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EFFICIENT MARKET HYPOTHESIS AND BEHAVIORAL FINANCE IN A COVID-19 ENVIRONMENT: EVIDENCE FROM ITALY

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To my Grandmother Chiara Maria,
in loving memory

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Introduction

This study aims to investigate the effects of the Covid-19 pandemic on the Italian financial market. The intent is to assess if the FTSE MIB and the companies listed on the Italian index were informationally efficient, according to Fama's (1970) definition of the Efficient Market Hypothesis (EMH), or if anomalies and inefficiencies have emerged that are not fully explained by the EMH. Furthermore, to understand if there is a correlation between anomalies and psychological traits of investors through the analysis of two biases proposed by Behavioral Finance: the overconfidence bias and the conservatism bias.

According to the overconfidence bias, investors do not objectively perceive their own judgment capacity and overestimate their analytical skills. The bias increases investors' propensity to trade, thus increasing trading volumes.

The conservatism bias refers to the tendency of investors to react slowly to new information. This will lead to under-reaction in stock prices adjustment as well, generating momentum in returns.

The main objective of the research is to empirically understand if any of the theories cited can explain the current scenario of the Italian market through the analysis of share price movements.

To achieve this purpose, several tests have been employed.

The weak-form EMH has been tested using: the parametric Ljung-Box test and the non-parametric runs test to look for serial correlation in returns; the ADF test, PP test and KPSS test to look for unit root, i.e., non-stationarity, in the series of stock price movements; and the variance ratio test, which assess if returns follow a random walk.

A vector autoregressive model and impulse response functions have been implemented to study the relationship between stock returns and trading volumes to assess if the overconfidence bias can be observed in the Italian market.

Finally, the conservatism bias has been tested through the implementation of momentum strategies, to verify if it is possible to obtain significant returns based on this trading system.

The tests have been performed on daily prices of the FTSE MIB and of the forty companies listed on the index during the period 2020-2022. Specifically, public prices were collected from March 9, 2020, the date of the first lockdown in Italy, to May 6, 2022.

Chapter 1. Theoretical Framework

1.1 The Concept of Efficiency

The conceptualization and affirmation of the Efficient Market Hypothesis (EMH) can be attributed to the works of Eugene Fama (1965a and 1965b) and Paul Samuelson (1965).
In his work "The Behavior of Stock-Market Prices" of 1965, Fama summarized the most important findings of his PhD thesis discussed earlier in the same year: the independence of successive changes in stock prices and their leptokurtotic behavior.
Furthermore, Fama empirically demonstrated that stock prices movements are unpredictable and can be approximated to a random walk, thus the price variation process is made up of random steps. The random walk model is based on two main assumptions: the independence of the series considered, which was empirically proved by Fama in his paper, and the fact that the data followed a certain distribution. The independence assumption holds if the analysis of past price patterns will not be useful in predicting future price movements. If observation of past prices does not yield any benefit to investors, then there is no value in technical analysis, as it is not possible to obtain greater profits than a buy-and-hold investment strategy.
Fama noted that investors look for "intrinsic value" in securities, a concept related to economic, financial and political factors that may be specific to a single company or which may also affect other competitors in the market. Intrinsic or fundamental value depends on forecasted and expected earnings of a company.
Intrinsic values differ from market prices for several reasons. Due to uncertainty, fundamental values are not precisely known. Therefore, several evaluations can occur, leading to disagreement among investors. Also, intrinsic values can change over time due to new information.
The uncertainty in the market has been given the name of "noise".
Fama supposed that "the noise generating process in the stock market is dependent."
The discrepancies between intrinsic values and actual price will be reduced by the actions of "sophisticated" traders, as Fama identifies chartist and fundamentalist analysts.
Sophisticated traders will be able to understand if a company's stock price is trending above or below its fundamental value and they will base their strategies on such observation to increase their profits.
If there are enough sophisticated traders exploiting such differences, their actions will tend to reduce and nullify the dependency in the noise generation process, leading to independent price movements.

The same reasoning can be applied when the dependence is observed in the information production process. This will also imply a dependence in price movements.

Many sophisticated traders who seek to take advantage of dependencies in present and future information will make price changes independent. Then, how intrinsic values are affected by new information will be "almost instantly" reflected in actual prices.

The concept of fundamental value is not incompatible with the defined random walk model. As Fama (1965a) stated, independent price changes are consistent with an "efficient" market, that is a market in which stock prices, given all the information available at the time, are a good approximation of intrinsic values.

Actual prices are on average an adequate estimate as, in an efficient market, stock prices will fluctuate around their intrinsic values.

If the market is efficient, securities will be appropriately priced and stock prices will fully incorporate and reflect all available information. If that is the case, it should not be possible to use new information to outperform the market.

In Fama (1965b) the concept of "sophisticated" investors, used to refer to chartists and fundamentalist analysts, will no longer be used. As in Fama (1965a), the market is defined as "efficient" when stock price is a good estimate of the intrinsic value. Equivalently, a market is efficient when it is composed of "rational profit-maximizers investors actively competing" and "where […] information is almost freely available to all participants".

In conclusion, for Fama (1965b) the random characteristic of price changes can be explained by the convergence of actual prices to their fundamental values, due to investors rational behavior.

In his paper "Proof That Properly Anticipated Prices Fluctuate Randomly" of 1965, Samuelson assumed that price changes do not follow a random walk. He was the first to consider the martingale process as a more appropriate model to describe price movements behavior.

A stochastic process x_t is a martingale with respect to a sequence of information sets Φ_t if the expected value of x_{t+1} given the available information set, is equal to the value at time t

$E[x_{t+1}|\Phi_t] = x_t$

The implication is that the best forecast of future values is today's value, so prices movements are unpredictable.

Samuelson derived the result that price movements would follow a martingale using the Law of Iterated Expectation. The Law defines the relationship between two random variables defined on the same probability space, $E[X] = E_y[E_x[X|Y]]$. The expected value of X is equal to the expectation of the conditional expected value of X given Y.

As exposed in Campbell et al. (1997), suppose that the stock price at time t P_t can be written as a rational expectation of some intrinsic value V conditional on a set of information I_t at time t, such that $P_t = E[V|I_t] = E_tV$. This equation also holds one period ahead. Therefore, the stock price at time t+1 will be written as $P_{t+1}=E[V|I_{t+1}] = E_{t+1}V$.

The expectation of the price change over t and t+1 would be $E_t [P_{t+1}-P_t] = E_t [[E_{t+1}|V]]- E_t [E_t|V]$.

The information at time t can be considered as a subset of the information available at time t+1, $I_t \subset I_{t+1}$, then $[E_{t|}V] = E_t [[E_{t+1}|V]]$ by the Law of Iterated Expectation, so Et $[P_{t+1}-P_t] =0$.

The effective realization of price changes between t+1 and t will be unpredictable, given the information set I_t.

Samuelson states that the martingale process is a more suitable stochastic process for describing a competitive market with respect to the random walk model.

The martingale does not require price movements to be independent, thus making the model less restrictive than the random walk process.

The key assumption of the martingale model developed by Samuelson is that the market is competitive. Random movements in stock prices will be the consequence of competition and rational profit-maximizing investor behavior.

Both Fama and Samuelson conclude that the randomness of price changes is explained by the actions of rational investors. While Fama argued that random movements are related to the convergence of actual prices to intrinsic values, Samuelson claimed that randomness is observed due to competition among investors.

The EMH has been properly formalized by Fama in his paper "Efficient Capital Markets" of 1970. The main implication of this work is that the EMH has now been made testable, thanks to a more specific definition of the concept of efficiency and a new identification of the price formation process.

Fama argues that the previous definition of an efficient market, where prices "fully reflect" all available information, is not sufficient to make the EMH empirically verifiable. Thus, the goal of his work would be to better identify what should be intended by "fully reflect".

Fama identifies three models to define the process of price formation: the expected return or fair game model, the random walk model and the submartingale model.

Fama observes that previous works expressed market equilibrium's conditions in terms of expected returns. He identifies the following equation, $E(p_{j,t+1}|\Phi_t) = [1+E[r_{j,t+1}|\Phi_t]]p_{j,t}$, where $p_{j,t}$ is the price of the security j at time t, $r_{j,t+1}$ is the return over the period t and t+1, Φ_t is the information set available at time t. The information is considered as "fully reflected" in the formation of the stock price $p_{j,t}$, in the sense that the expected return of equilibrium $E[r_{j,t+1}|\Phi_t]$ will be calculated on the basis of such information.

These assumptions imply that trading only on the available information will fail to provide abnormal profits. Let $x_{j,t+1} = p_{j,t+1} - E(p_{j,t+1}|\Phi_t)$, where $x_{j,t+1}$ is the difference of the effective realization of the stock price at time t+1 and its expected value conditioned on information at time t. In economic terms, $x_{j,t+1}$ is interpreted as the excess market value of the j security at time t+1.

Then, $E[x_{j,t+1}|\Phi_t]=0$, implying that the sequence $\{x_{j,t}\}$ is a fair game with respect to the information set $\{\Phi_t\}$.

The same results can be implied for the excess returns sequence $\{z_{j,t}\}$. $z_{j,t+1}$ is the excess return over the expected return of equilibrium. Let $z_{j,t+1}= r_{j,t+1}- E[r_{j,t+1}|\Phi_t]$, then $E[z_{j,t+1}|\Phi_t]=0$.

The fair game implies that the expectation of the total excess market value, generated by a trading system based on the information set Φ_t, will be equal to zero.

According to Fama, the submartingale and the random walk are special cases of the fair game. Assuming a submartingale for the price sequence, with respect to the information set, means that the expected value of the t+1 price conditional on information Φ_t, is equal or greater than the current stock price. In formula, $E(p_{j,t+1}|\Phi_t) \geq p_{j,t}$. This implies that the expected returns will be equal or greater than zero, $E(r_{j,t+1}|\Phi_t) \geq 0$.

The main empirical implication is that it is not possible to develop a trading rule, based only on information Φt, that will obtain higher returns than a buy and hold strategy.

The random walk can be considered as an extension of the expected return model in the sense that the fair game expresses market equilibrium's conditions in terms of expected returns. The random walk model also specifies the details of the stochastic process generating returns.

In conclusion, empirical tests of the random walk model will be more powerful in support of the EMH than tests of the independence assumption.

Furthermore, Fama (1970) identifies three sufficient but not necessary conditions for an efficient capital market: 1) no transactions costs; 2) no costs to obtain all available information; 3) there is a general agreement between market participants on how information will affect actual prices and on the distribution of future prices.

According to these requirements, shareholders cannot earn extra returns and beat the market based on available information, as the stock price will "fully reflects" all the information.

To make the EMH testable, Fama divided the information reflected in stock prices into three sub-sets. From this categorization different forms of the EMH are observed:

- the weak-form, in which only past information, i.e., past prices or returns history, is incorporated in stock prices;

- the semi-strong form, in which all public information is instantly incorporated into share prices. Some examples of public information are annual reports, stock splits or dividends announcements, etc;
- The strong form, in which both public and private information are instantly incorporated into stock prices. Therefore, there is no set of information that will allow investors to outperform the market. Even those who have access to relevant information that has not yet been made public, will not be able to obtain abnormal returns.

1.2 Review of Existing Literature

The definition of market efficiency, as proposed by Fama and Samuelson, would not have been possible without the findings of previous studies. The origins of the EMH can be traced almost a hundred years before their articles.

In his paper "Calcul des Chances et Philosophie de la Bourse" of 1863, Regnault observed that "the deviation of prices is directly proportional to the square root of time". In his attempt to model short-term speculation, he defined a stock prices behavior that resembles a random walk, although he never used such term.

John Venn (1888) presented the first graph of a random walk.

Gibson (1889) was the first one to refer to market informational efficiency in his analysis of the London, New York and Paris' stock exchanges. He wrote that when "'shares become publicly known in an open market, the value which they acquire may be regarded as the judgment of the best intelligence concerning them", so that views and opinions of "smartest" investors will be reflected in stock prices.

Bachelier (1900), following the intuitions of Regnault (1863), will be the first one to propose the concept of efficiency as the "fair game" economics. He developed a mathematical model for the Brownian motion and deduced that "the mathematical expectation of the speculator is zero".

Five years later, Karl Pearson (1905) introduced the term "random walk".

John Maynard Keynes (1923) argues that financial market investors are rewarded for taking risks and not for making better predictions about future movements. This is a consequence of the EMH.

MacCauley (1925), observing the fluctuations of the market, stated that they resemble a chance curve which would be obtained by throwing a dice.

Mills (1927) proved the leptokurtosis in the distribution of returns.

Cowles (1933) studied how professional investors performed and observed that, in their recommendations, they failed to exhibit any skills in selecting stocks and investments.

Working (1934) showed the random characteristics of stock prices movements.

Cowles and Jones (1937) found significant inefficiencies by observing evidence of serial correlation in the average time series indexes of stock prices.

Maurice Kendall (1953) examined weekly and monthly data for 22 economic series between stock and commodities. Following his empirical findings, he suggested that stock price movements are random. Kendall argued that price changes are unpredictable and that there is no relationship between past and future prices. Furthermore, he was the first one to state a time dependency in the empirical variance.

Harry Roberts (1959) showed that the behavior of the price series significantly resembles that of a random walk.

Osborne (1959) demonstrated that the logarithm of stock prices follows a Brownian motion.

Using spectral analysis, Granger and Morgenstern (1963) concluded that short-run price movements follow a simple random walk model, while long-run movements do not. Furthermore, both seasonal variations and the business cycle are of little or no importance.

Mandelbrot (1963) introduced and tested a stable Pareto distribution on the series of natural logarithms of prices. Fama (1963) empirically supported Mandelbrot's Pareto hypothesis.

Harry Roberts (1967) coined the term “efficient markets hypothesis” and suggested the distinction between weak and strong form tests of the EMH that will be used by Fama (1970).

Malkiel (1973) observed that, in the short run, price fluctuations are random and show signs of a random walk. Instead, in the long run, price movements do not follow a random behavior.

LeRoy (1973) argued that there is “no rigorous theoretical justification” for the martingale property under risk-aversion.

Grossman (1976) developed a mathematical model to show that, if stock markets are informationally efficient, private investors have no incentive to gather information. In an efficient market, an investor who does not collect information and observes actual prices can achieve the same results as an investor who has paid for information.

Jensen (1978) simplified the definition of efficiency, stating that "a market is efficient with respect to the information set θ_t if it is impossible to make economic profits by trading on the basis of the information set θ_t". Furthermore, he argued that empirical findings have been overwhelmingly in support of the EMH.

Lucas (1978) replicated the conclusions of LeRoy (1973) by defining a theoretical model of rational agents: under risk-aversion the martingale’s property does not hold.

Grossman and Stiglitz (1980) stated that a perfectly informationally efficient market cannot exist.

If markets are efficient, there would be no advantage in spending resources to gather information privately. Since information is costly, stock prices do not fully reflect all the available information or investors who paid for such information would receive no compensation.

If information has a cost and the EMH holds true, there would be little or no reason to trade and the markets will eventually collapse.

Market equilibrium is achieved when there is a degree of inefficiency sufficient to compensate investors for the costs of trading and gathering information.

LeRoy and Porter (1981) showed that stock prices exhibit greater volatility than is consistent with the EMH. Therefore, they rejected the efficiency of the market.

Shiller (1981) observed that shares prices exhibit excessive volatility that cannot be entirely attributed to new information about future real dividends, thus rejecting the EMH.
Stiglitz (1981) has shown that the allocation of resources in an apparently competitive and efficient market may not be Pareto efficient.
French and Roll (1986) found that the variance in stock return is significantly higher on trading days than on non-trading days. They argued that such phenomena can be explained by the different flow and incorporation of information during trading and non-trading day; furthermore, most of the information behind the higher variance is private.
Fischer Black (1986) introduced the concept of 'noise traders', those investors who trade on noise as if it were information. The presence of noise traders creates incentive to privately collect costly information. Thus, it will be profitable to trade on such information.
Black argues that noise trading is what makes the market inefficient, as such noise will be reflected along with information in stock prices. Noise is also what makes the market liquid, as more trades are made, thus allowing market prices to be observed. With more noise traders it is more profitable for investors with information to trade as there is more noise in actual prices.
Black's conclusion is that what is required for a liquid market is also what "causes prices to be less efficient".
Returns variance increases linearly under the random walk hypothesis. Lo and MacKinlay (1988) showed that this relationship is empirically rejected using weekly US stock market returns.
They constructed a variance estimator-based specification test that strongly rejected the random walk hypothesis.
Their results showed that the variance grows more than linearly as the holding period increases, thus implying a positive serial correlation in weekly returns.
Positive autocorrelation on short-run equity returns was found by Poterba and Summers (1988), while negative autocorrelation was observed over longer horizons. However, they could not reject the random walk model for stock prices at the conventional statistical levels.
Fama and French (1988) analyzed monthly returns of NYSE's stocks for the period 1926-1985 and found large negative autocorrelation for longer horizons. Their explanation was that there exists a "slowly mean-reverting component" in stock prices that will cause such negative autocorrelation. Furthermore, they observed that negative autocorrelation over the entire period may be largely explained by the first fifteen years of their sample.
Kim, Nelson and Startz (1991) will confirm that the mean-reversion phenomenon was particularly significant for the period 1926-46 but that it will not be observed after 1946, as stock returns have shown persistence.

Richardson (1993) argued that the significant autocorrelation found by previous research was a result that should be expected from random walk data and under the hypothesis of serial independence.
Through the implementation of a VAR model on the world's nine major stock markets of the time, Eun and Shim (1989) showed that “a substantial amount of interdependence exists among national stock markets”. Therefore, their results are consistent with an informationally efficient market.
Lehmann (1990) empirically found reversals in weekly security returns and rejected the efficient market hypothesis.
Lo (1991) constructed a test for long-term memory, robust to short-term correlations, and noted that there is little support for the presence of long-term memory in stock prices. Hence, deviations from the random walk model can be fully explained by stochastic models of short-term dependence.
Malkiel (1992) added some aspects to the definition of efficiency proposed by Fama (1970).
A market is efficient, with respect to an information set, if disclosure of that information to all market participants will not affect stock prices. This suggests that efficiency can be tested by observing and measuring market prices fluctuations after revealing the information.
Efficiency implies that trading on such information should not produce an abnormal return.
Measuring the results obtained from trading on such information can be used as another way to test the efficiency of the market.
Jegadeesh and Titman (1993) found that momentum strategies, trading strategies that consist of buying stocks that have performed well in the past and selling stocks that have performed poorly, realized significant abnormal returns over holding periods ranging from three to twelve months.
Chan et al. (1996) analyzed momentum strategies and concluded that the stock market reacts only gradually to the disclosure of new information.
Chan et al. (1997) performed a cointegration test on the equity markets of eighteen countries and found that only a few of them were cointegrated. The analysis of each market suggested that they are individually efficient according to the weak-form EMH.
By analyzing cross-correlation of returns on the NYSE, Tóth and Kertész (2006) concluded that the financial market has become increasingly efficient over time.
Several papers, such as Smith and Ryoo (2003), Worthington and Higgs (2004) and Borges (2008). regarded the study of the weak-form EMH on European financial markets.
Smith and Ryoo (2003) used a multiple variance ratio test on weekly data from five middle-size European markets to assess whether the indices followed a random walk. Their results rejected the random walk hypothesis for Greece, Hungary, Poland and Portugal due to autocorrelation in errors' return, but accepted it for Turkey. One of the reasons suggested by the authors of the Turkey's

result was the higher liquidity of the Turkish index compared to other markets. Higher liquidity means more trades in the market, thus affecting the formation process of stock prices that will be more active.

Worthington and Higgs (2004) conducted a detailed study of twenty European countries, using different tests such as ADF, PP and KPSS unit root tests, multiple variance ratio tests, autocorrelation tests and runs tests on daily returns from 1986 to 2003. Their objective was to assess whether the European indices were compliant with the weak-form EMH.

