pacf of the squared standardized residuals of the model GARCH (1,1) with Skew t-Student distribution.
Source: author's elaboration.

GARCH(1,2) with Skewed T:

```
Dependent variable: DAILY_RET_STOXX600EUROPE
Sample: 1999-01-05-2016-02-11 (T = 4463), VCV method: Robust

    Conditional mean equation

             coefficient   std. error      z      p-value
  -----------------------------------------------------
  const      0.000450526   0.000134785   3.343   0.0008  ***

    Conditional variance equation

             coefficient   std. error      z       p-value
  ------------------------------------------------------
  omega      1.83733e-06   5.08658e-07    3.612   0.0003  ***
  alpha_1    0.0480126     0.0164495      2.919   0.0035  ***
  alpha_2    0.0688747     0.0233087      2.955   0.0031  ***
  beta       0.873600      0.0175383     49.81    0.0000  ***

    Conditional density parameters

             coefficient   std. error     z        p-value
  -------------------------------------------------------
  ni          9.25941      1.20633       7.676   1.65e-014 ***
  lambda     -0.101691     0.0193648    -5.251   1.51e-07  ***

        Llik:  14116.19970        AIC: -28218.39941
        BIC:  -28173.57437        HQC: -28202.59820
```

Diagnostics:

```
Test for normality of stduhat_stoxx_garch12skt:

 Doornik-Hansen test = 152.412, with p-value 8.02052e-034

 Shapiro-Wilk W = 0.98965, with p-value 1.44254e-017

 Lilliefors test = 0.0393559, with p-value ~= 0

 Jarque-Bera test = 289.264, with p-value 1.53876e-063
```

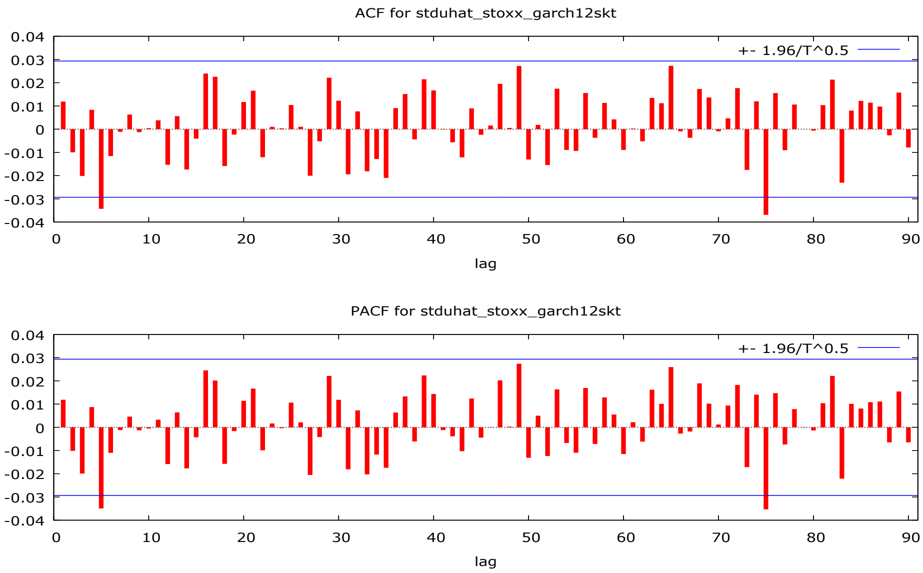


Figure 38. Acf and pacf of the squared residuals of the model GARCH (1,1) with Skew t-Student distribution.
Source: author’s elaboration.

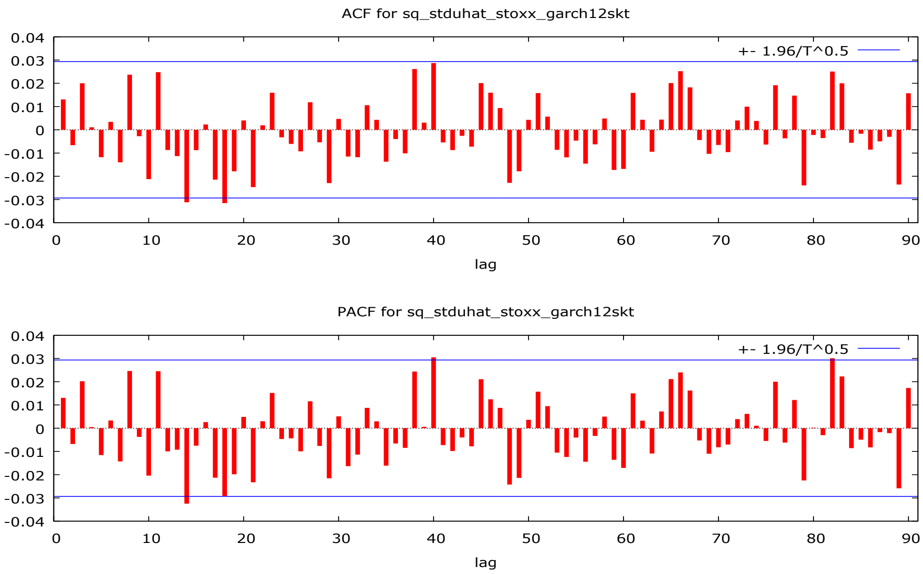


Figure 39. Acf and pacf of the squared standardized residuals of the model GARCH (1,1) with Skew t-Student distribution.
Source: author’s elaboration.

