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Market Anomalies:
the exception that proves Market Efficiency

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Introduction

Economics, like the other sciences, has been subject to a continuous modernization process to stay in line with changes in society. Since the beginnings of the twentieth century, the classical economic theory was thought to be the only one capable of explaining real life events caused by economic agents' actions. According to this theory, individuals are fully rational and take actions with the objective to maximize their expected level of wealth on the base of information equally and freely available to everyone. Anyway, as historical evidence suggests, individuals are not rational and, therefore, the classical economic theory, which was used as an explanatory model for economic knowledge, ended up being not always applicable.

In the 70's, scientists coming from different fields, in particular psychologists and neuroscientists, started working with economists with the purpose to understand and explain the behavior of the individual in conditions of uncertainty. Extremely important was the support of the two Israeli psychologists D. Kahneman and A. Tversky, which enriched classical finance with new tools aiming to comprehend the limits of human rationality in the decision-making process. The integration of neurosciences and psychology to the classical financial theory is even known as behavioral finance.

Behavioral finance did not only provide explanations to biases and heuristics which lead to cognitive and emotional errors, but it even supplied some guidelines to correct them. Since recent times, these guidelines have been put into practice by intermediaries, banks, and regulators through instruments like financial education, disclosure and transparency policies.

One of the main causes of investors' irrationality which is empirically observable in the markets are those anomalies concerning stock prices. The goal of this thesis is to show how the evolution of financial theories is of fundamental importance to find, explain and correct these market anomalies which otherwise would lead to market inefficiency if relying only on the assumptions of the classical financial theory.

The thesis is articulated in three chapters:

Chapter one firstly introduces the classical theory and then explains how crucial it was the contribution of psychology in explaining the errors in the individual's decision-making process.

The second chapter describes the evolution of financial theories from the Efficient Market Hypothesis to the Adaptive Market Hypothesis going through the introduction of the behavioral finance and the financial evolution principles. At the end of the chapter are then described some measures adopted in real-world finance to correct such behavioral errors.

Finally, the third chapter analyzes different studies reporting empirical evidence of specific market anomalies. The anomalies analyzed are two intraday effects, one regarding returns and one concerning bid-ask spreads. The former, suggests that theoretically there exist abnormal returns opportunities, and so that markets are not efficient. In contrast, after later analyses of studies to find evidence about the aforementioned second anomaly, it is shown how that profitable cyclicality in returns patterns is wiped out by transaction costs.

At the end of the paper I ran an empirical test to find evidence of a daily cyclicality in stock prices over three different market indexes: the Dow Jones, the NASDAQ Composite, and the S&P 500. The analysis wants to test two different intraday anomalies in returns frequently recurring in the economic literature and is conducted over May and June 2020 for two specific reasons. The first is that data for price patterns are available only within a limited lass of time. The second and most important reason is because of the current societal and financial crisis caused by the global pandemic triggered by the virus “COVID-19”. This virus, most commonly known as “Coronavirus”, induced a high volatility and uncertainty in financial markets which has distorted ordinariness. For this, it is reasonable to think that the bimester May-June 2020, comprehending what currently are the furthest months from the financial crisis epicenter, is the most suitable period to run this test.

Chapter 1

The irrational investor according to Behavioral Finance

1. Premise

Since its origins, the classical financial theory, starting from the expected utility theory, has been subject to a slow and constant evolutionary and refining process. In particular, attention should be set to the evolution of the notion of fully rational agents as a limitation to the classical theory.

The fundamental pillars of the classical financial theory are the following:

- Investors are described as fully rational individuals.
- Markets are efficient and there is no information asymmetry.
- Investors operate through the efficient portfolio theory, following the mean-variance analysis.

The classical finance, even though played a key role in financial markets from the post-war years to date, has turned out to be far from reality, such that researchers started to study its discrepancies.
Behavioral finance is the implementation of a branch of economics, called behavioral, to financial markets. The objective of this science is to analyze the behavior of economic agents in conditions of uncertainty, by joining the work of economists and psychologists, in trying to give answers and new ways to correct men's behaviors labeled as "anomalous", through the study of human psychology. Behavioral finance origins after the 70's with the psychological studies conducted by Daniel Kahneman, Amos Tversky e Paul Slovic, which have been the firsts to point out the importance that psychology instruments could provide in renovating the economic and financial theories.