Only five more developed countries (Germany, Ireland, Portugal, Sweden and UK) and one emerging market (Hungary) met the stricter criteria of the random walk, thus implying full acceptance of the weak-form.

Borges (2008) replicated Worthington and Higgs (2004) approach using several tests (serial correlation test, runs test, ADF test and multiple variance ratio test) on six European indexes: three from more developed countries (France, Germany and UK) that have been used as "a control for the quality of the […] tests" and three from less developed countries (Greece, Portugal and Spain). The tests were conducted on daily and monthly data from 1993 to 2007.

The results were mixed, as for France, Germany, UK and Spain most of the tests were in favor of the random walk on daily data, while only Germany, UK and Spain met all the characteristics of the random walk on monthly level. The random walk was rejected for Greece and Portugal due to positive autocorrelation, but post-2003 data highlighted their approach to a random walk behavior.

1.3 An Alternative Approach: Behavioral Finance

Several empirical studies challenged the EMH, leading to the development of alternative approaches that seek to explain markets' patterns. One of the most relevant is Behavioral Finance, which questions the assumption of investors rationality.

Behavioral Finance suggests that market participants are usually affected by irrationality in their investment decisions process (Shleifer, 2000), thus exhibiting predictable and financially unprofitable behavior.

Behavioral Finance aims to study the influence of psychological traits on investor behavior, as investors can act irrationally due to their biases. These behaviors led to incorrect assessments of situations and information, which will lead to systematic errors in their investments. Such errors will affect stock price formation process, thereby creating inefficiencies.

Nobel prize Kahneman and Tversky are known as the "fathers of Behavioral Finance".

They showed that investors' decisions are not always rational and can deviate in identifiable ways from economic models. Therefore, departures from rationality can be anticipated as errors are considered predictable.

Their first major discovery was the so-called representativeness bias, discussed in their 1971 article "Belief in the Law of Small Numbers", which states that people draw conclusions based on statistical samples that are not representative of the entire population. Investors try to forecast future patterns by seeking the closest match to past patterns, thus ignoring the true probability distribution.

Kahneman and Tversky (1974) described three types of bias or heuristic that led to systematic errors. Such biases typically occur in situations of uncertainty. The biases are the representativeness bias, the anchoring bias and the availability bias.

Anchor bias occurs when investor's decisions are influenced by a particular starting or reference point. Predictions based on the reference point will be biased as changing the starting point will lead to a whole different estimate.

Availability bias refers to the assessment of a circumstance based on past examples that can be easily recalled. The easier the information can be called up, the more important it will be considered. A person's opinion will be heavily biased towards those previous experiences that will be remembered, ignoring other possible alternatives that have not come to mind.

Furthermore, Kahneman and Tversky defined the concept of prospect theory in their paper "Prospect theory: An analysis of decision under risk" of 1979.

Prospect theory describes how investors value losses and gains in different ways, openly criticizing the expected utility theory based on rational decisions made by rational investors.

Investors are more upset by losses than they are pleased by equivalent gains. They tend to be risk averse, thus avoiding selling losing stocks and holding them longer than winning stocks.
People want to avoid being put in a situation where they will have to make psychologically difficult decisions.
This research will focus on two biases proposed by the Behavioral Finance: the conservatism bias and the overconfidence bias.

1.3.1 Overconfidence Bias

The overconfidence bias arises when investor's perception of his own valuation capacity is significantly greater than the objective accuracy of his estimates.
If an investor believes that his predictions about asset values are more correct than those of other market participants, he will be more willing to trade with investors with different information.
Benos (1998) and Odean (1998) suggested that overconfidence will cause investors to trade excessively. The more an investor is affected by excessive confidence, the more he will trade and the lower his expected utility will be. Investors are assumed to overestimate the accuracy of their information signals. Overconfident traders in the market will lead to a higher expected transactions volume and greater market depth.
Odean (1999) stated that overconfident investors trade too much in the sense that their returns are reduced through trading. Those investors "may trade even when their expected gains are not enough to offset trading costs". He concluded that there is a misinterpretation in the information available to these investors.
Gervais and Odean (2001) suggested that the overconfidence bias can be empirically verified by studying intertemporal variations in trading volume.
Investors who believe that general market increases can be attributed to their own judgment will become overconfident. Therefore, they will start to trade more and increase the overall volume of market trading.
Statman, Thorley, and Vorkink (2006) followed this insight and tested the relationship between overconfidence and high trading volumes. High past returns were used as a proxy of the degree of overconfidence. If previous investments produced significant gains, investors will tend to be more confident, thus past high returns will lead to more trades.
They found a statistically significant tendency for turnover to increase after periods of high market performance, both at market level and at individual stock level. They concluded that turnovers and lag returns can predict future returns.

1.3.2 Conservatism Bias

Conservatism bias, as firstly described by Edwards (1968), refers to the tendency of individuals to react slowly and insufficiently to the announcement of new information or to the appearance of new evidence. It means that people tend to overweight their previous beliefs and underweight new evidence. Therefore, conservatism indicates that investors will tend to under-react to corporate events, such as dividends and stock splits announcements.

Conservatism bias has previously been explained as an extension of Kahneman and Tversky's (1974) anchor bias, but it can also be viewed as an investor overconfidence in his information set that led to certain investment decisions. The overconfidence will slow down the process of adjusting to new information and the investor will under-react to new evidence.

Under-reaction to new information implies that conservatism will also generate under-reaction in the pricing process, thus creating momentum in returns.

Jegadeesh and Titman (2001) evaluated their study of 1993 on momentum strategies, analyzing various possible explanation for their results. Their conclusions were in support of the behavioral models proposed by Barberis et al. (1998) and Daniel et al. (1998).

Specifically, Barberis et al. (1998) stated that conservatism alone will create under-reaction, but conservatism considered along with Kahneman and Tversky's (1971) representativeness, will lead to a reversal for past winners. Stocks that have performed well in the past will produce negative returns over long horizon.

Chapter 2. Data

The dataset used in the research consists of daily observations of the FTSE MIB and of the forty companies listed on the Italian index. Since not all stocks were part of the index for the entire period analyzed, only the companies that have formed the index at the beginning of 2022 were considered.

The data of the following companies are collected: A2A SpA (A2A.MI); Amplifon SpA (AMP.MI); Assicurazioni Generali SpA (G.MI); Atlantia SpA (ATL.MI); Azimut Holding SpA (AZM.MI); Banca Generali SpA (BGN.MI); Banca Mediolanum Spa (BMED.MI); Banco BPM SpA (BAMI.MI); BPER Banca SpA (BPE.MI); Buzzi Unicem SpA (BZU.MI); Campari-Milano NV (CPR.MI); CNH Industrial NV (CNHI.MI); DiaSorin SpA (DIA.MI); Enel SpA (ENEL.MI); Eni SpA (ENI.MI); Exor NV (EXO.MI); Ferrari NV (RACE.MI); FinecoBank SpA (FBK.MI); Hera SpA (HER.MI); Interpump Group SpA (IP.MI); Intesa Sanpaolo SpA (ISP.MI); Inwit SpA (INW.MI); Italgas SpA (IG.MI); Leonardo SpA (LDO.MI); Mediobanca SpA (MB.MI); Moncler SpA (MONC.MI); Nexi SpA (NEXI.MI); Pirelli & C. SpA (PIRC.MI); Poste Italiane SpA (PST.MI); Prysmian SpA (PRY.MI); Recordati SpA (REC.MI); Saipem SpA (SPM.MI); Snam SpA (SRG.MI); Stellantis NV (STLA.MI); STMicroelectronics NV (STM.MI); Telecom Italia SpA (TIT.MI); Tenaris SA (TEN.MI); Terna – Rete Elettrica Nazionale SpA (TRN.MI); Unicredit SpA (UCG.MI); Unipol Gruppo SpA (UNI.MI).

Adjusted closing prices, highs and lows (i.e., the highest and lowest daily price of the stocks) and trading volumes were downloaded from Yahoo Finance.

Adjusted closing prices consider stock splits, dividends, rights offers and any other company events that may affect the stock's value.

The research covers the period between March 9, 2020, the day of the announcement of the first lockdown in Italy, and May 6, 2022.

Adjusted closing prices are used to calculate the daily return as follows, $Return_t = \log\left(\frac{Price_t}{Price_{t-1}}\right)$.

The range, a proxy for daily volatility proposed by Alizadeh et al. (2002), is obtained from highs and lows. It is calculated as follows $range = \log(high) - \log(low)$.

2.1 Descriptive Statistics

Table 1 presents a summary of descriptive statistics for daily returns of the whole sample.

Table 1. Descriptive statistics for daily returns

	Observations	Mean	Maximum	Minimum	Standard Deviation	Skewness	Excess Kurtosis	Jarque-Bera statistic
FTSE MIB	551	0,0004	0,0855	-0,1854	0,0169	-2,3450	28,165	18717**
A2A	551	0,0005	0,0756	-0,2112	0,0190	-2,4375	28,398	19060**
Amplifon	551	0,0009	0,1057	-0,2163	0,0245	-1,2403	12,114	3510,6**
Assicurazioni Generali	551	0,0007	0,1049	-0,1387	0,0164	-0,8407	12,746	3794,5**
Atlantia	551	0,0007	0,2363	-0,2514	0,0300	0,0054	19,920	9110,4**
Azimut Holding	551	0,0007	0,1430	-0,1731	0,0237	-0,5653	10,523	2571,7**
Banca Generali	551	0,0008	0,1004	-0,1483	0,0209	-0,8301	8,844	1859,1**
Banca Mediolanum	551	0,0007	0,1141	-0,1271	0,0236	-0,4175	5,737	771,68**
Banco BPM	551	0,0018	0,1403	-0,1827	0,0281	-0,1634	5,065	591,49**
BPER Banca	551	-0,0002	0,2022	-0,1954	0,0315	0,4722	7,118	1183,8**
Buzzi Unicem	551	0,0003	0,1370	-0,1277	0,0231	0,1451	5,507	698,32**
Campari	551	0,0006	0,1013	-0,1757	0,0199	-0,8900	15,362	5490,7**
CNH Industrial	551	0,0013	0,1135	-0,1888	0,0290	-1,2103	6,896	1226,4**
DiaSorin	551	0,0004	0,0920	-0,1803	0,0262	-0,8325	6,039	900,97**
Enel	551	-0,0001	0,0725	-0,2212	0,0192	-2,6957	32,164	24418**
Eni	551	0,0012	0,1392	-0,1998	0,0231	-0,7544	13,849	4455,2**
Exor	551	0,0002	0,1956	-0,1368	0,0255	0,1068	9,757	2186,5**
Ferrari	551	0,0008	0,1017	-0,1082	0,0186	-0,1080	5,283	641,88**
FinecoBank	551	0,0009	0,1121	-0,1297	0,0219	-0,0006	5,774	765,28**
Hera	551	0,0001	0,1417	-0,1921	0,0187	-1,2155	25,671	15265**
Interpump Group	551	0,0008	0,0759	-0,1192	0,0214	-0,5923	3,578	326,19**
Intesa Sanpolo	551	0,0006	0,1976	-0,1958	0,0246	-0,1320	16,679	6388,2**
Inwit	551	0,0003	0,1035	-0,1604	0,0187	-0,9253	13,030	3976,3**
Italgas	551	0,0005	0,0720	-0,1474	0,0160	-1,1158	14,691	5069,3**
Leonardo	551	0,0005	0,1507	-0,2504	0,0295	-0,4388	12,773	3763,5**
Mediobanca	551	0,0009	0,1303	-0,2069	0,0242	-1,0501	13,044	4007,4**
Moncler	551	0,0007	0,1331	-0,1215	0,0239	0,1957	4,742	519,84**
Nexi	551	-0,0006	0,1577	-0,2169	0,0268	-0,6251	10,434	2535,1**
Pirelli & C	551	0,0004	0,1330	-0,1951	0,0262	-0,5510	8,240	1586,6**
Poste Italiane	551	0,0003	0,0932	-0,2489	0,0218	-2,5832	32,136	24322**
Prysmian	551	0,0011	0,0825	-0,1575	0,0216	-0,7686	6,798	1115,1**
Recordati	551	0,0003	0,1716	-0,1799	0,0201	-0,0463	21,735	10846**
Saipem	551	-0,0012	0,1235	-0,3593	0,0324	-2,3280	27,900	18368**
Snam	551	0,0006	0,0953	-0,2130	0,0178	-3,0272	39,668	36967**
Stellantis	551	0,0012	0,1210	-0,1968	0,0285	-0,7366	7,684	1405,4**
STM	551	0,0009	0,1349	-0,1738	0,0271	-0,6779	6,792	1101,4**
Telecom Italia	551	-0,0006	0,2642	-0,2042	0,0307	0,3253	17,061	6692,6**
Tenaris	551	0,0018	0,1287	-0,1622	0,0280	0,1616	4,280	423,03**
Terna	551	0,0007	0,0752	-0,1619	0,0166	-1,4527	17,437	7174,4**
UniCredit	551	0,0002	0,1286	-0,1895	0,0303	-0,7107	6,362	975,58**
Unipol Gruppo	551	0,0009	0,1632	-0,1923	0,0237	-0,4139	12,418	3555,8**

Notes: ** Null hypothesis rejection at the 1% significance level. Under the null hypothesis of the Jarque-Bera test, returns follow a normal distribution.

Number of observations, mean, standard deviation, skewness, excess kurtosis, Jarque-Bera (JB) statistics and their level of significance are reported for each company and for the Italian index. The JB test[1] is used to assess deviations from normality in returns distribution. The JB is a two-sided goodness-of-fit measure which tests if the sample skewness and kurtosis match a normal distribution.

The test statistic is defined as $JB = \frac{n}{6}\left(s^2 + \frac{(k-3)^2}{4}\right)$, where n is the sample size, s is the sample skewness and k is the sample kurtosis.

Under the null hypothesis of normality, the skewness and excess kurtosis are jointly equal to zero and the test statistic asymptotically follows a chi-squared distribution with two degrees of freedom.

The highest mean returns are observed for Tenaris (0,0018), Banco BPM (0,0018) and CNH Industrial (0,0013) while the lowest mean returns are detected for Nexi (-0,0006), Telecom Italia (-0,0006) and Saipem (-0,0012).

Telecom Italia (0,2642), Atlantia (0,2363) and Bper Banca (0,2022) have the highest maximum returns while Leonardo (-0,2504), Atlantia (-0,2514) and Saipem (-0,3593) have the lowest minimum returns in the sample.

Returns standard deviations range from 0,0324 (Saipem) to 0,0160 (Italgas). The most volatile securities are Saipem, Bper Banca (0,0315) and Telecom Italia (0,0307), while Terna (0,0166), Assicurazioni Generali (0,0164) and Italgas presents the lowest volatility.

Thirty-three companies and the FTSE MIB show negatively skewed returns, which implies a greater likelihood of generating negative returns than the normal distribution.

Bper Banca, Buzzi Unicem, Exor, Moncler, Telecom Italia and Tenaris show a positive skewness in the return's distribution, indicating a greater probability of large increases than falls.

The excess kurtosis is positive for all companies and for the FTSE MIB, ranging from 3,5784 for Interpump Group to 39,6677 for Snam. Excessive positive kurtosis implies a leptokurtic distribution, which presents higher peaks than would be expected in a normal distribution.

The null hypothesis of normality of the JB test is rejected, at the significance level of 1%, for all the companies and for the Italian index.

[1] Jarque, C. M., & Bera, A. K. (1987). A test for normality of observations and regression residuals. International Statistical Review, 55(2), 163–172.

Chapter 3. Methodology

3.1 Tests of the Weak-Form Efficient Market Hypothesis

Under the weak-form of the EMH, price movements follow a random walk.
The random walk hypothesis, according to Campbell et al. (1997), can be divided into three sub-models characterized by more restrictive requirements.
The weakest form is a random walk with dependent but uncorrelated increments.
A stricter version is a random walk with independent but not identically distributed increments.
Finally, the most restrictive model is a random walk with independent and identically distributed increments, which is also the more general definition of a random walk.
Therefore, information on past prices will not be useful in predicting future movements or future market volatility.
Considering the discussed forms of the random walk, different tests can be implemented to evaluate the requirements of each sub-model.

3.1.1 Ljung-Box Test

A statistical test useful to check for serial correlation in returns is the Ljung-Box test, a portmanteau parametric test proposed by Ljung and Box (1978). Portmanteau means that only the null hypothesis is well specified, while the alternative is specified more loosely.
The test statistic is defined as $Q = n(n+2)\sum_{t=1}^{m}\frac{\hat{\rho}^2(t)}{n-t}$, where n is the sample size, m is the number of lags tested and $\hat{\rho}(t)$ is the sample autocorrelation at lag t.
Under the null hypothesis all the autocorrelation coefficients up to the first m lags are jointly equal to zero, meaning that there is no serial correlation. $H_0\colon \hat{\rho}(1) = \hat{\rho}(2) = \cdots = \hat{\rho}(m) = 0$
Under the null hypothesis the Q statistic follows a chi-square distribution.
The Ljung-Box test is preferred over the autocorrelation Box-Pierce Q statistic[2] as it provides a better fit to the chi-squared distribution for smaller samples.

[2] Box, G. E. P., & Pierce, D. A. (1970). Distribution of Residual Autocorrelations in Autoregressive-Integrated Moving Average Time Series Models

3.1.2 Runs Test

The runs test is a non-parametric test proposed by Wald and Wolfowitz (1940), which is used to check for serial dependence in stock price movements that may not have been captured by a parametric serial correlation test.

Unlike the Ljung-Box test, the runs test does not require returns to be normally or identically distributed.

The test compares the expected number of runs and the observed number of runs. Under the null hypothesis, the two values are close, implying that the series of price changes is random.

A run is defined as a series of successive price changes (i.e., returns) with the same sign.

In this thesis a positive sign (+) is observed whenever the return is above the mean return, a negative sign if it is below the mean and 0 if it is equal to the mean.

The number of runs above the mean will be denoted by n_1 and the number of runs below the mean by n_0, while n is the number of total runs.

The test statistic is Z, $Z = \frac{n-\mu_n}{\sigma_n}$, where μ_n is the expected number of runs and it is equal to

$\mu_n = \frac{2n_1n_0}{n} + 1$ and $\sigma_n = \sqrt{\frac{2n_1n_0(2n_1n_0 - n)}{n^2(n-1)}}$

For large sample sizes the test statistic is approximately normally distributed.

3.1.3 Unit Root Tests

A time series following a random walk contains a unit root. The presence of a unit root implies that the series is not stationary.

Three tests can be used to verify the existence of a unit root in the series of price changes: the ADF test, the PP test and the KPSS test.

The Augmented Dickey-Fuller[3] (ADF) tests assumes that a time series follow an autoregressive process. It tests the null hypothesis of a unit root by estimating the following equation using OLS

$\Delta p_t = \alpha + \beta t + \gamma p_{t-1} + \sum_{i=1}^{k} \delta_i \Delta \mathrm{p}_{t-i} + \varepsilon_t$

where $\Delta p_t = p_t - p_{t-1}$, α is a constant, β is the estimated coefficient for the trend t, δ and γ_i are coefficients to be estimated, k is the number of lagged terms and ε is a mean zero innovation process.

[3] Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366), 427–431.

Under the null hypothesis δ = 0 and the series of price changes exhibits a unit root.

Under the alternative δ ≠ 0 and the series is stationary, meaning that past price information can be used to better predict future values.

The number of lagged terms k is determined by the Akaike information criterion[4] (AIC).

A non-parametric unit root test was developed by Phillips and Perron (1988) to account for serial correlation in the innovation process. The PP test estimates the non-augmented Dickey-Fuller test equation and uses a different test statistic with an asymptotic distribution that is not affected by serial correlation.

Finally, the KPSS test, developed by Kwiatkowski et al. (1992), uses a parametric correction for autocorrelation and tests the null hypothesis that the time series is trend-stationary against the alternative of a non-stationary unit root series.