GARCH (1,1) with GED distribution:

```
Dependent variable: DAILY_RET_STOXX600EUROPE
Sample: 1999-01-05-2016-02-11 (T = 4463), VCV method: Robust

    Conditional mean equation

             coefficient   std. error      z      p-value
  -------------------------------------------------------
  const      0.000581645   0.000131531   4.422    9.77e-06 ***

    Conditional variance equation

             coefficient   std. error      z        p-value
  ---------------------------------------------------------
  omega      1.63098e-06   4.10478e-07    3.973    7.09e-05  ***
  alpha      0.0993847     0.0119467      8.319    8.87e-017 ***
  beta       0.891952      0.0122664     72.71     0.0000    ***
    Conditional density parameters
```

```
             coefficient   std. error     z      p-value
  -------------------------------------------------------
  ni            1.45100    0.0479011    30.29   1.48e-201 ***

        Llik:  14103.98441       AIC: -28197.96882
        BIC:  -28165.95094       HQC: -28186.68224
```

Diagnostics:

```
Test for normality of stduhat_stoxx_garch11ged:

 Doornik-Hansen test = 150.315, with p-value 2.28849e-033

 Shapiro-Wilk W = 0.98973, with p-value 1.71608e-017

 Lilliefors test = 0.04024, with p-value ~= 0

 Jarque-Bera test = 285.454, with p-value 1.03404e-062
```

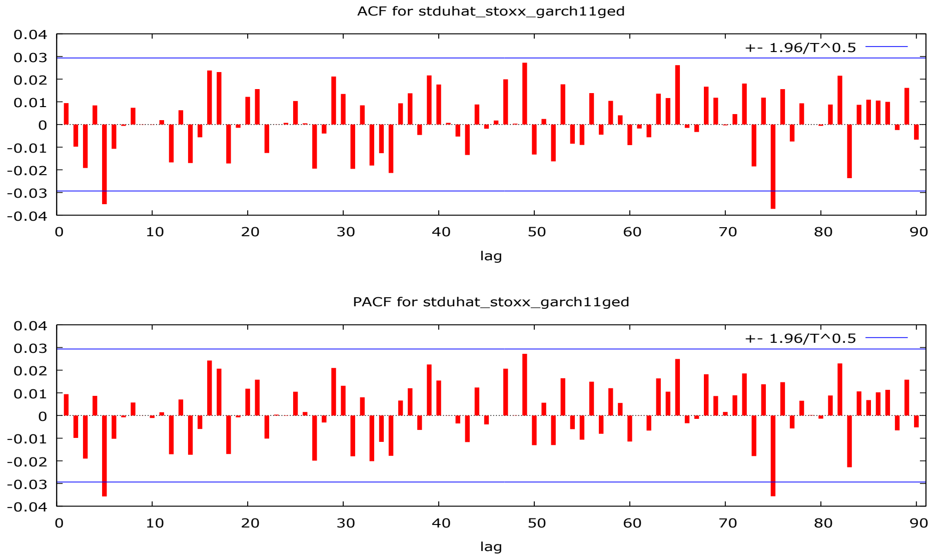


Figure 40. Acf and pacf of the standardized residuals of the model GARCH (1,1) with GED distribution.
Source: author's elaboration.

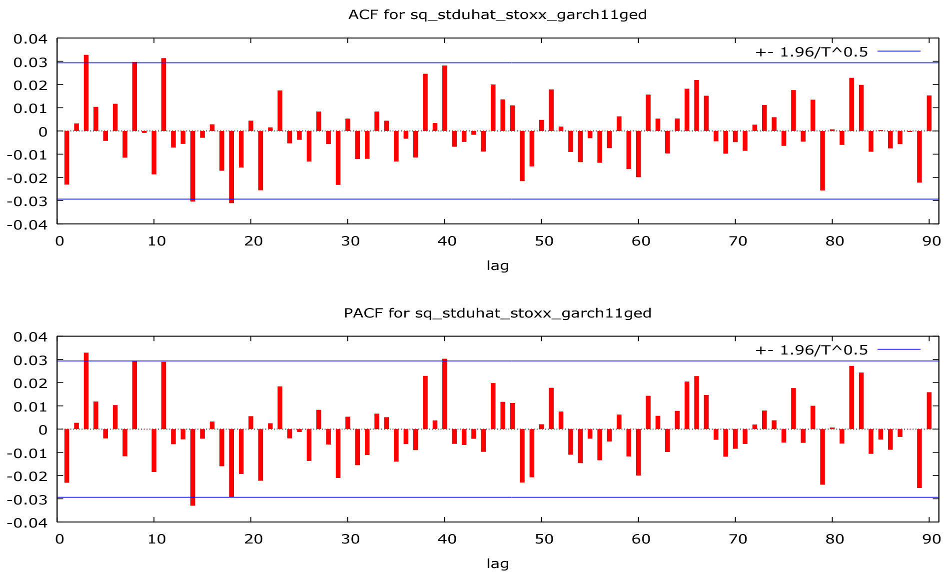


Figure 41. Acf and pacf of the squared standardized residuals of the model GARCH (1,1) with GED distribution.
Source: author's elaboration.