2. Psychology in finance and Behavioral Finance

Since the actions of individuals are not predictable (Tvede 2002)[1], it is implied that financial markets are not characterized by laws of physics or mathematics. Econometric models are not able to fully express subjective variables that lead to the final determination of the market price.
To better interpret the pricing mechanism of all the activities offered by the market, it is necessary to go beyond the logic, the coherence and the rationality of markets. Knowing that the variables connected to the stock

[1]Tvede, L., *The Psychology of Finance: Understanding the Behavioral Dynamics of Markets* (USA: Wiley, 2002).

quotes determination are countless and various, elements coming from psychological analysis can contribute to the explanation of price trends.
If investors who operate in the market act according to anxieties, worries and fears, in other words, according to their feelings, then market prices will include even the behaviors and the emotions of all traders.
As stated by Loeb (1957)[2], there are both objective and subjective variables that determine prices since it does not exist a definitive answer to the value of shares because these only partially reflect financial statements and balance sheets. They are more a representation of expectations and fears of humanity: greed, ambition, inventions, stress, tensions and cases of force majeure. The most important factor giving shape to the stock market is human psychology. Any investor operating in financial markets, does not know the "real value" of the securities he is trading; it is difficult, almost impossible to achieve a univocal value.
Another important factor which indirectly influences assets quotation, are the news published by the press. News come from anomalies in price movements, like shifts from initial trends, about which market participants try to give an explanation at the end of the day. The fact is that news represents an ex-post explanation to a previously verified phenomenon, which would have not been even spoke about if there wasn't any news about it. News influence market sentiment and, at the same time, investors decisions.
Generally speaking, investors feelings decide the pricing mechanism, by affecting each other, until they take shape in the final price. Several times, history showed how collective emotions led to stock prices determination, such as the tulip bulb market bubble known as "Tulip Mania". This may be considered as the first speculative bubble in capitalism history which hit the Netherlands in 1636 and saw tulip bulbs price increasing disproportionately and then drastically dropping after short time. Furthermore, there is even the dot.com speculative bubble, developed between 1997 and 2000, which arose as a result of the formation of a large number of small and medium sized firms lacking capital and owned by sole shareholders. In this case, investors overlooked traditional evaluation parameters relying only on technological innovation.
Then, we can conclude that the financial system is controlled by the volatility of financial agents' feelings, which causes prices to follow a slightly forecastable trend. They are a concrete expression of news coming from the market. For this reason, since these variables are dynamic and unpredictable, econometric models can represent only a small portion of reality. It follows that the estimated fair value is always questionable, right because of the intrinsic chaos which runs financial markets.
As a straight consequence of the empirical evidence offered by history, in the last decades, the economists who believed in the man to be fully rational and logic, started to take into account even its emotional side. On the other hand, even behaviorists started to not consider the man as totally irrational.
In conclusion, the modern approach is not completely detached from the old paradigm, indeed it is its straight consecution and continuation.

[2] Loeb G. M., *The Battle for Investment Survival* (USA: Simon & Schuster, 1957), 2.

3. The Expected Utility Theory

An important theme at the base of behavioral finance are the preferences that investors express through their investment choices. According to the classical theory, investors should base their choices in reference to the expected utility theory, but even here, empirical evidence suggests that the investor, most of the times, does not follow those behavioral rules.

The Expected Utility Theory (Gardenal G. 2016)[3], developed by Von Neumann and Morgenstern, defines the bases upon which the economic agent would implement all his choices of economic nature in uncertainty conditions, by maximizing his expected utility. If in a context of certainty, the individual is able to know the consequences of his actions, in a context of uncertainty, more consequences can correspond to a single action. This theory studies the consequences of human behavior, viewing man as predictable and endowed of rationality.

With the term utility, it is defined the index of the preferences of the individual in uncertainty conditions, that is the level of "satisfaction" or "well-being" that the agent will achieve by satisfying his needs.