3.1.4 Variance Ratio Test

The variance ratio test proposed by Lo and MacKinlay (1988) is a parametric test which assesses the null hypothesis that a univariate time series y_t is a random walk.

The model under the null is $y_t = \mu + y_{t-1} + \varepsilon_t$, where μ is an unknown drift parameter and ε_t is an uncorrelated innovations series with mean zero.

The test assumes that if a time series is a random walk, then the variance of its q-th difference increases linearly with the observation interval q. Therefore, the variance of the qth-differenced variable is q times the variance of its first difference. The variance of the q-th difference scaled by q, divided by the variance of the first difference, should tend to one.

Considering the time series of stock prices p_t the test can be defined as

$$V(q) = \frac{var(p_t - p_{t-q})}{q\ var(p_t - p_{t-1})} = \frac{\sigma^2(q)}{\sigma^2(1)}$$

where $\sigma^2(q)$ is 1/q the variance of the q-th difference and $\sigma^2(1)$ is the variance of the first difference. Under the null hypothesis VR(k)=1.

The unbiased estimates of $\sigma^2(q)$ and $\sigma^2(1)$ have been proposed by Lo and MacKinlay (1988):

$\sigma^2(q) = \frac{1}{m}\sum_{t=q}^{nq}(p_t - p_{t-q} - q\hat{\mu})^2$ and $\sigma^2(1) = \frac{1}{(nq-1)}\sum_{t=1}^{nq}(p_q - p_{q-1} - \hat{\mu})^2$

where $\hat{\mu}$ is the sample mean of (p_t-p_{t-1}) and $m = q(nq - q + 1)(1 - \frac{q}{nq})$.

[4] Akaike, H. (1974). A new look at the statistical model identification. IEEE Transactions on Automatic Control, 19(6), 716–723.

Furthermore, they developed two test statistics, Z(q) and Z*(q), the first for the null hypothesis of a random walk with homoscedastic increments and the second for a random walk with heteroskedastic increments. The test statistic is the following, $Z(q) = \frac{VR(q)-1}{\phi(q)}$.

Assuming homoscedastic increments, $\phi(q) = \left[\frac{2\ (q-1)\ (q-1)}{3q\ (nq)}\right]^{\frac{1}{2}}$.

Assuming heteroskedastic increments, $\phi(q) = \left[4 \sum_{t=1}^{q-1} \left(1 - \frac{t}{q}\right) \hat{\delta}_t\right]^{\frac{1}{2}}$,

where $\hat{\delta}_t = \frac{\sum_{k=t+1}^{nq} (p_k - p_{k-1} - \hat{\mu})^2 (p_{k-t} - p_{k-t-1} - \hat{\mu})^2}{\left[\sum_{k=1}^{nq} (p_k - p_{k-1} - \hat{\mu})^2\right]^2}$

Under the null hypothesis the test statistic is asymptotically normally distributed.

A rejection of the null hypothesis assuming homoscedasticity can be caused by heteroscedasticity or serial correlation in returns. Therefore, a rejection of the null under the assumption of heteroscedastic increments indicates the presence of autocorrelation in stock price movements.

Considering the procedure developed by Lo and MacKinlay (1988), we can test individual variance ratio tests for specific q-difference.

Following Borges’ (2008) approach, four values for q, q = 2, 4, 8, 16, are tested in this thesis.

3.2 Overconfidence Bias Test: VAR Models and IRFs

To look for the overconfidence bias in the Italian market, the relationship between stock returns and trading volumes is tested through the implementation of a Vector Autoregressive model (VAR).
The VAR model is a multivariate time series model composed of m equations of m endogenous variables. Each variable has an equation to describe its evolution over time. Each equation contains lagged values of the variable considered, as well as lagged values of the other variables, and an error term.
The model considered in this study is a bivariate VAR(p) with two endogenous variables, a control (exogenous) variable and p lagged terms for each variable. The number of lags p has been determined by the Bayesian information criterion[5] (BIC).
Daily volatility is used as a control variable following Karpoff's (1987) suggestion, as he observed that volume is positively related to volatility and its magnitude.
The range, i.e., the logarithmic difference between daily highs and lows, is used as a proxy for volatility, as suggested by Alizadeh et al. (2002).
The bivariate VAR(p) can be formalized as:

$$Y_t = \delta + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \sum_{i=0}^{p} \Theta_i X_{t-i} + \varepsilon_t$$

where δ is a constant; Y_t is the matrix of endogenous variables (returns and trading volumes); Xt is the control variable (volatility); Φ_i is the matrix of estimated autoregressive coefficients, that measures how volume and returns react to their lagged values; Θ_i is the matrix of estimated coefficients that describe the relationship between endogenous variable and lagged values of the control variable; ε_t are random Gaussian innovations with mean zero.
The time series of log trading volumes has been detrended, using the filter proposed by Hodrick and Prescott (1997), to remove the unit root and make it stationary. Considering that daily observations have been used, the lambda λ factor used in the filter has been set equal to 13322500.
Additionally, impulse response functions (IRFs) are plotted for ten days to examine how volumes are affected by a one-standard-deviation shock on returns.
The IRFs measure the impact of the shock and the time it takes for the process to absorb it.
Granger's causality test[6] is implemented to assess whether a variable is statistically significant when predicting another variable. Granger's test shows the forecasting ability of a variable on another,

[5] Schwarz, G. (1978). Estimating the dimension of a model. The Annals of Statistics, 6(2), 461–464.
[6] Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica, 37(3), 424–438.

but it does not provide information on the true causal relationship between the variables in the model.
The relationship between volumes and returns is tested with a bi-directional Granger's test.
Under the null hypothesis, the coefficients of all lags of one variable are jointly equal to zero in the equation for the other variable. Therefore, under the null, there is no Granger causality.
If the null is rejected and returns do Granger-cause trading volume, then there is empirical evidence to support the overconfidence bias.
Instead, the rejection of the null hypothesis that volumes do not Granger-cause returns, can be interpreted as evidence suggesting market inefficiency.

3.3 Conservatism Bias Test: Momentum Trading Strategies

The approach proposed by Jegadeesh and Titman (1993) has been replicated to assess whether the conservatism bias can be observed in the Italian market.
The method consists of studying a series of momentum strategies. After a given formation period J, stocks are ranked based on their daily cumulative returns and classified into deciles.
The top four performers of the period are assigned to the "winner portfolio", while the last four stocks are assigned to the "loser portfolio". Returns over a holding period K are computed for each portfolio.
The momentum strategy consists of taking a long position on the winner portfolio and a short position on the loser portfolio. A period between the formation period J and the holding period K is skipped to avoid potential microstructure biases.
Different momentum strategies will be created using different combination of the formation period J and of the holding period K.
In this thesis, sixteen strategies will be considered, based on four formation periods, J = 3, 6, 9 and 12 months and four holding periods, K = 3, 6, 9 and 12 months.
A new momentum strategy is built each month as a new formation period begins and new portfolios of winners and losers are built. Including overlapping horizons increases efficiency and adds power to the test. The return of the momentum portfolio is computed as the average returns of the portfolios constructed each month.
Finally, a t-test is used to assess whether the returns of the sixteen strategies are significantly different from zero. If the returns are significantly higher than zero, then momentum effects exist. If they are significantly less than zero, then we observe a contrarian effect.

Chapter 4. Results

4.1 Weak-Form Efficient Market Hypothesis Results

4.1.1 Ljung-Box Test

If the market is informationally efficient, stock returns should follow a random walk and they should not be correlated at any lags.

Failure to reject the null hypothesis of serial correlation of the Ljung-Box test represents empirical evidence in support of EMH.

In consensus with the previous literature, if the assumption of no autocorrelation is rejected for at least one lag, efficiency is rejected for the entire stock price series.

Table 2 summarizes the estimates of the LB test on the forty companies of the Italian index.

The results show that only four companies fail to reject the null hypothesis at all lags: Banca Mediolanum, DiaSorin, Nexi and Tenaris.

Evidence of serial correlation at the significance level of 5% or better is observed for thirty-six companies.

Overall, considering all ten lags, most of the significant lag coefficients are negative, indicating a tendency for mean reversion of returns.

Focusing on lag 1, the nineteen coefficients significant at the 5% level are all negative.

The highest mean reversion is observed for Hera (–0,2455), Recordati (–0,2430) and FinecoBaank (–0,2204), while on average it is equal to –0,1501.

At lag 10, nineteen out of the twenty-nine significative coefficients are negative.

Campari (–0,1546), FinecoBank (–0,1147) and Moncler (–0,0807) show the highest mean reversion, while on average it is equal to –0,0490.

The ten positive coefficients indicate return persistence, which is higher for STMicroelectronics (0,0541), Telecom Italia (0,0444) and Exor (0,0420). On average, the persistence is equal to 0,0308.

The empirical findings support the rejection of the weak-form EMH for almost all the companies in the sample, thus implying inefficiencies. However, the conclusions drawn from these results may be misleading as the LB test assumes the normality of distribution, a condition that has been strongly rejected by the data through the implementation of the Jarque-Bera test.

Table 2. Ljung-Box serial correlation test

	Lag	1	2	3	4	5	6	7	8	9	10
A2A	**Coefficient**	-0,0661	0,0768	-0,0639	0,0078	-0,0032	0,0040	0,0129	-0,0773	0,0485	-0,0534
	Q statistic	2,4193	5,6945	7,9670*	8,0011	8,0067	8,0157	8,1083	11,4572	12,7802	14,3838
Amplifon	**Coefficient**	-0,1069	0,0955	-0,0558	-0,0114	-0,0299	-0,0635	0,0194	-0,0445	-0,0261	0,0314
	Q statistic	6,3344*	11,3916**	13,1211**	13,1940*	13,6924*	15,9503*	16,1603*	17,2712*	17,6541*	18,2081
Assicurazioni Generali	**Coefficient**	0,0503	0,1247	0,0007	0,0599	-0,0701	-0,0652	0,0004	-0,1504	-0,0284	0,0194
	Q statistic	1,4010	10,0330**	10,0333*	12,0313*	14,7763*	17,1534**	17,1535*	29,8402**	30,2937**	30,5062**
Atlantia	**Coefficient**	-0,0534	-0,0565	0,0158	-0,0078	0,0119	-0,1839	0,0292	-0,0466	-0,0017	-0,0077
	Q statistic	1,5778	3,3490	3,4879	3,5216	3,6010	22,51412**	22,9931**	24,2136**	24,2152**	24,2482**
Azimut Holding	**Coefficient**	-0,1479	0,1251	-0,0847	0,0091	0,0259	-0,0730	-0,0168	-0,1037	0,0261	-0,0105
	Q statistic	12,1160**	20,7960**	24,7876**	24,8335**	25,2070**	28,1871**	28,3452**	34,3811**	34,7652**	34,8277**
Banca Generali	**Coefficient**	-0,0943	0,1237	-0,0569	0,0358	-0,0438	-0,0250	0,0067	-0,1215	0,0168	-0,0443
	Q statistic	4,9238**	13,4163*	15,2179*	15,9305*	17,0022*	17,3529*	17,3779**	25,6611*	25,8191*	26,9233*
Banca Mediolanum	**Coefficient**	-0,0098	0,0731	-0,0905	0,0375	0,0044	-0,0566	0,0161	-0,0956	0,0451	0,0352
	Q statistic	0,0527	3,0191	7,5781	8,3610	8,3718	10,1654	10,3099	15,4337	16,5795	17,2779
Banco BPM	**Coefficient**	-0,1385	0,1671	-0,0812	0,0540	0,0308	-0,0048	0,0165	-0,1013	-0,0562	-0,0137
	Q statistic	10,6227**	26,1146**	29,7839**	31,4057**	31,9363**	31,9490**	32,1010**	37,8600**	39,6369**	39,7421**
BPER Banca	**Coefficient**	-0,0277	0,0714	-0,0722	0,0601	0,0430	0,0161	-0,0268	-0,0470	-0,0767	-0,0083
	Q statistic	0,4254	3,2567	6,1559	8,1665	9,1966	9,3411	9,7432	10,9835	14,2945	14,3332
Buzzi Unicem	**Coefficient**	-0,0243	-0,0078	-0,0680	-0,0517	-0,0058	-0,1278	0,1121	-0,0853	-0,0324	-0,0678
	Q statistic	0,3264	0,3602	2,9302	4,4204	4,4392	13,5761*	20,6161**	24,6951**	25,2863**	27,8759**
Campari	**Coefficient**	-0,0956	-0,0219	0,0073	-0,0179	-0,0500	-0,0250	0,0003	-0,0078	-0,0258	-0,1547
	Q statistic	5,0642*	5,3302	5,3596	5,5386	6,9348	7,2836	7,2837	7,3174	7,6906	21,1613*
CNH Industrial	**Coefficient**	-0,0477	-0,0500	-0,0706	0,0299	0,0419	-0,1061	0,0695	-0,0097	0,0408	-0,0668
	Q statistic	1,2597	2,6477	5,4158	5,9145	6,8945	13,1896*	15,8968*	15,9494*	16,8870	19,3981*
DiaSorin	**Coefficient**	-0,0143	-0,0209	-0,0014	0,0263	0,0441	-0,0195	0,0547	-0,0128	0,0139	0,0032
	Q statistic	0,1136	0,3571	0,3582	0,7421	1,8250	2,0378	3,7127	3,8054	3,9145	3,9203
Enel	**Coefficient**	-0,0692	0,0797	-0,0259	-0,0485	0,0272	-0,0915	0,0358	-0,0718	0,0356	-0,0512
	Q statistic	2,6491	6,1743*	6,5481	7,8605	8,2722	12,9552*	13,6712	16,5616*	17,2745*	18,75056*
Eni	**Coefficient**	-0,0226	0,0009	-0,0916	0,0453	0,1019	-0,0295	0,0382	-0,1723	-0,0342	0,0163
	Q statistic	0,2818	0,2823	4,9451	6,0890	11,8873*	12,3738	13,1918	29,8514**	30,5099**	30,6592**
Exor	**Coefficient**	-0,0143	0,0747	-0,0627	-0,0693	0,0339	-0,1372	0,0652	-0,0755	0,0262	0,0420
	Q statistic	0,1140	3,2134	5,3987	8,0747	8,7155	19,2422**	21,6204**	24,8153**	25,2021**	26,1964**
Ferrari	**Coefficient**	-0,1338	0,0068	-0,0668	0,0203	0,0687	-0,0312	0,0540	-0,1666	0,0665	0,0174
	Q statistic	9,9135**	9,9394**	12,4239**	12,6532*	15,2857**	15,8288*	17,4608*	33,0321**	35,5145**	35,6843**
FinecoBank	**Coefficient**	-0,2204	0,1312	-0,0449	0,0241	-0,0195	-0,0766	0,0452	-0,0479	0,0441	-0,1147
	Q statistic	26,9131**	36,4681**	37,5912**	37,9147**	38,1269**	41,4049**	42,5474**	43,8367**	44,9305**	52,3366**
Hera	**Coefficient**	-0,2455	0,1091	-0,0516	-0,0640	0,0647	-0,1304	0,0783	-0,0366	0,0742	-0,0411
	Q statistic	33,3871**	39,9902*	41,4728**	43,7516**	46,0909**	55,5996**	59,0370**	59,7896**	62,8863**	63,8364**
Interpump Group	**Coefficient**	-0,0962	0,0458	-0,0266	0,0552	0,0246	-0,0771	0,0486	-0,0697	0,0017	0,0239
	Q statistic	5,1278*	6,2909*	6,6837	8,3791	8,7163	12,0393	13,3635	16,0894*	16,0911	16,4140
Intesa Sanpolo	**Coefficient**	-0,0867	0,1179	-0,0454	0,0791	0,0522	-0,0833	0,0341	-0,0728	0,0229	0,0155
	Q statistic	4,1650*	11,8754**	13,0192**	16,5066**	18,0280**	21,9045**	22,5558**	25,5277**	25,8213**	25,9570**
Inwit	**Coefficient**	-0,0693	0,1333	-0,0131	-0,1023	0,0231	-0,1024	0,0131	-0,0444	0,0338	0,0288
	Q statistic	2,6598	12,5276**	12,6230**	18,4530**	18,7512**	24,6125**	24,7083**	25,8150**	26,4581**	26,9257**
Italgas	**Coefficient**	-0,1673	0,0525	-0,0735	-0,0100	-0,0517	-0,0388	0,0339	0,0160	-0,0077	-0,0272
	Q statistic	15,5081**	17,0379**	20,0417**	20,0979**	21,5898**	22,4298**	23,0742**	23,2175**	23,2504**	23,6661**
Leonardo	**Coefficient**	0,0699	0,0979	-0,0729	0,0356	-0,0256	-0,0513	-0,0101	-0,0385	0,0209	-0,0171
	Q statistic	2,7100	8,0266*	10,9794*	11,6864*	12,0523*	13,5268*	13,5837	14,4139	14,6598	14,8253
Mediobanca	**Coefficient**	-0,0185	0,1974	-0,0821	0,0412	-0,0191	-0,0758	0,0196	-0,0960	-0,0234	-0,0355
	Q statistic	0,1892	21,8245**	25,5707**	26,5174**	26,7209**	29,9345**	30,1495**	35,3194**	35,6260**	36,3364**
Moncler	**Coefficient**	-0,1369	0,0394	0,0306	-0,0795	0,0441	-0,1141	0,0590	-0,0432	0,0026	-0,0807
	Q statistic	10,3806**	11,2434**	11,7635**	15,2880**	16,3753**	23,6567**	25,6033**	26,6491**	26,6529**	30,3210**
Nexi	**Coefficient**	-0,0116	0,0320	-0,0639	-0,0157	-0,0064	-0,0232	-0,0133	-0,0708	0,0608	-0,0992
	Q statistic	0,0751	0,6437	2,9138	3,0518	3,0749	3,3753	3,4741	6,2909	8,3697	13,9114
Pirelli & C	**Coefficient**	-0,1602	0,0031	-0,1055	0,0414	0,0227	0,0377	-0,0127	-0,0641	-0,0470	-0,0506
	Q statistic	14,2140**	14,2195**	20,4134**	21,3690**	21,6561**	22,4508**	22,5407**	24,8454**	26,0892**	27,5306**
Poste Italiane	**Coefficient**	-0,1242	0,1348	-0,0538	0,0387	-0,0669	-0,0042	-0,0290	-0,0882	0,0238	-0,0372
	Q statistic	8,5502**	18,6336**	20,2458**	21,0794**	23,5754**	23,5853**	24,0576**	28,4185**	28,7361**	29,5162**
Prysmian	**Coefficient**	-0,1850	0,0027	-0,0374	-0,0412	0,0121	0,0258	0,0140	-0,1045	0,0390	0,0178
	Q statistic	18,9599**	18,9640**	19,7398**	20,6850**	20,7663**	21,1376**	21,2469**	27,3759**	28,2303**	28,4089**

Recordati	**Coefficient**	-0,2430	0,0952	-0,0423	-0,0070	-0,0254	-0,0113	0,0315	0,0222	0,0579	-0,0564
	Q statistic	32,7195**	37,7508**	38,7479**	38,7750**	39,1346**	39,2056**	39,7609**	40,0376**	41,9233**	43,7171**
Saipem	**Coefficient**	0,0452	0,0015	-0,0584	0,0343	-0,0032	0,0443	-0,0080	-0,0943	-0,0144	0,0270
	Q statistic	1,1306	1,1318	3,0288	3,6837	3,6895	4,7849	4,8209	9,8132	9,9304	10,3424
Snam	**Coefficient**	-0,2112	0,0429	-0,0986	-0,0147	-0,0978	0,0262	0,0426	0,0205	-0,0271	-0,0091
	Q statistic	24,7082**	25,7293**	31,1359**	31,2560**	36,5942**	36,9783**	37,9971**	38,2332**	38,6471**	38,6934**
Stellantis	**Coefficient**	-0,0416	0,0540	-0,0474	-0,0368	0,1087	-0,1502	0,0693	-0,0333	-0,0433	0,0282
	Q statistic	0,9609	2,5767	3,8247	4,5776	11,1748*	23,7823**	26,4688**	27,0912**	28,1432**	28,5904**
STM	**Coefficient**	-0,0444	0,0800	-0,0569	0,0404	-0,0555	-0,1117	0,0034	-0,0594	-0,0497	0,0541
	Q statistic	1,0926	4,6469	6,4489	7,3598	9,0800	16,0551*	16,0616*	18,0383*	19,4241*	21,0752*
Telecom Italia	**Coefficient**	0,0045	0,1733	-0,0731	-0,0028	-0,0924	-0,1083	-0,0386	0,0328	-0,0327	0,0444
	Q statistic	0,0110	16,6759**	19,6501**	19,6544**	24,4145**	30,9743**	31,8100**	32,4122**	33,0135**	34,1234**
Tenaris	**Coefficient**	-0,0492	0,0913	-0,0393	0,0029	0,0046	-0,0253	-0,0074	-0,0278	0,0030	0,0007
	Q statistic	1,3433	5,9691	6,8284	6,8330	6,8451	7,2029	7,2334	7,6676	7,6727	7,6730
Terna	**Coefficient**	-0,1373	0,0486	-0,0952	-0,0436	-0,0717	0,0172	0,0806	-0,0027	-0,0054	-0,0671
	Q statistic	10,4511**	11,7629**	16,8063**	17,8651**	20,7340**	20,8996**	24,5403**	24,5445**	24,5607**	27,0993**
UniCredit	**Coefficient**	-0,0303	0,0934	-0,0685	0,0597	0,0502	-0,0543	0,0216	-0,0107	-0,0387	0,0236
	Q statistic	0,5092	5,3524	7,9647*	9,9498*	11,3544*	13,0042*	13,2645	13,3285	14,1688	14,4821
Unipol Gruppo	**Coefficient**	-0,1210	0,0807	0,0423	0,0782	-0,1201	-0,0294	-0,0338	-0,0543	-0,0036	-0,0626
	Q statistic	8,1056**	11,7188**	12,7135**	16,1204**	24,1766**	24,6588**	25,3005**	26,9550**	26,9622**	29,1683**

Notes: Serial correlation coefficients and Ljung-Box Q statistic are reported. * indicates null hypothesis rejection at the 5% significance level. ** indicates null hypothesis rejection at the 1% significance level. The null hypothesis assumes that serial correlation coefficients are jointly equal to zero.