GARCH(1,2) with GED distribution

```
Dependent variable: DAILY_RET_STOXX600EUROPE

Sample: 1999-01-05-2016-02-11 (T = 4463), VCV method: Robust

    Conditional mean equation

             coefficient   std. error      z      p-value
  -------------------------------------------------------
  const      0.000569080   0.000121825   4.671    2.99e-06 ***

    Conditional variance equation

             coefficient   std. error      z       p-value
  -------------------------------------------------------
  omega      2.13273e-06   5.82689e-07    3.660    0.0003  ***
  alpha_1    0.0527251     0.0167906      3.140    0.0017  ***
  alpha_2    0.0654633     0.0241024      2.716    0.0066  ***
  beta       0.870235      0.0188118     46.26     0.0000  ***

    Conditional density parameters

             coefficient   std. error     z       p-value
  -------------------------------------------------------
  ni           1.45582     0.0479074    30.39    7.85e-203 ***

        Llik:  14107.91580        AIC: -28203.83160
        BIC:  -28165.41014        HQC: -28190.28771
```

Diagnostics:

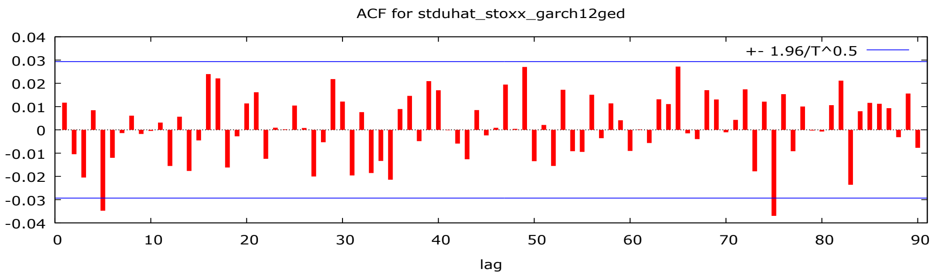
```
Test for normality of stduhat_stoxx_garch12ged:

 Doornik-Hansen test = 147.51, with p-value 9.30058e-033

 Shapiro-Wilk W = 0.989874, with p-value 2.35119e-017

 Lilliefors test = 0.0391768, with p-value ~= 0

 Jarque-Bera test = 277.98, with p-value 4.33921e-061
```



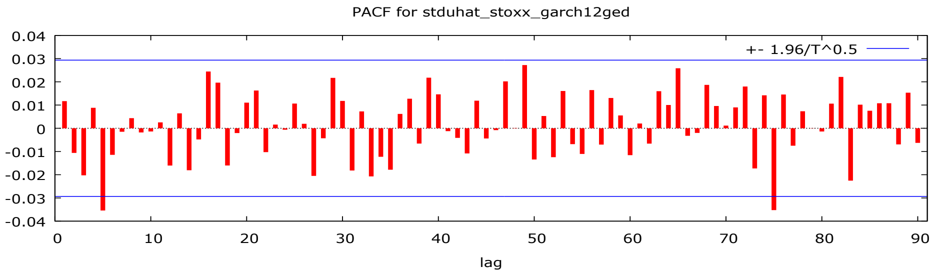


Figure 42. Acf and pacf of the standardized residuals of the model GARCH (1,2) with GED distribution. Source: author's elaboration.

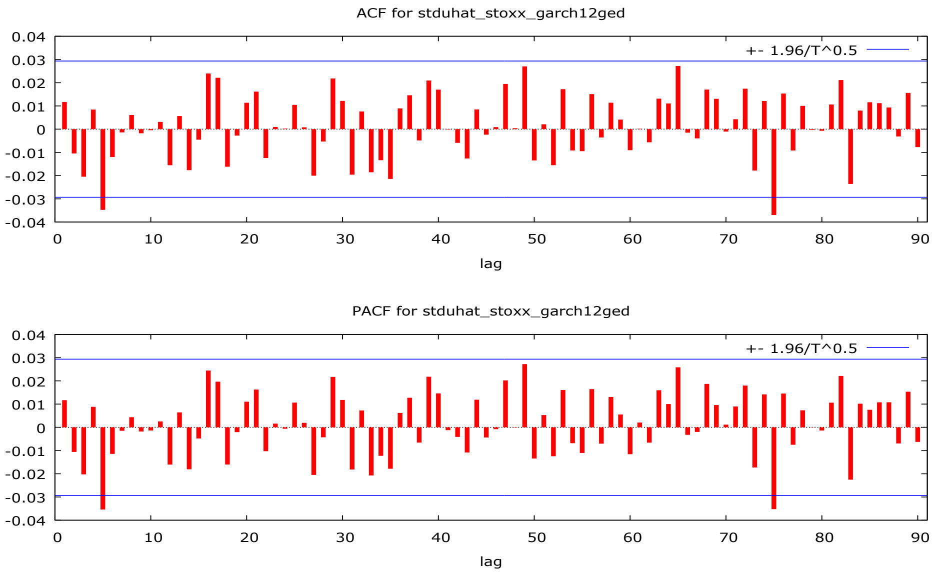


Figure 43. Acf and pacf of the squared standardized residuals of the model GARCH (1,2) with GED distribution.
Source: author's elaboration.