The individual, when is required to choose between two alternatives without having a perfect knowledge of what is going to happen as a consequence, but knowing only their probability, will choose the alternative having the greatest utility on the basis of his budget constraint, of his resources.

If we denote with p_k the probability attributed to each consequence k, and with $u(x_k)$ the utility assigned to the consequence x_k, the expected utility function of an action is given by the summation of the utilities weighted by their probability to realize:

$$U(a) = \sum_{k=1}^{n} p_k u(x_k)$$

If we have two lotteries, A and B, and lottery A is preferred to lottery B, then U(A) ≥ U(B).

Individuals do not behave in the same way with respect to risk.

If we consider the possible outcomes of the alternatives as if they are expressed in monetary amounts x and knowing that individuals always prefer greater imports with respect to smaller ones, then the function u is a monotonous and increasing function.

If we know the shape of the utility function of the individual, we can derive his attitude toward risk. Any function can take a concave, convex or linear shape.

Assume we have two different lotteries presenting the same expected value, one having a safe outcome and the other one being risky:

[3] Gardenal G.; Rigoni U., *Finanza comportamentale e gestione del rischio*, (Torino: Giappichelli Editore, 2016).

- If the utility function is concave, it means that the individual is risk averse, and so he prefers the alternative with the certain outcome.
- If the utility function is convex, it means that the individual is risk lover and thus he prefers the alternative with the risky outcome rather than the safe one.
- If the utility function is linear, the individual is risk neutral and therefore he is indifferent between the safe and the risky alternative.

4. From the anomalies in the empirical evidence to the Prospect Theory

The studies that had he strongest influence on economic theories have been the ones about the Prospect Theory[4], developed by the psychologists Daniel Kahneman from Princeton University and Amos Tversky from Stanford University.

This theory claims that people tend to fail probability calculations: people believe that the results which are very likely to happen are less probable than what they really are, that improbable results are more probable and, that those which are extremely improbable, but still potentially possible, have no possibility to happen.

Researchers found out that people are averse mainly to losses, that is to say that they behave differently with respect to wins or respect to losses. People suffer of loss aversion and tend to measure risk in a different way, we are not talking anymore about risk aversion but of loss aversion.

Moreover, when they take decisions, they tend to break away from the reference framework without relying on what surrounds them.

There are various anomalous behaviors showed by individuals with respect to the rationality pretended by the system which are studied by the empirical evidence. They are the certainty effect, the reflection effect, the isolation effect and the framing effect.

A first violation, known as certainty effect, derives by the way agents perceive probability. In other words, it has been analyzed that there is a different perception of certainty with respect to the theoretically forecasted one.

In real life it is observed a second violation called reflection effect. Classical portfolio theory believes that agents implement their choices according to their utility function, giving the same weight to wins and losses.

Here, risk aversion becomes variable and the individual attributes a greater weight to losses rather than to the overall wealth of the transaction. This effect describes how choices in case of losses are opposite to the case of earnings. Moreover, if investors are placed in front of potential wins, they will adopt a risk averse strategy, while in the case they have to choose a strategy to stem losses, agents will be inclined to risk more.

[4] Prospect is the economic term for lottery, which indicates the combination of the possible results of several alternatives and the probabilities attached to them. X : $(x_1,p_1;\dots;p_n)$ where, $p_1+\dots+p_n = 1$.

A third source of violation is the isolation effect, which is the capability of financial operators not to dwell on common aspects between more alternatives, but paying attention, in a successive analysis, only to discriminating matters. This leads to empirically highlight that when a problem is decomposed in common and distinct parts, heterogeneous choices arise.
Another empirical evidence analyzed by Kahneman and Tversky in the prospect theory, is the framing effect, the effect which influences the choices of the individual depending on the way they are introduced. It derives that the language used, the emphasis, the reference content and the attention to details, are elements really influencing the decision-making process of the individual.
In an experiment, the two researchers demonstrated, in disaccord to the principle of rationality, how the presentation in two different formulations of the same problem resulted in different choices. In particular, people reacted to a positive framework by choosing the sure event, while in the second negative framework, they chose the risk-based strategy.
So, the framing effect depends on how hose information deemed to be important for the decision maker is framed. Such information expressed both in a positive or in a negative way, even if representing the same solution, modify people's preferences.