4.1.2 Runs Test

Table 3 reports the results for the non-parametric runs test which, unlike the Ljung-Box test, does not require the normality of returns. The null hypothesis is that returns come in a random order.

Table 3. Runs test

	A2A	Amplifon	Assicurazioni Generali	Atlantia	Azimut Holding	Banca Generali	Banca Mediolanum	Banco BPM	BPER Banca	Buzzi Unicem
n	301	285	289	273	303	297	273	283	296	280
n1	284	294	290	259	279	287	280	261	256	262
n0	267	257	261	292	272	264	271	290	295	289
Z	2,0711*	0,7918	1,0915	-0,1722	2,2214*	1,7496	-0,2496	0,5784	1,7468	0,3130
p-value	0,0382	0,4286	0,2751	0,8633	0,0262	0,0801	0,8028	0,5631	0,0805	0,7543
	Campari	**CNH Industrial**	**DiaSorin**	**Enel**	**Eni**	**Exor**	**Ferrari**	**FinecoBank**	**Hera**	**Interpump Group**
n	305	279	279	279	283	275	282	303	283	291
n1	265	270	287	271	282	286	282	276	277	281
n0	286	281	264	280	269	265	269	275	274	270
Z	2,4255*	0,1800	0,2119	0,1769	0,5251	-0,0512	0,4397	2,2174*	0,5124	1,2038
p-value	0,0152	0,8571	0,8323	0,8596	0,5996	0,9591	0,6602	0,0265	0,6084	0,2286
	Intesa Sanpolo	**Inwit**	**Italgas**	**Leonardo**	**Mediobanca**	**Moncler**	**Nexi**	**Pirelli & C**	**Poste Italiane**	**Prysmian**
n	283	287	285	267	287	283	290	292	289	309
n1	284	274	283	262	280	282	284	279	277	293
n0	267	277	268	289	271	269	267	272	274	258
Z	0,5346	0,8535	0,7002	-0,7128	0,8593	0,5251	1,1321	1,2832	1,0241	2,8352**
p-value	0,5930	0,3933	0,4838	0,4760	0,3902	0,5996	0,2576	0,1994	0,3058	0,0045
	Recordati	**Saipem**	**Snam**	**Stellantis**	**STM**	**Telecom Italia**	**Tenaris**	**Terna**	**UniCredit**	**Unipol Gruppo**
n	289	279	296	274	262	279	269	283	277	289
n1	283	273	285	279	295	273	260	272	273	266
n0	268	278	266	272	256	278	291	279	278	285
Z	1,0416	0,1725	1,6502	-0,1668	-1,0816	0,1725	-0,5243	0,5156	0,0019	1,0526
p-value	0,2976	0,8630	0,0988	0,8676	0,2794	0,8630	0,6001	0,6062	0,9984	0,2925

Notes: * Null hypothesis rejection at the 5% significance level. ** Null hypothesis rejection at the 1% significance level. The null hypothesis assumes that returns come in a random order. n is the total number of runs, n1 is the number of runs above the mean, n0 is the number of runs below the mean.

Thirty-five of the forty z-values estimated for Italian companies fail to reject the null hypothesis at the 5% level of significance.

A2A, Azimut, Campari, Banco BPM and Prysmian show positive significant z values, meaning that the actual number of runs is greater than the expected number of runs if prices were in a random order. This indicates negative serial correlation in returns, thus confirming the results of the Ljung-Box test. Furthermore, Banca Mediolanum, DiaSorin, Nexi and Tenaris show no signs of dependence under the runs test and are efficient for both the implemented tests.

The results demonstrate that most of the stock price series do follow a random walk and are then weak-form efficient.

4.1.3 Unit Root Tests

If returns follow a random walk, we should observe a unit root, implying non-stationarity of the time series. The results of the unit root tests are collected in Table 4.

Table 4. Unit root tests

	Number of lags	ADF test statistic	ADF p-value	PP test statistic	PP p-value	KPSS test statistic	KPSS p-value
A2A	3	-1,5762	0,8014	-2,1125	0,5369	1,7612*	0,0100
Amplifon	5	-2,1177	0,5343	-1,5834	0,7983	1,4916*	0,0100
Assicurazioni Generali	11	-2,5977	0,2972	-3,3905	0,0538	0,3371*	0,0100
Atlantia	9	-2,5644	0,3137	-4,8625**	0,0010	0,1449	0,0520
Azimut Holding	14	-1,1053	0,9259	-1,7337	0,7241	0,4168*	0,0100
Banca Generali	5	-2,2960	0,4463	-1,8636	0,6599	0,8219*	0,0100
Banca Mediolanum	11	-2,3455	0,4218	-2,1472	0,4864	0,5806*	0,0100
Banco BPM	5	-2,7134	0,2401	-2,5320	0,3297	1,6212*	0,0100
BPER Banca	10	-3,0243	0,1267	-2,9221	0,1566	0,3685*	0,0100
Buzzi Unicem	14	-2,0050	0,5900	-2,0742	0,5559	0,7683*	0,0100
Campari	14	-1,1036	0,9262	-0,9505	0,9480	0,5100*	0,0100
CNH Industrial	10	-0,9215	0,9514	-1,6882	0,7466	1,0591*	0,0100
DiaSorin	3	-3,0745	0,1142	-3,0898	0,1104	0,9111*	0,0100
Enel	4	-2,4898	0,3505	-1,8082	0,6873	2,1457*	0,0100
Eni	11	-2,6711	0,2610	-2,9155	0,1587	0,4167*	0,0100
Exor	12	-1,6652	0,7579	-2,7775	0,2084	0,5695*	0,0100
Ferrari	3	-3,1373	0,0988	-2,9380	0,1515	0,4594*	0,0100
FinecoBank	4	-2,5792	0,3064	-1,9657	0,6094	1,2998*	0,0100
Hera	4	-2,5366	0,3274	-3,5643*	0,0340*	0,9902*	0,0100
Interpump Group	3	0,6441	0,9990	0,7181	0,9990	2,0734*	0,0100
Intesa Sanpolo	5	-2,1387	0,5240	-1,7248	0,7285	0,9832*	0,0100
Inwit	9	-3,7482*	0,0202	-3,9246*	0,0120	0,0861*	0,0100
Italgas	3	-3,8964*	0,0131	-3,6545*	0,0265	0,4886*	0,0100
Leonardo	13	-2,1821	0,5025	-3,4694*	0,0439	0,1817	0,0229
Mediobanca	17	-1,6047	0,7878	-2,7377	0,2281	0,4708*	0,0100
Moncler	11	0,2093	0,9974	-0,2073	0,9924	0,7629*	0,0100
Nexi	11	-1,3173	0,8821	-1,1541	0,9175	0,7750*	0,0100
Pirelli & C	7	-1,7237	0,7290	-2,0434	0,5711	0,6080*	0,0100
Poste Italiane	4	-1,1314	0,9215	-1,5112	0,8250	1,5350*	0,0100
Prysmian	9	-2,1126	0,5369	-1,7271	0,7273	0,9006*	0,0100
Recordati	4	-2,3010	0,4438	-1,8842	0,6497	0,7454*	0,0100
Saipem	0	-1,6369	0,7719	-1,6369	0,7719	6,3433*	0,0100
Snam	18	-2,6102	0,2911	-4,7120**	0,0010	0,1849	0,0217
Stellantis	7	-0,8839	0,9556	-1,1785	0,9129	1,4802*	0,0100
STM	11	-2,9514	0,1475	-2,7016	0,2459	0,3918*	0,0100
Telecom Italia	7	-1,7384	0,7217	-2,3033	0,4427	0,5422*	0,0100
Tenaris	3	-2,0405	0,5725	-2,2922	0,4481	0,6839*	0,0100
Terna	11	-3,2390	0,0781	-3,9110*	0,0125	0,2726*	0,0100
UniCredit	5	-2,4925	0,3492	-2,4871	0,3519	0,3649*	0,0100
Unipol Gruppo	9	-3,5166*	0,0387	-4,1945**	0,0049	0,3526*	0,0100

Notes: * Null hypothesis rejection at the 5% significance level. ** Null hypothesis rejection at the 1% significance level. The null hypothesis of ADF and PP test assumes a unit root in the stock price series. The null hypothesis of the KPSS test assumes stationaritity of the stock price series.

The number of lagged terms used in the tests is determined by the AIC.
The null hypothesis of the ADF test assumes the presence of a unit root. It is rejected for only three companies (Inwit, Italgas and Unipol Gruppo) at the significance level of 5%.
The non-parametric PP test assumes the same null hypothesis but considers autocorrelation in the innovation process. The null hypothesis is rejected for three companies at the 1% significance level and for eight companies at the 5% level of significance. The PP test confrms the non-stationary results of the ADF test for Inwit, Italgas and Unipol Gruppo. Furthermore, Unipol Gruppo rejects the hypothesis of a unit root at the 1% level.
Finally, the null hypothesis of stationarity of the parametric KPSS test is rejected for thirty-eight of the forty Italian companies at the significance level of 5%. Atlantia confirms the stationarity result obtained with the PP test, while Inwit is the only stock which returns are stationary under all the tests performed.
Unit root tests provide strong evidence for non-stationary returns, implying support for the random walk model and the weak-form EMH.

4.1.4 Variance Ratio Test

The results of the variance ratio test, which tests the null hypothesis of a random walk for stock movements, are shown in Table 5.

The variance ratio V(q) and two test statistics have been estimated: Z (q), which assumes a random walk with homoscedastic increments and Z*(q), which assumes heteroskedastic increments.

If stocks are efficient, we should not reject the null hypothesis for any period considered. Therefore, a rejection of the random walk for at least one period is considered as a rejection of the weak-form EMH for the entire price series.

The null hypothesis is rejected for twenty-six companies under the assumption of homoscedasticity at the significance level of 5%. However, we have to consider that a rejection of the null assuming homoscedasticity can result from heteroscedasticity and autocorrelation in returns.

For nearly all stocks that reject the random walk, the variance ratios are less than 1, indicating mean reversion in returns. The only two exceptions are Assicurazioni Generali, which ratios at lags 2, 4 and 8 are above 1 and Intesa Sanpaolo, which ratios are increasing, thus implying mean aversion in their returns.

Instead, the null hypothesis of a random walk with heteroscedastic increments is rejected for only five stocks: Ferrari, FinecoBank, Italgas, Pirelli & C. and Prysmian. These companies exhibit signs of mean reversion in their returns, as their variance ratios are all below 1.

The results of the variance ratio test under the heteroskedastic assumption, which confirms the presence of no serial correlation in returns, indicate that almost all Italian stocks follow a random walk and are informationally efficient.

Table 5. Variance ratio test

		q = 2	q = 4	q = 8	q = 16		q = 2	q = 4	q = 8	q = 16
VR(q)		0,9231	0,8166	0,6934	0,6012		0,9155	0,9497	1,0099	1,0696
Z(q)	A2A	-1,8039	-2,2943*	-2,4172*	-2,113*	Intesa Sanpolo	-1,9817*	-0,6295	0,0783	0,3685
Z*(q)		-1,1182	-1,2945	-1,4829	-1,4373		-1,2081	-0,3778	0,0497	0,2487
VR(q)		0,8870	0,8272	0,6844	0,6212		0,9272	0,9606	0,8063	0,7727
Z(q)	Amplifon	-2,6490**	-2,1621*	-2,4882*	-2,0070*	Inwit	-1,7067	-0,4925	-1,5271	-1,2045
Z*(q)		-1,2865	-1,0720	-1,4035	-1,3404		-0,9999	-0,2574	-0,8163	-0,6916
VR(q)		1,0516	1,1702	1,0833	0,8667		0,8233	0,6784	0,5247	0,4617
Z(q)	Assicurazioni Generali	1,2091	2,1303*	0,6569	-0,7062	Italgas	-4,1450**	-4,0237**	-3,7474**	-2,8523**
Z*(q)		0,9722	1,4662	0,4378	-0,4700		-2,0101*	-2,0014*	-2,0927*	-1,7405
VR(q)		0,9426	0,8073	0,5675	0,4200		1,0738	1,1408	1,0396	0,8782
Z(q)	Atlantia	-1,3463	-2,4114*	-3,4098**	-3,0734**	Leonardo	1,7301	1,7616	0,3122	-0,6452
Z*(q)		-1,0721	-1,3808	-1,9511	-1,8660		1,1007	1,0617	0,1969	-0,4248
VR(q)		0,8471	0,8195	0,7204	0,5362		0,9772	1,0837	1,0008	0,7947
Z(q)	Azimut Holding	-3,5849**	-2,2582*	-2,2048*	-2,4575*	Mediobanca	-0,5351	1,0479	0,0064	-1,0880
Z*(q)		-1,3115	-0,8930	-1,0137	-1,2806		-0,3116	0,5382	0,0034	-0,6220
VR(q)		0,8981	0,8994	0,7991	0,6625		0,8513	0,7982	0,7163	0,6213
Z(q)	Banca Generali	-2,3895*	-1,2590	-1,5844	-1,7881	Moncler	-3,4876**	-2,5249*	-2,2366*	-2,0065*
Z*(q)		-1,4316	-0,7051	-0,9426	-1,1672		-1,9386	-1,4921	-1,4689	-1,3977
VR(q)		0,9671	0,9483	0,8293	0,6937		0,9884	0,9522	0,8213	0,7152
Z(q)	Banca Mediolanum	-0,7709	-0,6471	-1,3456	-1,6230	Nexi	-0,2718	-0,5978	-1,4090	-1,5088
Z*(q)		-0,4157	-0,3426	-0,7279	-0,9412		-0,1468	-0,3390	-0,8439	-0,9290
VR(q)		0,8611	0,9095	0,9934	0,8119		0,8417	0,6930	0,6534	0,5735
Z(q)	Banco BPM	-3,2568**	-1,1325	-0,0522	-0,9969	Pirelli & C	-3,7117**	-3,8420**	-2,7332**	-2,2600*
Z*(q)		-1,6605	-0,6222	-0,0327	-0,7144		-2,0282*	-2,2003*	-1,6786	-1,5329
VR(q)		0,9734	0,9747	1,0628	0,9526		0,8685	0,8200	0,7202	0,6430
Z(q)	Bper Banca	-0,6236	-0,3170	0,4950	-0,2514	Poste Italiane	-3,0848**	-2,2524*	-2,2059*	-1,8915
Z*(q)		-0,2856	-0,1673	0,3023	-0,1687		-1,3540	-1,0543	-1,1708	-1,1244
VR(q)		0,9762	0,9195	0,7730	0,5295		0,8123	0,6675	0,5899	0,5626
Z(q)	Buzzi Unicem	-0,5582	-1,0069	-1,7901	-2,4931*	Prysmian	-4,4031**	-4,1605**	-3,2335**	-2,3177*
Z*(q)		-0,3721	-0,6872	-1,2568	-1,7609		-2,6726**	-2,6477**	-2,1631*	-1,6007
VR(q)		0,9086	0,7756	0,6154	0,5660		0,7470	0,6092	0,5627	0,5692
Z(q)	Campari	-2,1437*	-2,8075**	-3,0328**	-2,2997*	Recordati	-5,9335**	-4,8898**	-3,4480**	-2,2828*
Z*(q)		-1,0722	-1,5491	-1,6701	-1,3011		-1,7487	-1,6807	-1,4484	-1,1938
VR(q)		0,9541	0,8165	0,7241	0,5436		1,0491	1,0413	1,0787	1,0923
Z(q)	CNH Industrial	-1,0767	-2,2956*	-2,1756*	-2,4181*	Saipem	1,1519	0,5173	0,6204	0,4889
Z*(q)		-0,6921	-1,5438	-1,4330	-1,6521		0,9763	0,4607	0,5444	0,4484
VR(q)		0,9878	0,9574	1,0170	1,0828		0,7839	0,5866	0,4241	0,3512
Z(q)	DiaSorin	-0,2864	-0,5326	0,1339	0,4385	Snam	-5,0687**	-5,1726**	-4,54073**	-3,4381**
Z*(q)		-0,2320	-0,4370	0,1160	0,3950		-1,6950	-1,9124	-1,8752	-1,5740
VR(q)		0,9237	0,8399	0,7295	0,6887		0,9622	0,9595	0,8428	0,6826
Z(q)	Enel	-1,7894	-2,0029*	-2,1331*	-1,6495	Stellantis	-0,8862	-0,5063	-1,2397	-1,6817
Z*(q)		-0,8343	-0,9833	-1,1978	-1,0853		-0,5949	-0,2959	-0,7255	-1,0555
VR(q)		0,9810	0,8926	0,8991	0,7874		0,9591	0,9733	0,8295	0,6982
Z(q)	Eni	-0,4461	-1,3434	-0,7958	-1,1264	STM	-0,9604	-0,3336	-1,3441	-1,5992
Z*(q)		-0,3140	-0,9321	-0,5551	-0,7662		-0,7240	-0,2350	-0,8760	-1,0624
VR(q)		0,9865	1,0052	0,7903	0,5988		1,0035	1,1274	1,0061	0,9450
Z(q)	Exor	-0,3161	0,0651	-1,6538	-2,1257*	Telecom Italia	0,0817	1,5940	0,0480	-0,2915
Z*(q)		-0,2049	0,0415	-1,0060	-1,2873		0,0402	0,7361	0,0243	-0,1767
VR(q)		0,8685	0,7647	0,7775	0,7364		0,9531	0,9786	0,9541	1,0049
Z(q)	Ferrari	-3,0841**	-2,9448**	-1,7545	-1,3966	Tenaris	-1,1001	-0,2682	-0,3622	0,0257
Z*(q)		-1,995*	-2,0532*	-1,3531	-1,1061		-0,9710	-0,2271	-0,3136	0,0231
VR(q)		0,7696	0,7488	0,7096	0,6289		0,8626	0,7515	0,5931	0,5072
Z(q)	FinecoBank	-5,4045**	-3,1437**	-2,2895*	-1,9662*	Terna	-3,2229**	-3,1096**	-3,2082**	-2,6112**
Z*(q)		-2,9835**	-1,8247	-1,4503	-1,3290		-1,6798	-1,6509	-1,7085	-1,4811
VR(q)		0,7465	0,6358	0,5408	0,4433		0,9731	1,0050	1,0468	1,0830
Z(q)	Hera	-5,9448**	-4,5569**	-3,6206**	-2,9496**	UniCredit	-0,6303	0,0630	0,3687	0,4401
Z*(q)		-1,7013	-1,5205	-1,5029	-1,5073		-0,4055	0,0394	0,2362	0,2971
VR(q)		0,9056	0,8763	0,9078	0,8409		0,8791	0,8854	0,8102	0,6654
Z(q)	Interpump Group	-2,2141*	-1,5481	-0,7273	-0,8433	Unipol Gruppo	-2,8357**	-1,4337	-1,4967	-1,7728
Z*(q)		-1,6519	-1,2302	-0,6135	-0,7157		-1,6766	-0,8443	-0,8609	-1,0497

Notes: * Null hypothesis rejection at the 5% significance level. ** Null hypothesis rejection at the 1% significance level. The null hypothesis assumes that stock prices follow a random walk. The test statistics Z(q) and Z(q)* assume homoskedastic and heteroscedastic increments respectively under the null hypothesis.