GARCH (1,2) with Student's t distribution

```
Model: GARCH(1,2) [Bollerslev] (Student's t)*
Dependent variable: DAILY_RET_STOXX600EUROPE
Sample: 1999-01-05-2016-02-11 (T = 4463), VCV method: Robust

    Conditional mean equation

             coefficient   std. error      z      p-value
  -------------------------------------------------------
  const      0.000601681   0.000128953   4.666    3.07e-06 ***

    Conditional variance equation

             coefficient   std. error      z       p-value
  -------------------------------------------------------
  omega      1.88597e-06   5.29646e-07    3.561    0.0004  ***
  alpha_1    0.0500321     0.0166257      3.009    0.0026  ***
  alpha_2    0.0692755     0.0236099      2.934    0.0033  ***
  beta       0.872563      0.0180447     48.36     0.0000  ***

    Conditional density parameters

             coefficient   std. error     z       p-value
  -------------------------------------------------------
  ni           8.47888       1.03149      8.220   2.04e-016 ***

        Llik:  14104.09115        AIC: -28196.18231
        BIC:  -28157.76085        HQC: -28182.63842
```

Diagnostics:

```
Test for normality of stduhat_stoxx_garch12t:

 Doornik-Hansen test = 152.2, with p-value 8.91568e-034

 Shapiro-Wilk W = 0.989681, with p-value 1.54444e-017

 Lilliefors test = 0.0390061, with p-value ~= 0

 Jarque-Bera test = 289.462, with p-value 1.39337e-063
```

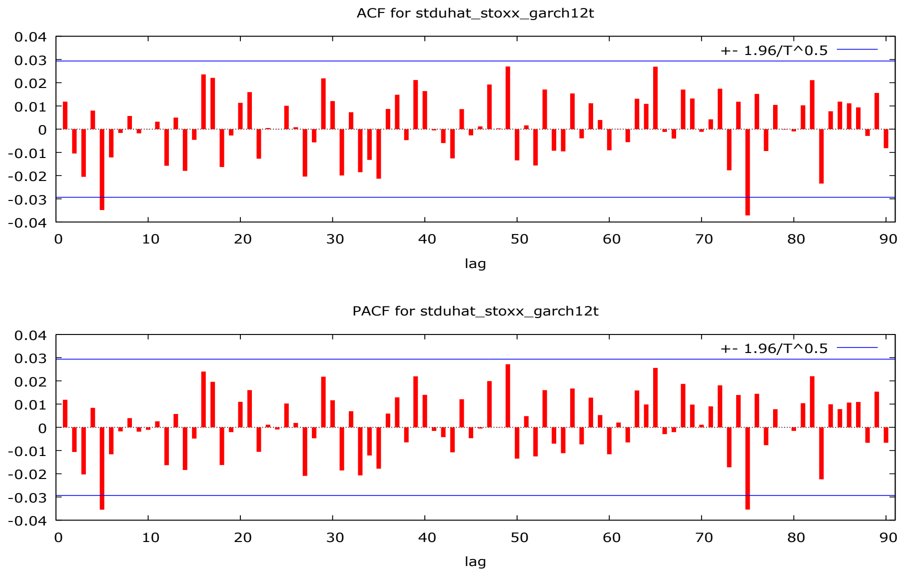


Figure 44. Acf and pacf of the squared standardized residuals of the model GARCH (1,2) with GED distribution.
Source: author's elaboration.

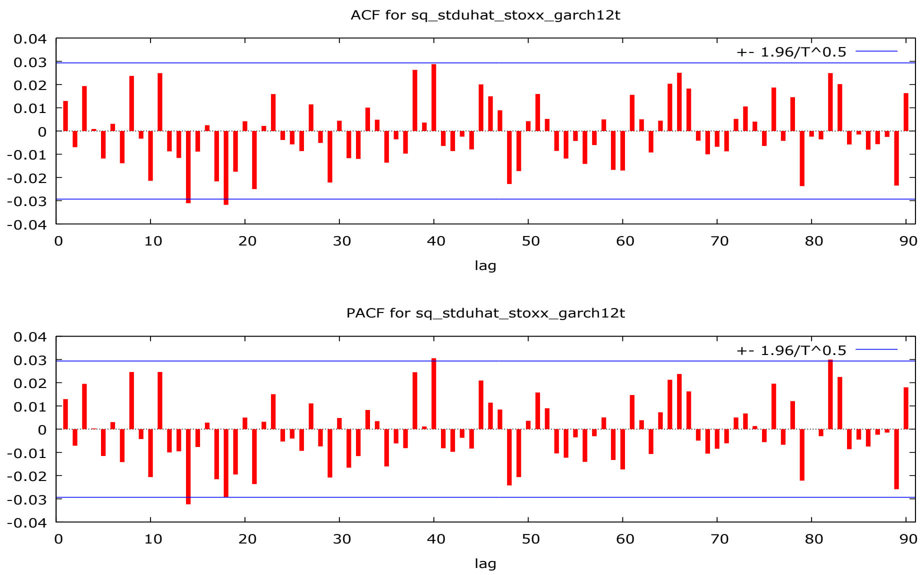


Figure 45. Acf and pacf of the squared standardized residuals of the model GARCH (1,2) with GED distribution.
Source: author's elaboration.

GARCH(2,1) with Skewed GED distribution

```
Dependent variable: DAILY_RET_STOXX600EUROPE
Sample: 1999-01-05-2016-02-11 (T = 4463), VCV method: Robust

    Conditional mean equation

                coefficient    std. error      z      p-value
  -----------------------------------------------------------
  const       0.000490042    0.000137530    3.563    0.0004   ***

    Conditional variance equation

                coefficient    std. error      z       p-value
  -------------------------------------------------------------
  omega       1.42745e-06    3.46466e-07    4.120    3.79e-05   ***
  alpha       0.0713777      0.0101832      7.009    2.39e-012  ***
```

```
   Conditional density parameters

              coefficient   std. error     z        p-value
  ---------------------------------------------------------
  ni           1.26632      0.0917323     13.80    2.39e-043 ***
  lambda      -0.346298     0.0865165     -4.003   6.26e-05  ***

       Llik:  14050.64035     AIC: -28091.28069
       BIC:  -28059.26281     HQC: -28079.99412
```

Diagnostics:

```
Test for normality of stduhat_stoxx_garch21skged:

 Doornik-Hansen test = 143.171, with p-value 8.14531e-032

 Shapiro-Wilk W = 0.990045, with p-value 3.42891e-017

 Lilliefors test = 0.0405496, with p-value ~= 0

 Jarque-Bera test = 267.794, with p-value 7.06875e-059
```

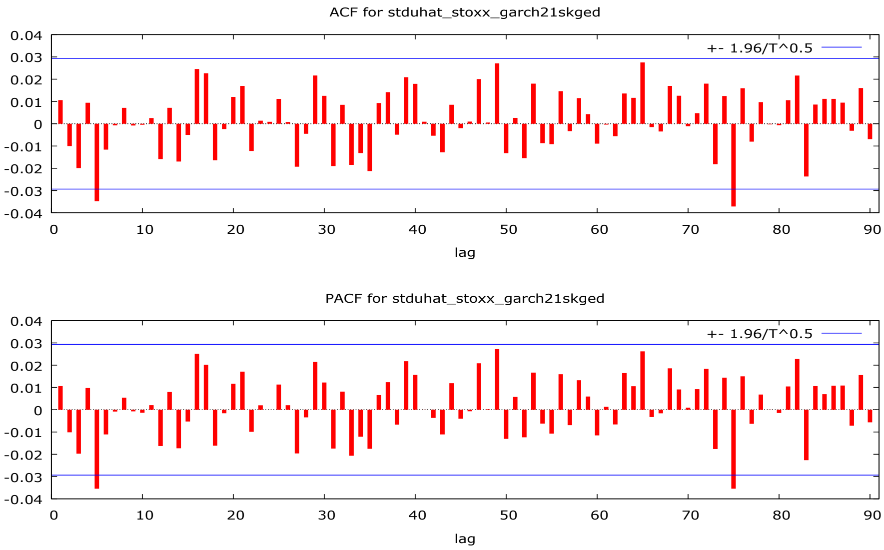


Figure 46. Acf and pacf of the squared standardized residuals of the model GARCH (1,2) with GED distribution.
Source: author’s elaboration.

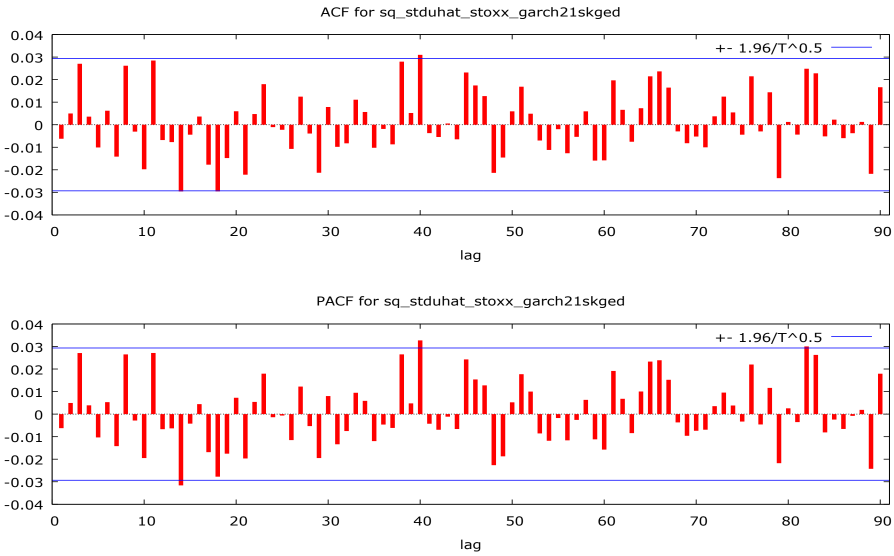


Figure 47. Acf and pacf of the squared standardized residuals of the model GARCH (1,2) with GED distribution.
Source: author’s elaboration.