4.1.5 FTSE MIB Results

Previous tests were also performed on the FTSE MIB. The results are reported in Table 6.

Table 6. FTSE MIB results

Ljung-Box serial correlation test

Lag	1	2	3	4	5	6	7	8	9	10
Coefficient	-0,1527	0,1395	-0,0698	0,0246	0,0251	-0,1170	0,0540	-0,1441	0,0085	-0,0280
Q statistic	12,9245**	23,7271**	26,4334**	26,7707**	27,1210**	34,7797**	36,4152**	48,0613**	48,1019**	48,5443**

Runs test

n	299
n1	294
n0	257
Z	1,991*
p-value	0,0463

Unit root tests

Number of lags	ADF test statistic	ADF p-value	PP test statistic	PP p-value	KPSS test statistic	KPSS p-value
6	-1,7908	0,6958	-2,0254	0,5800	1,2087*	0,01

Variance ratio test

	q = 2	q = 4	q = 8	q = 16
VR(q)	0,8459	0,8043	0,7148	0,5835
Z(q)	-3,6136**	-2,4486*	-2,2487*	-2,2072*
Z*(q)	-1,6532	-1,1512	-1,2042	-1,3109

Notes: * Null hypothesis rejection at the 5% significance level. ** Null hypothesis rejection at the 1% significance level.

The Ljung-Box test shows evidence of a strong serial correlation in returns as all Q statistics reject the joint hypothesis of non-autocorrelation in the first m lags at the 1% significance level. Furthermore, coefficients at lags 1 and 10 are negative, indicating mean reversion in returns. These results are confirmed by the runs test. The null hypothesis of a random order in price changes is rejected at the 5% significance level. The z-value is positive, indicating negative serial correlation in returns. The presence of serial autocorrelation does not support the random walk model.

The unit root tests clearly support the EMH, as the ADF test and the PP test null hypothesis of a unit root in the returns time series are not rejected. The null hypothesis of stationarity of the KPSS is rejected at the 5% significance level, thus strengthening the previous results.
Under the homoscedastic Z(q) statistic of the variance ratio test, the null hypothesis of a random walk is rejected at the 1% significance level for lag 2 and at the 5% level for other lags.
Instead, under the heteroskedasticity assumption, the test does not reject the null hypothesis and provides evidence to support the EMH.
In conclusion, the FTSE MIB shows signs of serial negative autocorrelation in returns that are not consistent with the random walk model. On the other hand, stationarity tests and, more importantly, the variance ratio test support the EMH.

4.1.6 Summary of Test Results

Table 7 summarizes the results of all the random walk tests performed.
Apart from the Ljung Box serial correlation test, which assumption of normality has been empirically rejected by the Jarque-Bera test, all other tests provide large evidence in support of the weak-form EMH.
Considering the ADF test and the KPSS test, thirty companies meet the most stringent requirements for a random walk, although the results differ in terms of stocks that reject the non-stationarity assumption.
According to the ADF test, Inwit, Italgas and Unipol Gruppo are trend-stationary and do not present a unit root, while for the KPSS test Atlantia and Inwit are stationary.
Instead, considering the PP test, twenty-seven companies meet all the criteria for the more rigorous random walk model.
The results of the variance ratio test reported in Table 7 refer to the null hypothesis of a random walk with heteroscedastic increments.
Among the thirty-five companies that do not show serial correlation based on runs test results, Ferrari, Italgas and Pirelli & C reject the null hypothesis of the variance ratio test. This rejection indicates the presence of autocorrelation in their returns that may not have been detected by the runs test.
Empirical results from the Italian financial market generally support the weak-form EMH, meaning that for the vast majority, stock prices are informationally efficient.

Table 7. Summary of the weak-form EMH tests:
Does the test result support the random walk?

	Ljung-Box test	Runs test	ADF test	PP test	KPSS test	Variance Ratio test
FTSE MIB	NO	NO	YES	YES	YES	YES
A2A	NO	NO	YES	YES	YES	YES
Amplifon	NO	YES	YES	YES	YES	YES
Assicurazioni Generali	NO	YES	YES	YES	YES	YES
Atlantia	NO	YES	YES	NO	NO	YES
Azimut Holding	NO	NO	YES	YES	YES	YES
Banca Generali	NO	YES	YES	YES	YES	YES
Banca Mediolanum	YES	YES	YES	YES	YES	YES
Banco BPM	NO	YES	YES	YES	YES	YES
BPER Banca	NO	YES	YES	YES	YES	YES
Buzzi Unicem	NO	YES	YES	YES	YES	YES
Campari	NO	NO	YES	YES	YES	YES
CNH Industrial	NO	YES	YES	YES	YES	YES
DiaSorin	YES	YES	YES	YES	YES	YES
Enel	NO	YES	YES	YES	YES	YES
Eni	NO	YES	YES	YES	YES	YES
Exor	NO	YES	YES	YES	YES	YES
Ferrari	NO	YES	YES	YES	YES	NO
FinecoBank	NO	NO	YES	YES	YES	NO
Hera	NO	YES	YES	YES	YES	YES
Interpump Group	NO	YES	YES	YES	YES	YES
Intesa Sanpolo	NO	YES	YES	YES	YES	YES
Inwit	NO	YES	NO	NO	NO	YES
Italgas	NO	YES	NO	NO	YES	NO
Leonardo	NO	YES	YES	NO	YES	YES
Mediobanca	NO	YES	YES	YES	YES	YES
Moncler	NO	YES	YES	YES	YES	YES
Nexi	YES	YES	YES	YES	YES	YES
Pirelli & C	NO	YES	YES	YES	YES	NO
Poste Italiane	NO	YES	YES	YES	YES	YES
Prysmian	NO	NO	YES	YES	YES	NO
Recordati	NO	YES	YES	YES	YES	YES
Saipem	NO	YES	YES	YES	YES	YES
Snam	NO	YES	YES	YES	YES	YES
Stellantis	NO	YES	YES	NO	YES	YES
STM	NO	YES	YES	YES	YES	YES
Telecom Italia	NO	YES	YES	YES	YES	YES
Tenaris	YES	YES	YES	YES	YES	YES
Terna	NO	YES	YES	YES	YES	YES
UniCredit	NO	YES	YES	YES	YES	YES
Unipol Gruppo	NO	YES	NO	NO	YES	YES

4.2 Overconfidence Bias Results

4.2.1 Granger Causality Test

Table 8 reports the results of the bi-directional Granger test and the number of lags used to construct the VAR models.

The null hypothesis assumes that there is no Granger causality between the two variables.

The test evaluates whether returns Granger-cause volumes, in which case a rejection of the null hypothesis provides evidence to support the overconfidence bias, and whether volumes Granger-cause returns, which rejection of the null hypothesis implies evidence of inefficiencies in the market.

Twenty-two companies reject the null hypothesis for the first case at the 5% significance level, pointing to some possible evidence in favor of overconfidence in investor behavior.

Instead, the null hypothesis that volumes do not Granger-cause returns is rejected only by three companies: Hera (p-value = 0,0096), Telecom Italia (p-value = 0,0178), which also reject the null hypothesis of the previous case and Prysmian (p-value = 0,0470).

This confirms the conclusions on the efficiency of Italian securities previously derived from EMH weak-form tests.

The FTSE MIB does not reject the null hypothesis for both tests.

Table 8. Granger causality test

		Returns Granger-cause volumes		Volumes Granger-cause returns	
	Number of lags	Test statistic	p-value	Test statistic	p-value
FTSE MIB	8	14,0077	0,0816	5,4524	0,7083
A2A	3	12,8588**	0,0050	3,1979	0,3621
Amplifon	7	8,1038	0,3235	9,8401	0,1978
Assicurazioni Generali	17	33,9524**	0,0085	20,2012	0,2641
Atlantia	10	10,5987	0,3896	12,1000	0,2784
Azimut Holding	17	42,5505**	0,0006	25,4056	0,0860
Banca Generali	5	8,0772	0,1520	6,4895	0,2615
Banca Mediolanum	13	25,9235**	0,0174	10,2434	0,6739
Banco BPM	5	19,2138**	0,0018	8,3390	0,1385
BPER Banca	10	15,2888	0,1219	6,5146	0,7703
Buzzi Unicem	14	14,7634	0,3945	12,1471	0,5945
Campari	20	17,1902	0,6406	17,9981	0,5875
CNH Industrial	10	23,0190*	0,0107	3,1212	0,9784
DiaSorin	10	4,4564	0,9244	16,2215	0,0935
Enel	7	4,9704	0,6636	8,8925	0,2605
Eni	13	29,6423**	0,0053	22,2610	0,0514
Exor	12	21,7689*	0,0402	8,9114	0,7105
Ferrari	4	9,2198	0,0558	3,1664	0,5304
FinecoBank	7	29,1490**	0,0001	1,9659	0,9617
Hera	4	11,4732*	0,0217	13,3615**	0,0096
Interpump Group	14	23,9991*	0,0458	18,2955	0,1937
Intesa Sanpolo	7	21,6022**	0,0030	3,0007	0,8849
Inwit	20	34,4095*	0,0235	13,3628	0,8613
Italgas	18	12,1822	0,8377	14,8523	0,6721
Leonardo	13	19,8300	0,0995	13,6831	0,3965
Mediobanca	17	50,7072**	0,0000	12,4604	0,7715
Moncler	12	29,5822**	0,0032	15,7723	0,2019
Nexi	11	10,4740	0,4883	11,9556	0,3670
Pirelli & C	8	19,7537*	0,0113	5,1852	0,7376
Poste Italiane	18	48,0981**	0,0001	19,0257	0,3902
Prysmian	11	14,1067	0,2271	19,8837*	0,0470
Recordati	4	2,0199	0,7321	6,6855	0,1535
Saipem	8	15,4049	0,0517	12,4866	0,1308
Snam Rete	18	20,6747	0,2961	26,5205	0,0884
Stellantis	14	31,6276**	0,0045	6,8455	0,9405
STM	15	17,8437	0,2710	11,7560	0,6974
Telecom Italia	7	24,6147**	0,0009	16,9367*	0,0178
Tenaris	5	14,6342*	0,0120	5,1540	0,3974
Terna	13	21,9459	0,0562	14,4675	0,3418
UniCredit	11	36,2376**	0,0002	19,2126	0,0574
Unipol Gruppo	10	38,9244**	0,0000	11,0257	0,3555

Notes: * Null hypothesis rejection at the 5% significance level. ** Null hypothesis rejection at the 1% significance level. The null hypothesis assumes no Granger-causality. The number of lags have been determined by the Bayesian Information Criterion (BIC).

4.2.2 Vector Autoregressive Model

Table 9 shows VAR coefficients for FTSE MIB and the Italian companies.

Table 9. Vector Autoregressive Model coefficients

	FTSE MIB		A2A		Amplifon		Assicurazioni Generali		Atlantia		Azimut Holding		Banca Generali		Banca Mediolanum		Banco BPM	
Vol$_t$	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**
Ret$_{t-1}$	1,0822	1,4470	2,0645	2,7642**	0,4889	0,8212	3,1362	3,5533**	1,1024	1,7942	2,9834	3,7348**	1,6005	2,0487*	2,1587	3,118**	1,4228	3,0227**
Ret$_{t-2}$	0,4207	0,5585	1,8592	2,4739*	-0,1036	-0,1740	0,8720	0,9783	-0,7288	-1,1885	2,3302	2,8462**	0,8856	1,1342	0,1229	0,1755	1,4172	2,9882**
Ret$_{t-3}$	0,6196	0,8269	0,3480	0,5251	-0,5939	-0,9993	1,7300	1,9330	0,7292	1,1551	1,1519	1,4047	0,9966	1,2891	0,5710	0,8173	0,6542	1,3726
Ret$_{t-4}$	-0,4316	-0,5770			-1,4612	-2,4520*	2,3562	2,6323**	0,5386	0,8570	1,6835	2,0188*	-0,1369	-0,1771	1,2153	1,7456	0,4112	0,8635
Ret$_{t-5}$	-0,0853	-0,1172			-0,2609	-0,4417	-1,1886	-1,3302	0,7239	1,1615	2,0236	2,4134*	-0,6653	-0,9040	0,5943	0,8620	0,0086	0,0185
Ret$_{t-6}$	-0,6697	-0,9201			0,4535	0,7700	-1,1020	-1,2325	-0,3587	-0,5759	-0,7293	-0,8711			-0,5985	-0,8772		
Ret$_{t-7}$	1,4648	2,0102*			0,0177	0,0304	1,3867	1,5500	0,3988	0,6413	1,5037	1,7971			1,5745	2,3202*		
Ret$_{t-8}$	-1,8084	-2,4537*					-0,7679	-0,8616	-0,7308	-1,1801	-0,2872	-0,3428			-1,2271	-1,7999		
Ret$_{t-9}$							1,3966	1,5739	0,4106	0,6841	1,8417	2,2102*			-0,0797	-0,1173		
Ret$_{t-10}$							1,1173	1,2681	-0,7280	-1,2276	1,7592	2,1554*			1,1291	1,6606		
Ret$_{t-11}$							-0,3528	-0,3996			-0,1683	-0,2055			-0,5318	-0,7832		
Ret$_{t-12}$							1,4118	1,6013			0,9449	1,1684			0,1824	0,2707		
Ret$_{t-13}$							-1,3608	-1,5455			-0,0864	-0,1096			0,8943	1,3500		
Ret$_{t-14}$							-0,0712	-0,0808			-1,3695	-1,7566						
Ret$_{t-15}$							0,4333	0,4924			-1,7092	-2,2044*						
Ret$_{t-16}$							1,4531	1,6748			-0,0600	-0,0780						
Ret$_{t-17}$							0,7079	0,8219			-0,6725	-0,8863						
Ret$_{t-18}$																		
Ret$_{t-19}$																		
Ret$_{t-20}$																		

	BPER Banca		Buzzi Unicem		Campari		CNH Industrial		DiaSorin		Enel		Eni		Exor		Ferrari	
Vol$_t$	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**
Ret$_{t-1}$	1,1037	2,3847*	1,0640	1,4477	-0,2548	-0,2981	1,3526	2,9905**	-0,0856	-0,1489	0,2745	0,3926	2,0686	3,7663**	2,2373	3,3560*	1,5281	2,3335*
Ret$_{t-2}$	0,0261	0,0567	-1,0064	-1,3715	-1,5041	-1,7390	0,5894	1,2942	-0,7511	-1,3090	0,6243	0,8975	0,5844	1,0483	-0,4402	-0,6505	0,5925	0,8965
Ret$_{t-3}$	0,6579	1,4184	-0,6450	-0,8893	-0,0774	-0,0891	1,1164	2,4285*	-0,2418	-0,4197	0,9915	1,4161	0,5491	0,9803	0,7151	1,0655	0,5155	0,7738
Ret$_{t-4}$	0,4208	0,8997	1,0384	1,4280	-0,3093	-0,3568	0,3251	0,6999	0,4414	0,7691	0,1394	0,1978	0,8679	1,5615	1,3927	2,0870*	-1,0199	-1,5574
Ret$_{t-5}$	0,5035	1,0729	0,9727	1,3463	0,0001	0,0001	0,4010	0,8627	0,5892	1,0373	0,1950	0,2770	-0,2912	-0,5234	-0,0389	-0,0583		
Ret$_{t-6}$	-0,1966	-0,4216	-0,4321	-0,6004	0,5651	0,6548	-1,0903	-2,3536*	-0,0881	-0,1555	0,4565	0,6514	-0,6394	-1,1518	0,5843	0,8764		
Ret$_{t-7}$	-0,0357	-0,0765	1,0685	1,5030	0,3739	0,4368	0,4163	0,8948	0,2367	0,4178	0,9510	1,3953	1,0688	1,9341	0,8869	1,3607		
Ret$_{t-8}$	-0,9984	-2,1348*	0,0210	0,0297	-1,6539	-1,9541	0,0636	0,1372	-0,1764	-0,3116			-0,3825	-0,7008	0,0939	0,1443		
Ret$_{t-9}$	0,3336	0,7105	-0,0366	-0,0517	0,3554	0,4223	0,3271	0,7117	-0,3374	-0,5978			0,7947	1,4486	1,4601	2,2544*		
Ret$_{t-10}$	0,5604	1,2183	-0,0459	-0,0653	0,4595	0,5445	-0,5054	-1,1446	-0,4688	-0,8401			0,6073	1,1026	-0,6077	-0,9595		
Ret$_{t-11}$			-1,1181	-1,6157	-0,2858	-0,3407							1,1194	2,0578*	-0,2167	-0,3428		
Ret$_{t-12}$			0,2333	0,3361	0,0116	0,0139							1,2504	2,3143*	0,0839	0,1369		
Ret$_{t-13}$			-0,3134	-0,4574	-0,6123	-0,7312							0,1888	0,3529				
Ret$_{t-14}$			-0,4966	-0,7401	0,7733	0,9236												
Ret$_{t-15}$					0,1048	0,1245												
Ret$_{t-16}$					-0,9150	-1,0860												
Ret$_{t-17}$					-0,2434	-0,2884												
Ret$_{t-18}$					-0,9614	-1,1411												
Ret$_{t-19}$					-1,6399	-1,9469												
Ret$_{t-20}$					0,9659	1,1990												

	FinecoBank		Hera		Interpump Group		Intesa Sanpaolo		Inwit		Italgas		Leonardo		Mediobanca		Moncler	
Vol$_t$	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**
Ret$_{t-2}$	1,4824	2,3796*	1,5826	1,7378	-0,2995	-0,3967	0,7027	1,3961	-0,9767	-0,9109	0,5054	0,4903	0,5795	1,1276	2,2009	2,8994**	0,5616	0,9143
Ret$_{t-3}$	1,0772	1,7492	2,0202	2,2183*	0,1873	0,2476	0,2855	0,5758	0,4271	0,3981	1,1019	1,0686	1,2655	2,4592*	2,9829	3,8382**	1,4181	2,2996*
Ret$_{t-4}$	-0,6468	-1,0480	-0,8774	-1,0295	1,1317	1,5017	0,2629	0,5270	-3,0132	-2,8200**	-0,2950	-0,2851	0,6761	1,2931	1,4061	1,7882	0,0837	0,1359
Ret$_{t-5}$	0,5443	0,8869			-0,9606	-1,2706	0,3568	0,7130	-0,2906	-0,2711	-0,0714	-0,0692	-0,3322	-0,6335	0,6049	0,7727	0,0468	0,0757
Ret$_{t-6}$	-0,5125	-0,8406			-0,9978	-1,3346	0,0026	0,0052	1,7174	1,6073	-0,0687	-0,0669	0,0083	0,0159	0,2902	0,3710	0,3000	0,4868
Ret$_{t-7}$	1,5475	2,5951**			0,3431	0,4600	0,8248	1,7033	4,5882	4,2897**	1,0929	1,0699	0,1907	0,3688	1,4626	1,8777	0,5973	0,9776
Ret$_{t-8}$					-1,4262	-1,9105			-0,2906	-0,2688	-0,5715	-0,5573	-0,2787	-0,5382	1,0620	1,3598	-0,1763	-0,2871
Ret$_{t-9}$					1,4198	1,9045			1,2668	1,2046	1,0633	1,0373	-0,2044	-0,3966	0,6811	0,8824	1,6835	2,7579**
Ret$_{t-10}$					0,5541	0,7451			0,1239	0,1176	1,4312	1,3962	0,3809	0,7388	0,7594	0,9977	-1,3814	-2,2354*
Ret$_{t-11}$					-1,1193	-1,4944			-0,5460	-0,5166	-0,3718	-0,3631	-0,8685	-1,6955	1,9842	2,6031**	0,1412	0,2276
Ret$_{t-12}$					1,5639	2,0889			-0,1971	-0,1872	-0,0200	-0,0195	0,1938	0,3795	0,9483	1,2482	0,9005	1,4803
Ret$_{t-13}$					-0,3998	-0,5371			-0,5411	-0,5155	-1,2633	-1,2439	-0,0271	-0,0536	-1,3715	-1,8189		
Ret$_{t-14}$					0,4916	0,6575			-0,0396	-0,0380	-0,9122	-0,9005			0,5146	0,6922		
Ret$_{t-15}$									-0,6255	-0,5992	0,2232	0,2224			-0,9673	-1,3072		
Ret$_{t-16}$									1,4773	1,4266	-2,0927	-2,0950			1,1821	1,6133		
Ret$_{t-17}$									-1,6809	-1,6291	-0,4954	-0,4948			-0,6474	-0,9052		
Ret$_{t-18}$									-1,0016	-0,9729	0,0502	0,0507						
Ret$_{t-19}$									-0,7371	-0,7176								
Ret$_{t-20}$									-0,0480	-0,0486								

	Nexi		Pirelli & C		Poste Italiane		Prysmian		Recordati		Saipem		Snam	
Vol_t	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**
Ret_{t-3}	-0,3981	-0,5365	0,8243	1,1943	1,1603	1,3718	0,5599	0,7939	0,2275	0,2655	-0,1182	-0,2793	-0,9289	-0,9017
Ret_{t-4}	1,3456	1,8264	0,1411	0,2041	0,8286	0,9839	-0,6019	-0,8568	0,7587	0,9621	-0,6372	-1,5051	0,4789	0,4668
Ret_{t-5}	0,2583	0,3509	-0,6457	-0,9378	1,9754	2,3284*	-0,4169	-0,5898			0,1915	0,4580	-0,1345	-0,1314
Ret_{t-6}	0,3630	0,5003	-2,0757	-3,0253**	1,1480	1,3486	-1,3566	-1,9536			-1,2841	-3,0764**	0,0580	0,0572
Ret_{t-7}	0,8354	1,1561	0,8843	1,2804	2,4043	2,8251**	0,3207	0,4627			0,2527	0,5984	2,1485	2,1389*
Ret_{t-8}	0,0855	0,1184	-0,4040	-0,5909	0,5325	0,6246	-0,6105	-0,9034			-0,2226	-0,5352	-0,4959	-0,4924
Ret_{t-9}	1,1659	1,6263			0,2543	0,2996	1,3433	1,9856*					-1,0367	-1,0340
Ret_{t-10}	-0,7656	-1,0746			-0,3500	-0,4127	-0,2310	-0,3404					-0,8763	-0,8761
Ret_{t-11}	0,6963	1,0229			1,6510	1,9625*	-0,1872	-0,2828					-0,7002	-0,7088
Ret_{t-12}					0,0228	0,0271							-0,1978	-0,2001
Ret_{t-13}					-0,8061	-0,9616							-0,5044	-0,5121
Ret_{t-14}					-1,9218	-2,3237*							-0,1306	-0,1332
Ret_{t-15}					-1,8490	-2,2526*							-2,7588	-2,8038**
Ret_{t-16}					-0,2181	-0,2652							-0,6603	-0,6682
Ret_{t-17}					-0,9640	-1,1852							-0,7030	-0,7215
Ret_{t-18}					-0,1704	-0,2185							0,8672	0,9088
Ret_{t-19}														
Ret_{t-20}														

	Stellantis		STM		Telecom Italia		Tenaris		Terna		UniCredit		Unipol Gruppo	
Vol_t	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**	**Coefficient**	**t stat.**
Ret_{t-3}	1,7495	3,3864**	0,1957	0,3925	0,4497	0,9663	0,6060	1,4663	0,8481	0,9892	0,3256	0,8205	1,7587	2,5035*
Ret_{t-4}	-0,1853	-0,3524	-0,0274	-0,0545	0,0184	0,0395	0,6820	1,6463	1,4029	1,6419	0,8970	2,2924*	-0,6098	-0,8668
Ret_{t-5}	-0,0475	-0,0902	0,1676	0,3379	-0,3426	-0,7393	-0,3345	-0,8186	-0,1797	-0,2096	0,6267	1,5941	-1,0821	-1,5505
Ret_{t-6}	-0,1750	-0,3325	-0,9955	-2,0109*	-0,4079	-0,8848			-0,1623	-0,1890	0,2117	0,5391	0,7189	1,0310
Ret_{t-7}	-0,2231	-0,4300	-0,3653	-0,7372	0,1165	0,2580			1,1027	1,2910	0,9741	2,5103	0,2163	0,3104
Ret_{t-8}	-0,9984	-1,9540	-0,7721	-1,5587					0,2466	0,2896	-0,3072	-0,7882	0,5183	0,7590
Ret_{t-9}	0,1751	0,3412	-0,1485	-0,3035					1,1764	1,4129	0,3796	0,9698	-0,3463	-0,5118
Ret_{t-10}	0,0686	0,1358	0,0041	0,0085					0,1388	0,1669	0,1835	0,4663	-0,2663	-0,4064
Ret_{t-11}	0,2694	0,5359	0,1959	0,4062					-1,1310	-1,3598	-0,8480	-2,2281*		
Ret_{t-12}	0,2198	0,4429	0,2845	0,5921					2,5863	3,0999**				
Ret_{t-13}	-0,7542	-1,5420	-0,0593	-0,1248					1,1467	1,3778				
Ret_{t-14}	-0,0490	-0,1002	-0,2609	-0,5521										
Ret_{t-15}			-0,7570	-1,6333										
Ret_{t-16}														
Ret_{t-17}														
Ret_{t-18}														
Ret_{t-19}														
Ret_{t-20}														

Notes: * Coefficient significant at the 5% level. ** Coefficient significant at the 1% level.

For brevity, only coefficients that relate detrended trading volumes to past returns are presented. Statistical significance is reported at levels of 1% and 5%.

The results show that past returns and volumes are generally positively related, especially at first lags. On the other hand, at higher lags and especially from lag 13 onwards, the relationship is reversed since more negative coefficients are observed.

However, only sixty-two of the estimated coefficients are significant at the 5% level or better.

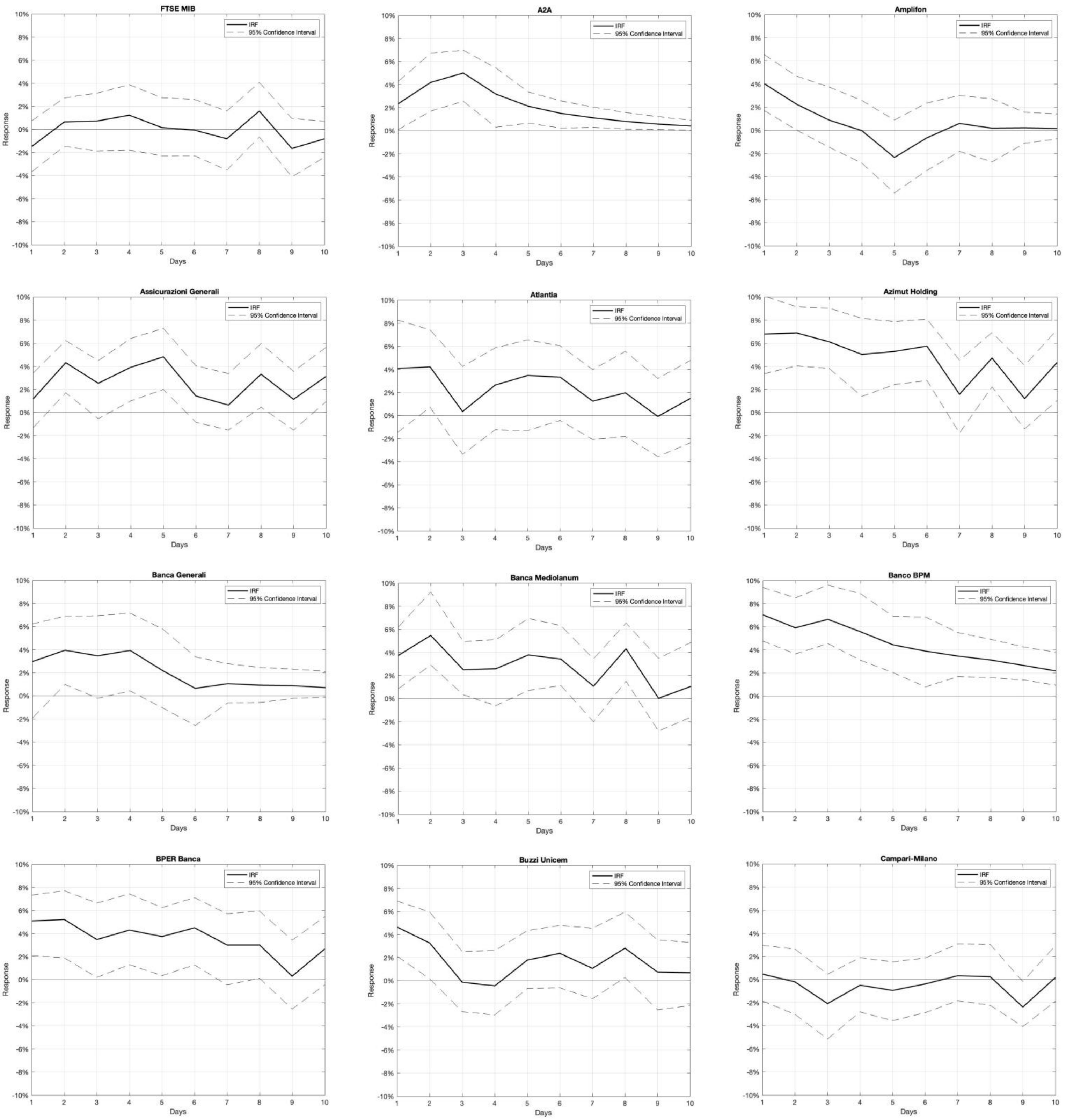
Most of the significant positive coefficients are observed at lag 1, as eighteen of the thirty-seven positive coefficients are significant at the 1% level and six of them at the 5% level. Furthermore, at the first three lags, all significant coefficients are positive.

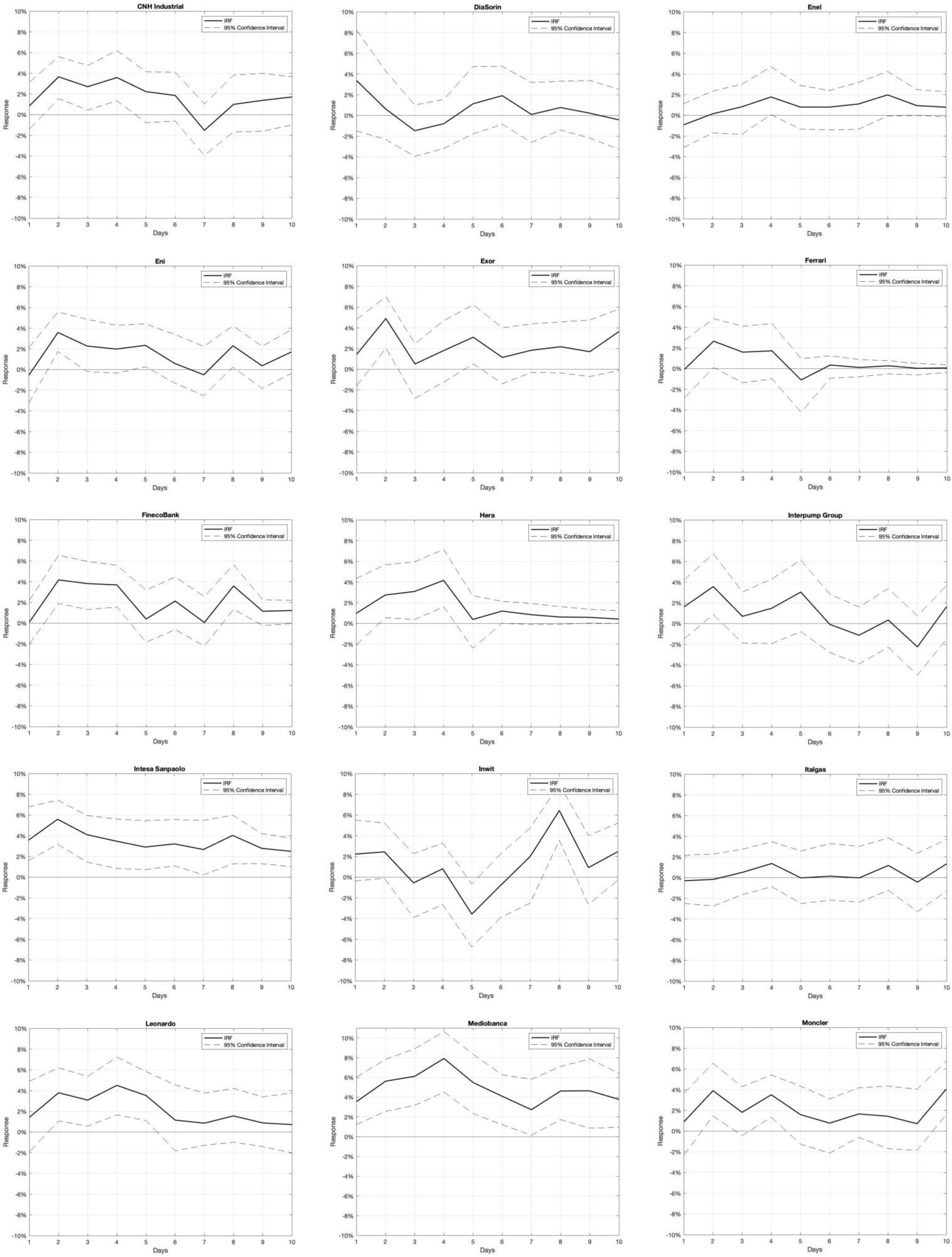
Specifically, the positive relationship between detrended volume and stock returns is significant for A2A (lag 1), Assicurazioni Generali (lag 1, 4), Azimut Holding (lag 1, 2, 4, 5, 9), Banca Generali (lag 1), Banca Mediolanum (lag 1), Banco BPM (lag 1, 2), BPER Banca (lag 1), CNH Industrial (lag 1, 3), Eni (lag 1, 11, 12), Exor (lag 1, 4), Ferrari (lag 1), FinecoBank (lag 1, 7), Hera (lag 3), Interpump Group (lag 1), Inwit (lag 7), Leonardo (lag 1, 3), Mediobanca (lag 1, 2, 3, 11), Moncler (lag 1, 9), Pirelli & C (lag 1), Poste Italiane (lag 1, 2, 7, 11), Snam (lag 1), Stellantis (lag 1, 3), STMicroelectronics (lag 2), Telecom Italia (lag 1, 2), Tenaris (lag1), Terna (lag 1, 2), Unicredit (lag 1, 4), Unipol Gruppo (lag 1 ,2).
Only eleven significant coefficients are negative and are observed after the fourth lag.
The coefficients are not significant at the 5% level for ten companies: Atlantia, Buzzi Unicem, Campari, DiaSorin, Enel, Intesa Sanpaolo, Italgas, Nexi, Prysmian, Recordati.
The FTSE MIB present only two significant coefficients: a positive one at lag 7 and a negative one at lag 8.
VAR results do not appear to provide much evidence in support of the overconfidence bias as most of the estimated coefficients are not significant. The first lag is the only one in which it is observed a positive and statistically significant relationship for more than half of the companies.
Only six companies have consistently significant positive coefficients after lag 1.
On the Italian index, on the other hand, there is no such relationship at any of the first lags, thus rejecting the hypothesis of the overconfidence bias.

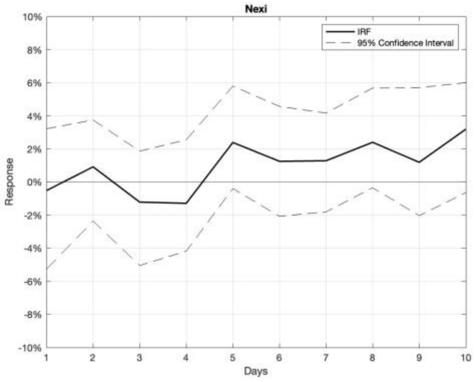
4.2.3 Impulse Response Functions

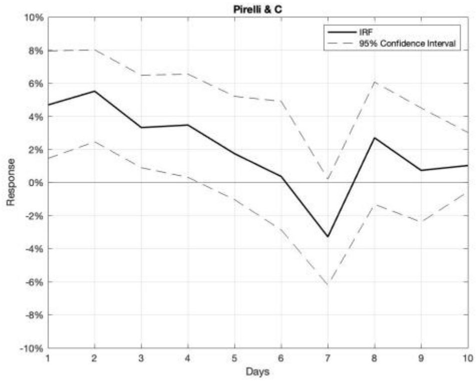
A clearer conclusion can be drawn from the impulse response functions, which are plotted for a period of ten days. For brevity, the following Figures illustrate only the response of trading volumes to a shock on equity returns.