Models and Diagnostics for Ftse Mib

GARCH (1,1) with GED distribution:

```
Model: GARCH(1,1) [Bollerslev] (GED)
Dependent variable: DAILY_RET_FTSEMIB
Sample: 1999-01-05-2016-02-11 (T = 4463), VCV method: Robust

    Conditional mean equation

             coefficient   std. error      z     p-value
  -------------------------------------------------------
  const      0.000475795   0.000131607   3.615   0.0003  ***

    Conditional variance equation

             coefficient   std. error      z       p-value
  ----------------------------------------------------------
  omega      1.17692e-06   4.14664e-07    2.838   0.0045    ***
  alpha      0.0858492     0.0107397      7.994   1.31e-015 ***
  beta       0.913068      0.0103968     87.82    0.0000    ***

    Conditional density parameters

             coefficient   std. error     z      p-value
  --------------------------------------------------------
  ni           1.40691     0.0460563    30.55   6.06e-205 ***

        Llik:  13172.77999        AIC: -26335.55999
        BIC:  -26303.54210        HQC: -26324.27341
```

Diagnostics:

```
Test for normality of stduhat_ftse_garch11ged:

 Doornik-Hansen test = 151.629, with p-value 1.18612e-033

 Shapiro-Wilk W = 0.988213, with p-value 7.41255e-019

 Lilliefors test = 0.0469224, with p-value ~= 0

 Jarque-Bera test = 297.009, with p-value 3.20174e-065
```

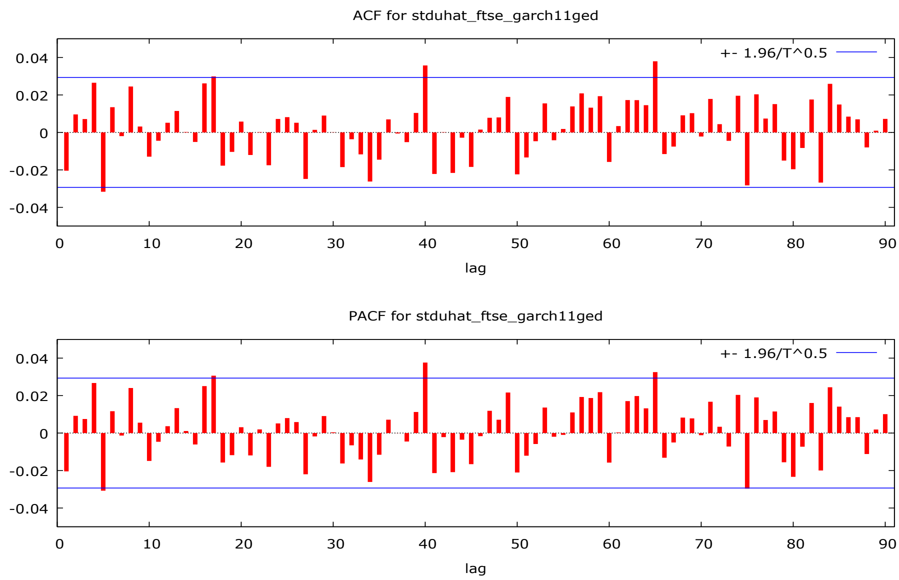


Figure 48. Acf and pacf of the standardized residuals of the model GARCH (1,1) with GED distribution. Source: author's elaboration.

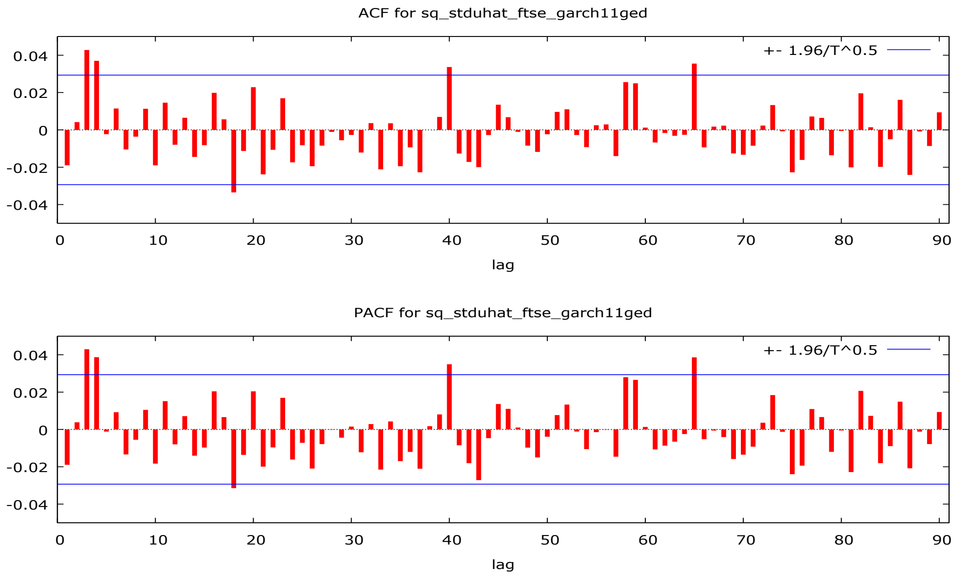


Figure 49. Acf and pacf of the squared standardized residuals of the model GARCH (1,1) with GED distribution.
Source: author's elaboration.