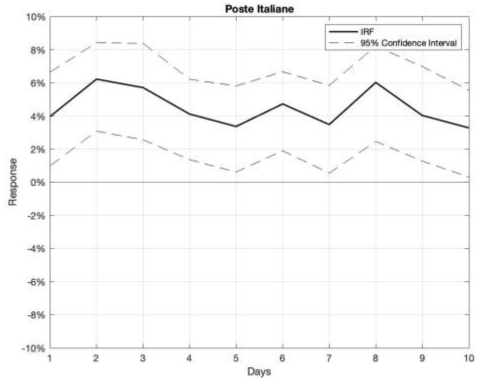
Figures: Impulse Response Functions

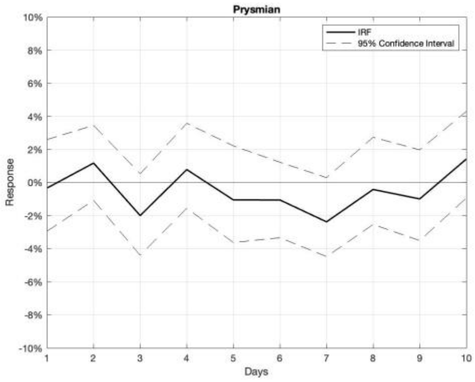


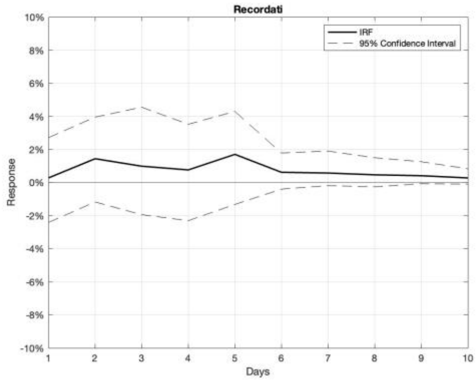

CNH Industrial
DiaSorin
Enel
Eni
Exor
Ferrari
FinecoBank
Hera
Interpump Group
Intesa Sanpaolo
Inwit
Italgas
Leonardo
Mediobanca
Moncler
IRF
95% Confidence Interval
Response
Days

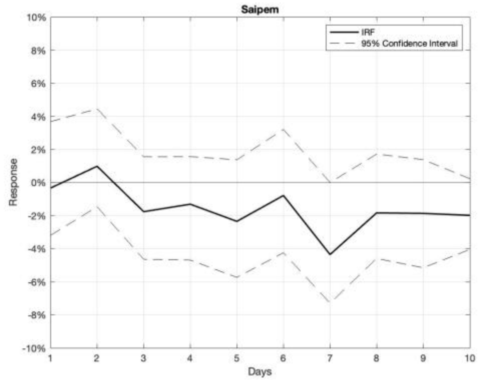

Nexi
IRF
95% Confidence Interval
Response
Days

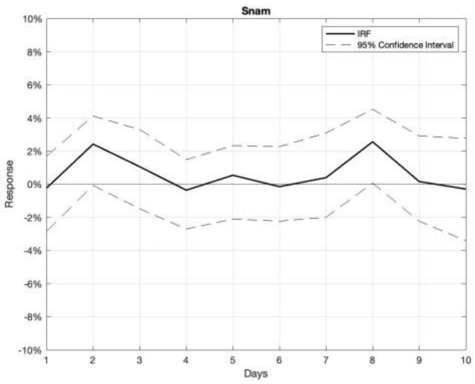

Pirelli & C
IRF
95% Confidence Interval
Response
Days

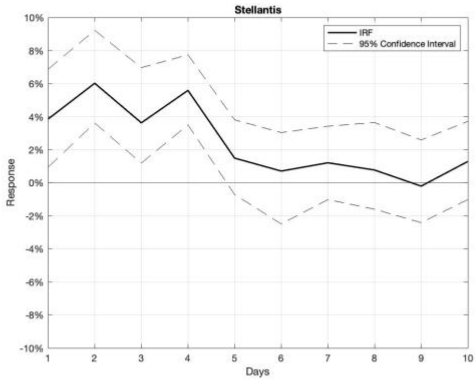

Poste Italiane
IRF
95% Confidence Interval
Response
Days

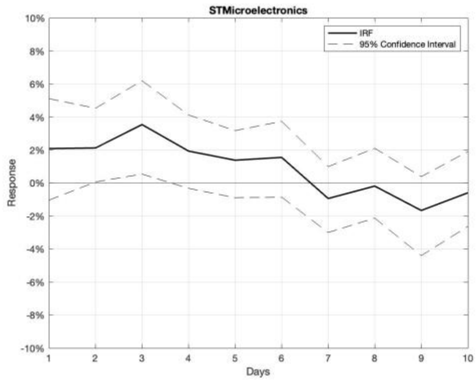

Prysmian
IRF
95% Confidence Interval
Response
Days

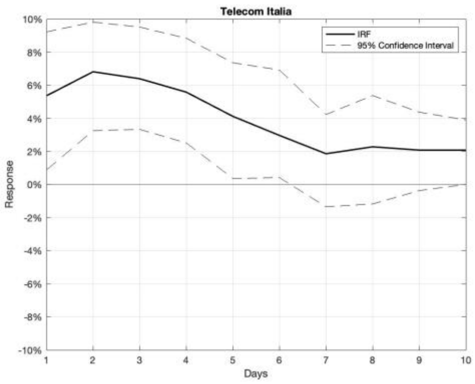

Recordati
IRF
95% Confidence Interval
Response
Days

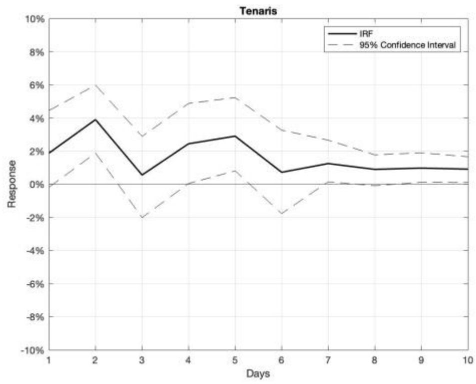

Saipem
IRF
95% Confidence Interval
Response
Days

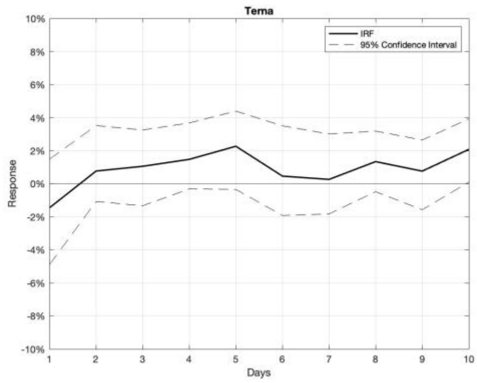

Snam
IRF
95% Confidence Interval
Response
Days

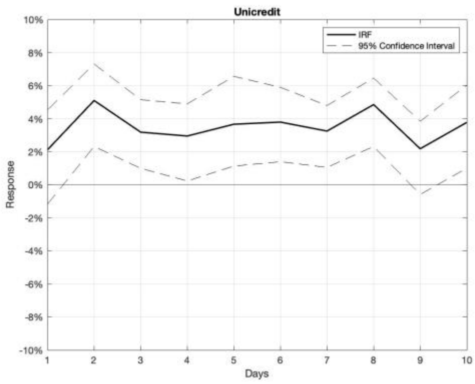

Stellantis
IRF
95% Confidence Interval
Response
Days

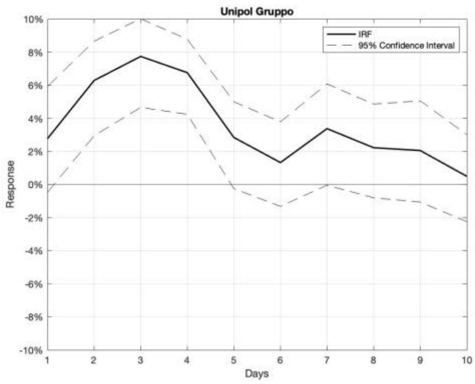

STMicroelectronics
IRF
95% Confidence Interval
Response
Days


Telecom Italia
IRF
95% Confidence Interval
Response
Days


Tenaris
IRF
95% Confidence Interval
Response
Days


Terna
IRF
95% Confidence Interval
Response
Days


Unicredit
IRF
95% Confidence Interval
Response
Days


Unipol Gruppo
IRF
95% Confidence Interval
Response
Days

Overall, volumes reactions to shock on returns were positive, but only fifteen companies presented statistically significant response at the 5% level or better.
A significantly increasing response is observed for Atlantia (from 4,08% on the 1st day to 4,22% on the 2nd day), Pirelli & C (from 4,68% on the 1st day to 5,51% on the 2nd day) and Unipol Gruppo (from 2.77% on the 1st day to 6,76% on the 4th day).
Amplifon shows a significant reaction on day 1 equal to 4,03%.
Instead, all other companies present significant responses that diminish as we move forward in time. IRFs graphs show an increase of 6,79%, 3,73%, 5,09%, 4,65%, 3,85% and 5,36% in the following day for Azimut Holding, Banca Mediolanum, BPER Banca, Buzzi Unicem, Stellantis and Telecom Italia. The reactions last 6 days, 3 days, 4 days, 2 days, 5 days, and 5 days, respectively.
Significant positive responses persist for all ten days for 5 companies: A2A, Banco BPM, Intesa Sanpaolo, Mediobanca and Poste Italiane.
An initial response of 2.34% is observed for A2A, reaching its maximum of 5,01% on day 3 and then slowly decreasing to 0,41% on day 10.
Banco BPM volumes increase by 7,03% on the following day, successively declining after the 3rd day to 2,18% on the 10th day.
Intesa Sanpaolo and Mediobanca showed a similar response on day 1, equal to 3,58% and 3,55% respectively. After a maximum of 5,59% in the next 2 days for Intesa Sanpaolo and 7,92% on the fourth day for Mediobanca, their reactions on volumes drop to 2,5% and 3,78% on day 10.
Finally, an increase of 3,96% in volumes is observed for Poste Italiane. Subsequently, responses range from a maximum of 6,02% on day 8 to a minimum of 3,28% on day 10.

4.3 Conservatism Bias: Momentum Strategies Results

Momentum strategies results are presented in Table 9.

Table 10. Momentum strategies results

J	K	3	6	9	12
3	**Winner**	0,0318	0,0496	0,1141	0,2108**
	Loser	0,0651	0,1473*	0,1848**	0,2039*
	Momentum	-0,0333	-0,0977	-0,0707	0,0068
	t statistic	-0,8684	-2,3127*	-1,4615	0,1298
	p-value	0,3960	0,0344	0,1676	0,8993
6	**Winner**	0,0224	0,0630	0,1560	0,2166*
	Loser	0,0697	0,0638	0,1015	0,1655
	Momentum	-0,0473	-0,0007	0,0546	0,0512
	t statistic	-1,6168	-0,0164	1,2163	1,0139
	p-value	0,1255	0,9872	0,2518	0,3444
9	**Winner**	0,0115	0,0470*	0,1131	0,0351
	Loser	0,0109	-0,0228	-0,0183	-0,0487
	Momentum	0,0007	0,0698	0,1315	0,0838
	t statistic	0,0149	2,6376*	2,775*	2,1167
	p-value	0,9884	0,0248	0,0275	0,1017
12	**Winner**	-0,0040	-0,0099	-0,0497	-0,0113
	Loser	-0,0312	-0,1237	-0,0799	-0,0642
	Momentum	0,0271	0,1138	0,0302	0,0529
	t statistic	0,9316	2,9064*	0,3677	0,3216
	p-value	0,3735	0,0228	0,7317	0,8019

Notes: * Null hypothesis rejection at the 5% significance level. ** Null hypothesis rejection at the 1% significance level. The null hypothesis of the t-test assumes that returns are equal to zero. J=formation period. K=holding period.

The strategies generally yielded positive returns, as observed for eleven of the sixteen momentum portfolios.

The returns produced ranged from 0,1315, observed for the formation period J and the holding period K both equal to nine, to -0,0977 for J equal to three and K equal to six. The average return of the strategies is positive and equal to 0,0233.

The p-values of the t-statistic show that only four strategies produced significantly non-zero returns at the 5% significance level.

We observe three significantly positive returns equal to 0,0698 for J = 9 and K = 6 (p-value = 0,0248), 0,1315 for J = 9 and K = 9 (p-value = 0,0275) and 0,1138 for J = 12 and K = 6 (p-value = 0,0228).

Therefore, momentum effect is mainly observed for medium-longer formation and holding periods.

In the short term, however, there is little evidence of the contrarian effect, as the portfolio J = 3 and K = 6 produced a significantly negative return of -0,0977 (p-value = 0,0344).

Most of the returns produced by momentum portfolios are not statistically significant, indicating weak support for conservatism bias and for the contrarian effect.

Conclusions

The empirical results clearly support the weak-form EMH, as the implemented tests consistently indicate that stock price movements of Italian companies follow a random walk.
The runs test shows that only five of the forty companies exhibit positive serial correlation in returns.
Unit root tests provide large evidence of non-stationarity in returns, particularly the KPSS test, which null hypothesis of stationarity is rejected for thirty-eight stocks.
Finally, the variance ratio test accepts the presence of a random walk, under the more suitable assumption of heteroscedastic increments, for thirty-five companies.
The results of the Ljung-Box test, which indicate strong inefficiencies in the Italian market, are considered as misleading since the assumption of normality has been significantly rejected by the Jarque-Bera test.
FTSE MIB results are mixed as the positive serial correlation indicated by the Ljung-Box test is confirmed by the runs test. Instead, unit root tests and the variance ratio test provide evidence in favor of the EMH.
Some evidence in support of the overconfidence bias in Italian stocks is confirmed by all the tests implemented.
Twenty-two companies accept the hypothesis that returns Granger-cause trading volumes, thus indicating support of the behavioral bias.
However, the evidence provided by VAR models and IRFs is weaker.
VAR models indicate twenty-four significant positive coefficients at lag, which rapidly decrease in numbers at the following lags.
IRFs indicate significant positive reactions of trading volumes to shock on returns for fifteen companies
The FTSE MIB does not present significant positive coefficients at the first lags of the VAR model, nor does show a significant positive response of its volumes to a shock on returns in the IRF graph.
In conclusion, the overconfidence bias is not observed on the Italian index, but it is present in less than half of the Italian companies.
Momentum strategies provide very weak evidence in support of the conservatism bias as only three of the sixteen strategies implemented provide significant positive returns. Specifically, these returns were observed for longer formation and holding periods.
Instead, in the short run, the contrarian effect has been observed for only one of the portfolios.

Since most of the returns obtained from momentum portfolios are not significant at the 5% level, these results tend to support the previous conclusions on the informational efficiency of the Italian market.

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Summary

The purpose of this research was to analyze the reaction of the Italian financial market to the outbreak of the Covid-19 pandemic.
The aim was to assess the efficiency of the FTSE MIB and of Italian stocks listed on the Index and to identifies anomalies that could have emerged during the period considered.
The first chapter of this thesis focuses on the review of the main theories empirically analyzed: the Efficient Market Hypothesis and Behavioral Finance.
The definition of market efficiency can be attributed to the research of Eugene Fama (1965a, 1965b and 1970) and Paul Samuelson (1965).
Fama (1965a) found that stock price movements are unpredictable and resemble a random walk. This model is based on the assumption of independence, thus past stock prices are not helpful in forecasting future changes. Its practical implication is that technical analysis is deemed to fail in providing extra-returns to investors, as using past information does not provide better predictions. Furthermore, Fama stated that an "efficient" market is a market in which stock prices fully reflect all the available information at the time.
Fama (1965b) implemented the above definition, stating that an efficient market is a market in which rational investors who seek to maximize their profits compete and where information is free and available to all market participants. Therefore, randomness observed in price movements can be explained by investors behavior, who make actual stock prices converge to their intrinsic values.
Indipendently from Fama's works, Samuelson (1965) argued that stock prices movements follow a martingale process, a stochastic process in which the best forecast for future values is today's value. Formally, a process x_t is a defined as a martingale, with respect to an information set Φ_t, if $E[x_{t+1}|\Phi_t] = x_t$, meaning that it should not be possible to predict future changes.
An important difference with the random walk is that the martingale does not require price movements to be independent.
Like Fama, Samuelson assumes a competitive market with rational investors, whose profit maximizing behavior generates the random pattern of stock prices.
Both authors argued that randomness can be explained by the presence of rational investors.
The key difference is that Fama describes randomness as the consequence of actual stock prices converging to intrinsic values, while for Samuelson it is the consequence of investors' competition.
Fama's work "Efficient Capital Markets" of 1970 represents one of the most important steps in the history of the EMH. The paper will give a proper formalization to the concept of efficiency through a more specific definition of the information sets reflected in stock prices.

Three sub-sets of information have been identified, which define three forms of the EMH:

- the weak form, where only past information is reflected;
- the semi-strong form, where share prices include all available public information, i.e., annual reports, dividend announcements and all other publicly available news that may affect actual prices;
- the strong form, in which also private information is incorporated into stock prices, implying that a trading strategy based only on the available information will not produce extra profits as it is already incorporated in market prices.

Furthermore, three sufficient but not necessary conditions for a market to be informationally efficient have been identified by Fama (1970) :

1. no transaction costs;
2. information is freely available to all market participants;
3. investors agree on the effect of information on actual prices and on the distribution of future prices.

Malkiel (1992) reinforced Fama's (1970) definition, stating that a market is efficient when the disclosure of new information to market participants do not affect stock prices.

The practical implication is that efficiency can be assessed by studying price movements after the announcement of new information.

The EMH has been challenged by numerous studies and several different approaches have been developed in contrast with the efficiency's framework.

Behavioral finance is one of the most significative alternatives, as it questions the rationality of market participants.

As explained by Shleifer (2000), behavioral finance states that investors are affected by biases and irrationalities that lead to systematic and predictable errors in their investment decision process.

The theory explains how specific psychological traits influence investors and lead to misjudgments of situations and information, thus resulting in irrational and unprofitable behaviors.

The consequences of the errors will be reflected in shares prices, leading to inefficiencies in financial markets.

Two specific biases have been analyzed in this thesis: the conservatism bias and the overconfidence bias.

Overconfidence bias refers to the tendency of investors to overestimate their assessment skills.

Investors affected by the bias will believe that their valuations are better than other market participants, thereby increasing their willingness to take more risks and trade more. The overall result will be an increasing of market volumes.

The relationship between trading volumes and the overconfidence bias was suggested by Gervais and Odean (2001). Their intuition was tested by Statman et al. (2006), who studied the influence of high past returns, used as a proxy for the overconfidence level, on trading volumes.
Through the implementation of a Vector Autoregressive Model (VAR) and Impulse Response Functions (IRFs), they found a significant relationship between returns and volumes.
The same approach has been replicated in this thesis.
VAR model is a multivariate time series model consisting of several equations, one for each endogenous variable. Two endogenous variables were used in this study: stock returns and trading volumes. The range, a proxy for daily volatility proposed by Alizadeh et al. (2002), has been used as a control variable following Karpoff (1987)'s findings of a positive relationship between volumes and volatility.
Each equation, which describes the evolution over time of the endogenous variables, is composed of lagged values of endogenous and exogenous variables and an error term.
The Bayesian Information Criterion was used to determine the number of lagged terms.
IRFs were plotted for ten days to examine the response of trading volumes to a one-standard-deviation shock on stock returns.
Furthermore, a bi-directional Granger's causality test was used to verify the statistical significance of returns when predicting volumes and vice versa. The presence of Granger's causality between returns and volumes can be considered as evidence in support of the overconfidence bias.
Instead, volumes granger-causing returns can be seen as evidence of inefficiencies in the market.
Conservatism bias, as formalized by Edwards (1968), describes the under-reaction of investors to new information or to new evidence. Slowly adjustment to new information will lead to a slow reaction also in the price formation process, thus generating momentum in returns.
Therefore, the bias can be empirically tested by constructing a series of momentum strategies, following the approach of Jegadeesh and Titman (1993).
Sixteen momentum portfolios were constructed by combining four different J formation periods (J = 3, 6, 9 and 12 months) and four K holding periods (K = 3, 6, 9 and 12 months).
Momentum portfolios consist of a long position in the winner portfolio, which collects the top four best performing stocks during formation periods, and a short position in the loser portfolio, made up of the four least performing stocks. Overlapping horizons were included to increase the power and efficiency of the test.
A t-test was used to verify the statistical significance of portfolios results.

Daily data have been collected for the FTSE MIB and for the companies listed on the index.

The stocks in the sample are the ones that have been part of the Italian index at the beginning of 2022. Table 1 specifies the name of the companies and the number of observations analyzed, providing descriptive statistics for their daily returns.

Returns have been calculated as $Return_t = \log\left(\frac{Price_t}{Price_{t-1}}\right)$.

Table 1. Descriptive statistics for daily returns

	Observations	Mean	Maximum	Minimum	Standard Deviation	Skewness	Excess Kurtosis	Jarque-Bera statistic
FTSE MIB	551	0,0004	0,0855	-0,1854	0,0169	-2,3450	28,165	18717**
A2A	551	0,0005	0,0756	-0,2112	0,0190	-2,4375	28,398	19060**
Amplifon	551	0,0009	0,1057	-0,2163	0,0245	-1,2403	12,114	3510,6**
Assicurazioni Generali	551	0,0007	0,1049	-0,1387	0,0164	-0,8407	12,746	3794,5**
Atlantia	551	0,0007	0,2363	-0,2514	0,0300	0,0054	19,920	9110,4**
Azimut Holding	551	0,0007	0,1430	-0,1731	0,0237	-0,5653	10,523	2571,7**
Banca Generali	551	0,0008	0,1004	-0,1483	0,0209	-0,8301	8,844	1859,1**
Banca Mediolanum	551	0,0007	0,1141	-0,1271	0,0236	-0,4175	5,737	771,68**
Banco BPM	551	0,0018	0,1403	-0,1827	0,0281	-0,1634	5,065	591,49**
BPER Banca	551	-0,0002	0,2022	-0,1954	0,0315	0,4722	7,118	1183,8**
Buzzi Unicem	551	0,0003	0,1370	-0,1277	0,0231	0,1451	5,507	698,32**
Campari	551	0,0006	0,1013	-0,1757	0,0199	-0,8900	15,362	5490,7**
CNH Industrial	551	0,0013	0,1135	-0,1888	0,0290	-1,2103	6,896	1226,4**
DiaSorin	551	0,0004	0,0920	-0,1803	0,0262	-0,8325	6,039	900,97**
Enel	551	-0,0001	0,0725	-0,2212	0,0192	-2,6957	32,164	24418**
Eni	551	0,0012	0,1392	-0,1998	0,0231	-0,7544	13,849	4455,2**
Exor	551	0,0002	0,1956	-0,1368	0,0255	0,1068	9,757	2186,5**
Ferrari	551	0,0008	0,1017	-0,1082	0,0186	-0,1080	5,283	641,88**
FinecoBank	551	0,0009	0,1121	-0,1297	0,0219	-0,0006	5,774	765,28**
Hera	551	0,0001	0,1417	-0,1921	0,0187	-1,2155	25,671	15265**
Interpump Group	551	0,0008	0,0759	-0,1192	0,0214	-0,5923	3,578	326,19**
Intesa Sanpolo	551	0,0006	0,1976	-0,1958	0,0246	-0,1320	16,679	6388,2**
Inwit	551	0,0003	0,1035	-0,1604	0,0187	-0,9253	13,030	3976,3**
Italgas	551	0,0005	0,0720	-0,1474	0,0160	-1,1158	14,691	5069,3**
Leonardo	551	0,0005	0,1507	-0,2504	0,0295	-0,4388	12,773	3763,5**
Mediobanca	551	0,0009	0,1303	-0,2069	0,0242	-1,0501	13,044	4007,4**
Moncler	551	0,0007	0,1331	-0,1215	0,0239	0,1957	4,742	519,84**
Nexi	551	-0,0006	0,1577	-0,2169	0,0268	-0,6251	10,434	2535,1**
Pirelli & C	551	0,0004	0,1330	-0,1951	0,0262	-0,5510	8,240	1586,6**
Poste Italiane	551	0,0003	0,0932	-0,2489	0,0218	-2,5832	32,136	24322**
Prysmian	551	0,0011	0,0825	-0,1575	0,0216	-0,7686	6,798	1115,1**
Recordati	551	0,0003	0,1716	-0,1799	0,0201	-0,0463	21,735	10846**
Saipem	551	-0,0012	0,1235	-0,3593	0,0324	-2,3280	27,900	18368**
Snam	551	0,0006	0,0953	-0,2130	0,0178	-3,0272	39,668	36967**
Stellantis	551	0,0012	0,1210	-0,1968	0,0285	-0,7366	7,684	1405,4**
STM	551	0,0009	0,1349	-0,1738	0,0271	-0,6779	6,792	1101,4**
Telecom Italia	551	-0,0006	0,2642	-0,2042	0,0307	0,3253	17,061	6692,6**
Tenaris	551	0,0018	0,1287	-0,1622	0,0280	0,1616	4,280	423,03**
Terna	551	0,0007	0,0752	-0,1619	0,0166	-1,4527	17,437	7174,4**
UniCredit	551	0,0002	0,1286	-0,1895	0,0303	-0,7107	6,362	975,58**
Unipol Gruppo	551	0,0009	0,1632	-0,1923	0,0237	-0,4139	12,418	3555,8**

Notes: ** Null hypothesis rejection at the 1% significance level. Under the null hypothesis of the Jarque-Bera test, returns follow a normal distribution.

The observations cover the period between March 9, 2020, the day of the announcement of the first lockdown in Italy, and May 6, 2022.

Tenaris (0,0018), Banco BPM (0,0018) and CNH Industrial (0,0013) present the highest mean returns, while Nexi (-0,0006), Telecom Italia (-0,0006) and Saipem (-0,0012) have the lowest mean returns during the period considered.
The highest volatility is observed for Saipem (0,0324), Bper Banca (0,0315) and Telecom Italia (0,0307), while Terna (0,0166), Assicurazioni Generali (0,0164) and Italgas (0,0160) have the less volatile returns.
Daily returns are generally negatively skewed, as only seven of the forty companies present positive skewness. Negative skewness implies a greater probability of observing negative returns than the normal distribution.
Excess kurtosis also shows deviations of returns from normality, as all the companies present a positive value. Snam (39,6677) has the highest excess kurtosis, while Interpump Group (3,5784) has the lowest.
The conclusion of non-normality drawn from skewness and excess kurtosis are largely confirmed by the Jarque-Bera test, a two-tailed goodness-of-fit test which assumes normality of under the null hypothesis
The null hypothesis is rejected at the 1% significance level for all the companies.
The FTSE MIB has a negative skewness of -2,3450 and a large excessive kurtosis equal to 28,165. The Jarque-Bera test confirms non-normality of the distribution of daily returns also for the Italian index.

If stock prices follow a random walk, it is possible to assess the weak-form efficiency of the Italian market.
Following Campbell et al. (1997), three sub-models of the random walk can be identified through the definition of more stringent characteristics:

- a random walk with dependent but uncorrelated increments;
- a random walk with independent but not identically distributed increments;
- a random walk with independent and identically distributed increments.

These assumptions can be tested through different statistical tests.
The Ljung box test and the runs test are implemented to assess the presence of serial correlation in returns.
The Ljung-Box test is a portmanteau parametric test, meaning that the alternative hypothesis is not fully specified. Under the null hypothesis, the first m serial correlation coefficients are equal to zero, thus implying no autocorrelation in returns. m indicates the number of lags considered, which in this thesis is equal to ten.

Unlike the Ljung-Box test, the runs test is non-parametric and does not require returns to follow a normal distribution. This test is used to find serial correlation that may have been ignored by a parametric test. The null hypothesis assumes that price movements came in a random order.
A time series following a random walk is not stationary, thus it should contain a unit root.
Three tests have been implemented to check for a unit root in stock prices: the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test.
The ADF test and the PP test assume a unit root in the series under the null hypothesis.
The PP test differs from the ADF test in that it is non-parametric and accounts for autocorrelation in the innovation process.
The KPSS test assumes trend-stationarity under the null hypothesis and account for serial correlation through a parametric correction.
The number k of lagged terms used for the tests is determined by the Akaike information criterion.
Finally, the variance ratio test is used to assess whether stock price movements follow a random walk by looking at the variance of the increments.
Under the null hypothesis of a random walk, the variance of the q-th difference increases linearly with the time interval q considered.
The test was proposed by Lo and MacKinlay (1988), who also suggested two test statistics, Z(q) and Z*(q). The first assumes homoscedastic increments in the random walk, while the second assumes heteroscedasticity in the increments.
The null hypothesis in the case of homoscedasticity can be rejected due to heteroscedasticity or serial correlation. Therefore, a rejection of the null assuming heteroscedastic increments indicates autocorrelation in returns.
Four periods were considered for this test, q = 2, 4, 8, 16.

When interpreting Ljung-Box test results, a rejection of the null hypothesis of no serial correlation at any lags is considered as a rejection of efficiency for the entire price series.
The Ljung Box test results strongly reject the weak-form EMH as only four companies (Banca Mediolanum, DiaSorin, Nexi and Tenaris) do not show serial correlation at the 5% significance level.
Among the thirty-six companies that exhibit serial correlation, most of the autocorrelation coefficients are negative, thus implying mean reverting returns.
We observe nineteen negative and significant coefficients at lag 10. Campari (–0,1546),

FinecoBank (–0,1147) and Moncler (–0,0807) present the highest mean reverting returns, while on average mean reversion at lag 10 is equal to –0,0490.

The test assumes under the null hypothesis that stock prices follow a normal distribution. This assumption was rejected by the data as shown by the Jarque-Bera test results. Therefore, the conclusions drawn from the Ljung-Box test should not be considered as absolute.

The null hypothesis of no serial correlation of the runs test, which do not depend on the assumption of normality, has been rejected for thirty-five companies at the 5% level of significance.

The results of the test confirm mean reverting returns for A2A, Azimut, Campari, Banco BPM and Prysmian.

Furthermore, Banca Mediolanum, DiaSorin, Nexi and Tenaris do not show serial correlation in their returns under both tests.

In conclusion, the runs test provides great evidence in support of the random walk model as almost all the companies show no signs of serial correlation in their price movements.

The results of unit root tests at the 5% significance level are clearly in favor of the random walk.

The null hypothesis of a unit root of the ADF test is rejected for only three companies (Inwit, Italgas and Unipol Gruppo).

The PP test, which assumes the same null hypothesis as the ADF test, provides evidence of non-stationarity for thirty-two companies.

Finally, the null hypothesis of trend-stationarity of the KPSS test is rejected for thirty-eight companies.

Inwit is the only company which stationarity is indicated by all the tests implemented.

The rejection of the null hypothesis of the variance ratio test for at least one period has been interpreted as a rejection of the random walk for the entire price series.

The homoscedastic-robust test statistic rejects the null hypothesis for twenty-six companies at the 5% level of significance. Most stocks that reject the random walk present variance ratios lower than 1, thus implying mean reversion in returns.

Instead, under the assumption of heteroscedastic increments, only five companies (Ferrari, FinecoBank, Italgas, Pirelli & C. and Prysmian) reject the null hypothesis due to serial correlation in returns. Their variance ratios are all below 1, indicatin mean-reverting returns.

The variance ratio test results are clearly in favor of the weak-form EMH, as almost all stock prices follow a random walk.

Previous tests were also performed on the FTSE MIB. The results are shown in Table 6.

Table 6. FTSE MIB results

Ljung-Box serial correlation test

Lag	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Coefficient	-0,1527	0,1395	-0,0698	0,0246	0,0251	-0,1170	0,0540	-0,1441	0,0085	-0,0280
Q statistic	12,9245**	23,7271**	26,4334**	26,7707**	27,1210**	34,7797**	36,4152**	48,0613**	48,1019**	48,5443**

Runs test

n	299
n1	294
n0	257
Z	1,991*
p-value	0,0463

Unit root tests

Number of lags	**ADF test statistic**	**ADF p-value**	**PP test statistic**	**PP p-value**	**KPSS test statistic**	**KPSS p-value**
6	-1,7908	0,6958	-2,0254	0,5800	1,2087*	0,01

Variance ratio test

	q = 2	**q = 4**	**q = 8**	**q = 16**
VR(q)	0,8459	0,8043	0,7148	0,5835
Z(q)	-3,6136**	-2,4486*	-2,2487*	-2,2072*
Z*(q)	-1,6532	-1,1512	-1,2042	-1,3109

Notes: * Null hypothesis rejection at the 5% significance level. ** Null hypothesis rejection at the 1% significance level.

The null hypothesis of no serial correlation of the Ljung-Box test has been rejected at all lags at the 1% significance level. We observe a negative coefficient at lag 10, implying mean reverting returns. The runs test confirms the presence of a strong serial correlation in the returns of the FTSE MIB as the null hypothesis is rejected at the 5% level and the z-value is positive. A positive z-value indicates negative autocorrelation in returns, meaning that price movements will tend to mean revert in the long run. Both serial correlation tests do not provide evidence in support of the EMH. Instead, unit root tests consistently confirm the presence of a unit root in the price series.
The null hypothesis of non-stationarity was rejected for both the ADF test and the PP test, while the null hypothesis of trend-stationarity of the KPSS test has been rejected at the 5% significance level. The variance ratio test results support the random walk model, as the null hypothesis under the assumption of heteroscedastic increments has not been rejected at the significance level of 5%.

Table 7 summarizes the results of all the tests performed.
Random walk tests provided large evidence in support of the weak-form EMH.

Table 7. Summary of the weak-form EMH tests:
Does the test result support the random walk?

	Ljung-Box test	Runs test	ADF test	PP test	KPSS test	Variance Ratio test
FTSE MIB	NO	NO	YES	YES	YES	YES
A2A	NO	NO	YES	YES	YES	YES
Amplifon	NO	YES	YES	YES	YES	YES
Assicurazioni Generali	NO	YES	YES	YES	YES	YES
Atlantia	NO	YES	YES	NO	NO	YES
Azimut Holding	NO	NO	YES	YES	YES	YES
Banca Generali	NO	YES	YES	YES	YES	YES
Banca Mediolanum	YES	YES	YES	YES	YES	YES
Banco BPM	NO	YES	YES	YES	YES	YES
BPER Banca	NO	YES	YES	YES	YES	YES
Buzzi Unicem	NO	YES	YES	YES	YES	YES
Campari	NO	NO	YES	YES	YES	YES
CNH Industrial	NO	YES	YES	YES	YES	YES
DiaSorin	YES	YES	YES	YES	YES	YES
Enel	NO	YES	YES	YES	YES	YES
Eni	NO	YES	YES	YES	YES	YES
Exor	NO	YES	YES	YES	YES	YES
Ferrari	NO	YES	YES	YES	YES	NO
FinecoBank	NO	NO	YES	YES	YES	NO
Hera	NO	YES	YES	YES	YES	YES
Interpump Group	NO	YES	YES	YES	YES	YES
Intesa Sanpolo	NO	YES	YES	YES	YES	YES
Inwit	NO	YES	NO	NO	NO	YES
Italgas	NO	YES	NO	NO	YES	NO
Leonardo	NO	YES	YES	NO	YES	YES
Mediobanca	NO	YES	YES	YES	YES	YES
Moncler	NO	YES	YES	YES	YES	YES
Nexi	YES	YES	YES	YES	YES	YES
Pirelli & C	NO	YES	YES	YES	YES	NO
Poste Italiane	NO	YES	YES	YES	YES	YES
Prysmian	NO	NO	YES	YES	YES	NO
Recordati	NO	YES	YES	YES	YES	YES
Saipem	NO	YES	YES	YES	YES	YES
Snam	NO	YES	YES	YES	YES	YES
Stellantis	NO	YES	YES	NO	YES	YES
STM	NO	YES	YES	YES	YES	YES
Telecom Italia	NO	YES	YES	YES	YES	YES
Tenaris	YES	YES	YES	YES	YES	YES
Terna	NO	YES	YES	YES	YES	YES
UniCredit	NO	YES	YES	YES	YES	YES
Unipol Gruppo	NO	YES	NO	NO	YES	YES

The Ljung-Box test, which showed serial correlation for most of the Italian companies, was the only test that did not support the random walk model. As previously stated, the conclusions drawn from the test should be taken with caution, as the assumption of normality of daily returns was strongly rejected by the data.

If we consider the ADF test and the KPSS test, thirty companies meet the most restrictive definition of a random walk. The results of the tests differ in that for the ADF test Inwit, Italgas and Unipol Gruppo are stationary, while for the KPSS test Atlantia and Inwit are the securities showing stationarity.

When the PP test is considered, however, the number of companies that have met all the requirements decreases to twenty-seven.

Variance ratio test results considered in Table 7 refer to the heteroscedastic-robust test statistic. Therefore, a rejection of the null hypothesis indicates the presence of serial correlation in returns.

Thirty-five companies showed no serial correlation under the runs test. However, three of them (Ferrari, Italgas and Pirelli & C) rejected the null hypothesis of a random walk with heteroscedastic increments, indicating autocorrelation in price movements that may not have been detected by the runs test.

Presence of the overconfidence bias in the Italian market was indicated by all the tests performed. The bi-directional Granger causality test showed that for twenty-two companies stock returns Granger-caused volumes at the 5% significance level. Instead, significant Granger-causality between volumes and returns was observed for only three companies, confirming the conclusions previously drawn on the efficiency of Italian securities.
The FTSE MIB does not present Granger-causality between returns and volumes and vice versa.
Weaker evidence in support of the bias was presented by VAR models and IRFs.
VAR results indicated a positive relationship between returns and detrended volumes especially at lag 1, as more than half of the companies showed significant positive coefficients at the 5% level. Consistently significant positive coefficients are observed for only six stocks.
However, most of the computed coefficients are not statistically significant. Therefore, VAR results provide little evidence in support of the bias.
The coefficients of the FTSE MIB at first lags are not significant, indicating rejection of the overconfidence bias.
According to the IRFs, which were plotted for a period of ten days, fifteen stocks showed positive and statistically significant responses of trading volumes to a shock on equity returns.
Only five companies (A2A, Banco BPM, Intesa Sanpaolo, Mediobanca and Poste Italiane) presented a significant response for the entire period analyzed.
Apart from Atlantia, Pirelli & C and Unipol Gruppo, which significant responses were increasing, all other companies presented shock reactions that have decreased over time.
The FTSE MIB IRF graph indicated a non-statistically significant response. Therefore, the overconfidence bias was not detected on the Italian index during the sampling period.
Weak evidence of the bias has been reported for less than half of Italian stocks.

Momentum strategies, which results are summarized in Table 9, provided little evidence to support the conservatism bias.

Table 10. Momentum strategies results

J	K	3	6	9	12
3	**Winner**	0,0318	0,0496	0,1141	0,2108**
	Loser	0,0651	0,1473*	0,1848**	0,2039*
	Momentum	-0,0333	-0,0977	-0,0707	0,0068
	t statistic	-0,8684	-2,3127*	-1,4615	0,1298
	p-value	0,3960	0,0344	0,1676	0,8993
6	**Winner**	0,0224	0,0630	0,1560	0,2166*
	Loser	0,0697	0,0638	0,1015	0,1655
	Momentum	-0,0473	-0,0007	0,0546	0,0512
	t statistic	-1,6168	-0,0164	1,2163	1,0139
	p-value	0,1255	0,9872	0,2518	0,3444
9	**Winner**	0,0115	0,0470*	0,1131	0,0351
	Loser	0,0109	-0,0228	-0,0183	-0,0487
	Momentum	0,0007	0,0698	0,1315	0,0838
	t statistic	0,0149	2,6376*	2,775*	2,1167
	p-value	0,9884	0,0248	0,0275	0,1017
12	**Winner**	-0,0040	-0,0099	-0,0497	-0,0113
	Loser	-0,0312	-0,1237	-0,0799	-0,0642
	Momentum	0,0271	0,1138	0,0302	0,0529
	t statistic	0,9316	2,9064*	0,3677	0,3216
	p-value	0,3735	0,0228	0,7317	0,8019

Notes: * Null hypothesis rejection at the 5% significance level. ** Null hypothesis rejection at the 1% significance level. The null hypothesis of the t-test assumes that returns are equal to zero. J=formation period. K=holding period.

Only four momentum portfolios yielded statistically significant returns at the level of 5%.

Three of them (J = 9 and K = 6, J = 9 and K = 9, J = 12 and K = 6) produced positive results, indicating evidence of momentum in stock returns. These results are concentrated in longer formation and holding periods.

On the other hand, in the short run, we observe a negative significant return (for J = 3, K = 6) which is consistent with the contrarian effect.

However, most of the results here presented were not statistically significant, thus reinforcing the conclusion that the Italian market was informationally efficient during the Covid-19 pandemic.