GARCH (1,2) with GED distribution:

```
Model: GARCH(1,2) [Bollerslev] (GED)
Dependent variable: DAILY_RET_FTSEMIB
Sample: 1999-01-05-2016-02-11 (T = 4463), VCV method: Robust

    Conditional mean equation

             coefficient   std. error      z      p-value
  --------------------------------------------------------
  const      0.000462897   0.000149237   3.102   0.0019   ***

    Conditional variance equation

             coefficient   std. error      z       p-value
  --------------------------------------------------------
  omega      1.47362e-06   5.28209e-07    2.790    0.0053  ***
  alpha_1    0.0452337     0.0153860      2.940    0.0033  ***
  alpha_2    0.0530298     0.0200914      2.639    0.0083  ***
  beta       0.900083      0.0142049     63.36     0.0000  ***

    Conditional density parameters

             coefficient   std. error     z       p-value
  --------------------------------------------------------
  ni           1.40848     0.0458791    30.70    5.74e-207 ***

        Llik:  13175.71774        AIC: -26339.43549
        BIC:  -26301.01403        HQC: -26325.89160
```

Diagnostics:

```
Test for normality of stduhat_ftse_garch12ged:

 Doornik-Hansen test = 147.41, with p-value 9.77901e-033

 Shapiro-Wilk W = 0.98852, with p-value 1.36558e-018

 Lilliefors test = 0.0466948, with p-value ~= 0

 Jarque-Bera test = 283.919, with p-value 2.22681e-062
```

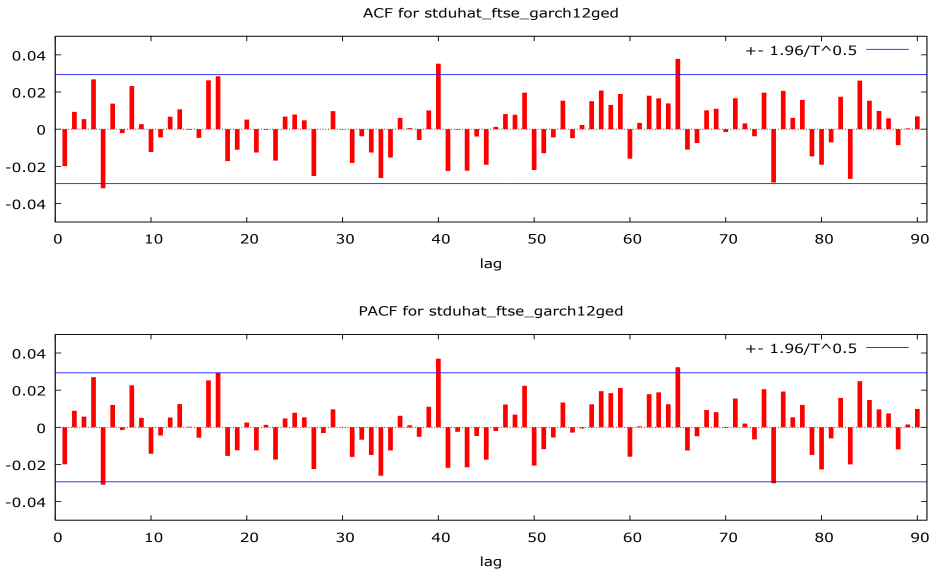


Figure 50. Acf and pacf of the standardized residuals of the model GARCH (1,2) with GED distribution.
Source: author's elaboration.

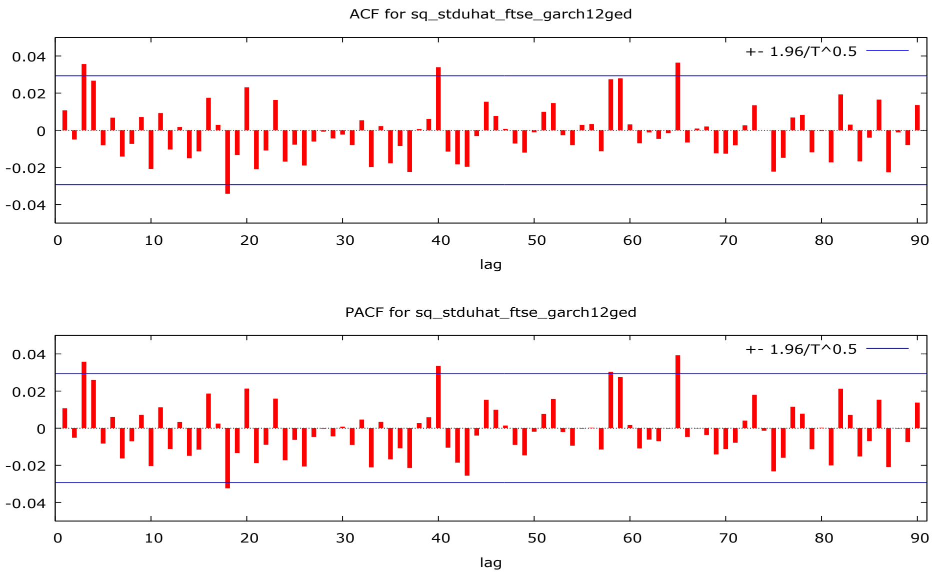


Figure 51. Acf and pacf of the squared standardized residuals of the model GARCH (1,2) with GED distribution.
Source: author's elaboration.

GARCH (2,1) with Skewed GED distribution:

```
Model: GARCH(2,1) [Bollerslev] (Skewed GED)
Dependent variable: DAILY_RET_FTSEMIB
Sample: 1999-01-05-2016-02-11 (T = 4463), VCV method: Robust

    Conditional mean equation

             coefficient   std. error     z     p-value
  -------------------------------------------------------
  const      0.000300388   0.000156011   1.925   0.0542   *

    Conditional variance equation

             coefficient   std. error     z      p-value
  ---------------------------------------------------------
  omega      1.12642e-06   3.66709e-07   3.072   0.0021    ***
  alpha      0.0643259     0.00994619    6.467   9.97e-011 ***

    Conditional density parameters
```

```
             coefficient   std. error      z       p-value
  --------------------------------------------------------
  ni            1.24432     0.0945749    13.16    1.55e-039 ***
  lambda       -0.311067    0.0894052    -3.479   0.0005    ***

        Llik:  13108.72656         AIC: -26207.45313
        BIC:  -26175.43524         HQC: -26196.16655
```

Diagnostics:

```
Test for normality of stduhat_ftse_garch21skged:

 Doornik-Hansen test = 145.32, with p-value 2.78027e-032

 Shapiro-Wilk W = 0.988586, with p-value 1.55954e-018

 Lilliefors test = 0.0467601, with p-value ~= 0

 Jarque-Bera test = 278.503, with p-value 3.34152e-061
```

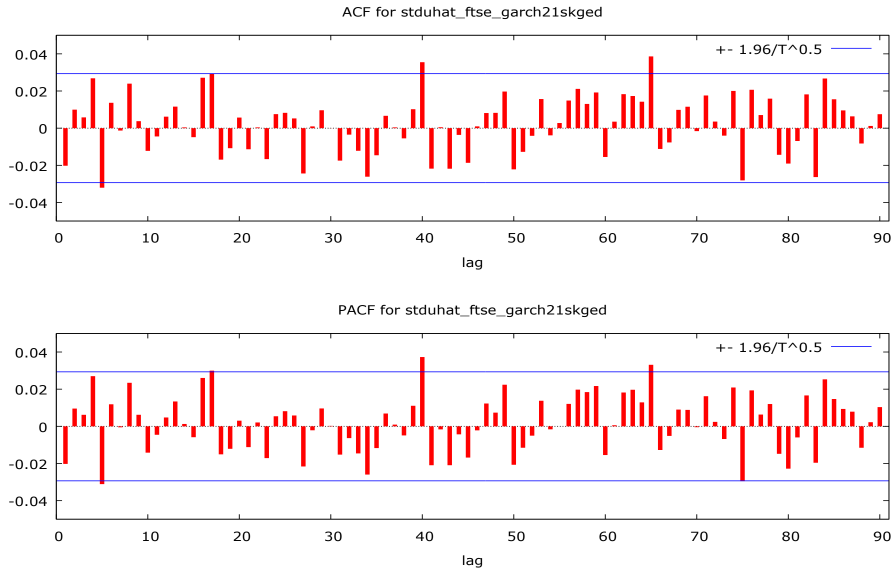
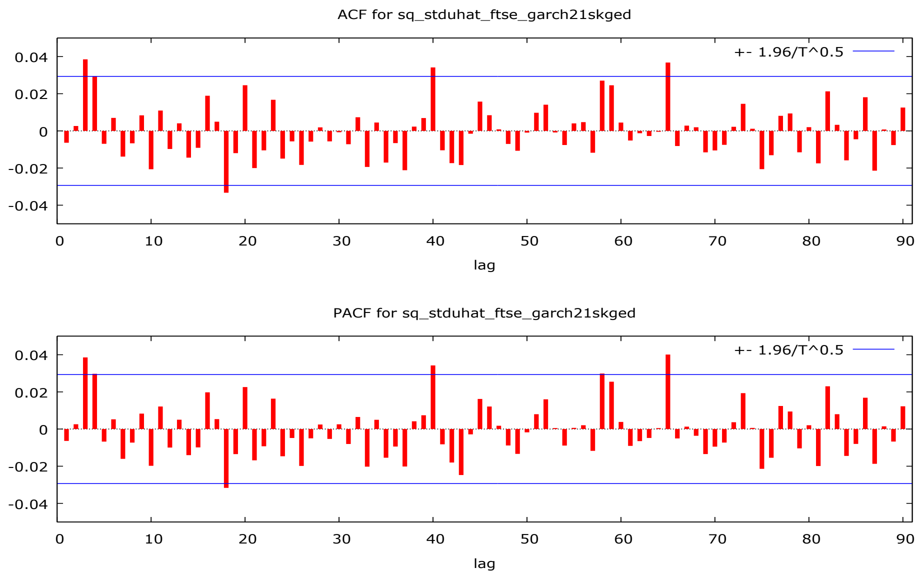


Figure 52. Acf and pacf of the standardized residuals of the model GARCH (2,1) with Skew GED distribution. Source: author's elaboration.



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Source: author's elaboration.

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