4.1 The Prospect Theory

The Prospect Theory of Kahneman e Tversky (1979)[5], was born from the idea that in uncertainty conditions, psychological factors such as behavioral heuristics and bias, have an impact on individuals' preferences. This theory improves the classical vision of strategic choices, with the attempt to analyze and comprehend the behavior of individuals.
The prospect theory articulates the choices of individuals in two distinct stages: in a first phase of structuring and analysis of the phenomenon and a second one of evaluation.
In the first stage, called editing, the agent gets to a simplified representation of reality in order to make faster choices. Rubatelli (2016/2017)[6], affirms that it is in this moment that individuals fall in cognitive and choice errors, which have as a consequence an altered perception of probabilities.
The editing phase is made of additional sub-phases[7]:

- Coding: this phase sees the results of a prospect to be evaluated with respect to a reference point, in fact, people evaluate gains and losses relying to their current situation. For example, from an investor's

[5] Kahneman D.; Tversky A., j., *Econometrica*, Vol. 47, N. 2, (New York University, The Econometric Society, 1979), 263-292.
[6] Rubatelli E., *Teoria del Prospetto*, (Università di Padova, Ce.R.D. - Centro di Ricerca sul Rischio e a Decisione, 2016/2017), 1-20.
[7] The following operations have not a specific order but appear to investor's mind according to his evaluations. Then, the choosing process results to be completely individual and unpredictable because choosing the order could preclude other actions of simplification.

point of view, a win of $500 should always be considered as a gain, but actually, it could be seen as negative result if the pre-arranged win was $1000.

- Combination: here, the individual groups results with the same outcome but with different probabilities. For instance, prospect A: (100, 0.25; -200, 0.3; 100, 0.45) could be simplified with prospect B: (100, 0.7; -200, 0.3).
- Segregation: in this stage, safe outcomes are separated from the risky ones. For example, prospect X: (400, 0.8; 150, 0.2) could be simplified with prospect Y: (150; 250, 0.8).
- Cancellation: through this phase, elements common to all lotteries are eliminated in order to simplify the decision-making process. For instance, if the choice is between prospect A: (1000, 0.25; -100, 0.75) and prospect B: (1000, 0.1; 500, 0.4; −200, 0.5), they could be simplified in the following way: A': (1000, 0.15; −100, 0.75) and B′ : (500, 0.4; −200, 0.5).
- Simplification: consists in facilitating the evaluation of the elements of a prospect in case it is not immediate to achieve it. For example, a way to simplify is to round the outcomes and the probabilities attached to them: X: (199, 0.49; −201, 0.49; −100, 0.02) could be simplified with Y: (200, 0.5; −200, 0.5).
- Dominance: the agent rejects those projects which are dominated by alternatives.

In the second phase, evaluation, the individual chooses the option with the greatest value with respect to the alternatives resulting from the first stage.
In this phase people use the value function and the weighting function to compare the prospects in a subjective way.
If we point the probability of the ith outcome with p_i; the ith outcome with x_i; the probability weighting function with π; and the value attribution function to single outcomes with v, the utility function of Kahneman and Tversky is defined as:

$$Value = \sum_{i=1}^{n} \pi(p_i)v(x_i)$$

Single probabilities and outcomes are the result of a resolution process of a single individual, which could show significant differences compared to other subjects. The problem formulation process varies from subject to subject.
Single probabilities are weighted by the function π, which means that the sum of the weights in the value function is < 1, differently from the classical utility function where it is equal to 1.
The outcomes are analyzed and categorized in gains or losses with respect to a reference point rather than in absolute terms. Those who incurred in losses in the short term will be more risk averse, which translates into

a steeper inclination of the utility curve in the loss side (loss aversion). Those who incurred in substantial gains in the last period will be more inclined to risk, since they have the chance to mitigate eventual losses with the previously accumulated gains.

Since investors do not behave specularly in front of gains and losses, the utility function assumes a “S” shape: which is to say that the curve results to be concave in the gains side and convex in the losses area. Moreover, in the losses area the curve is steeper than in the gains area (Fig. 1).

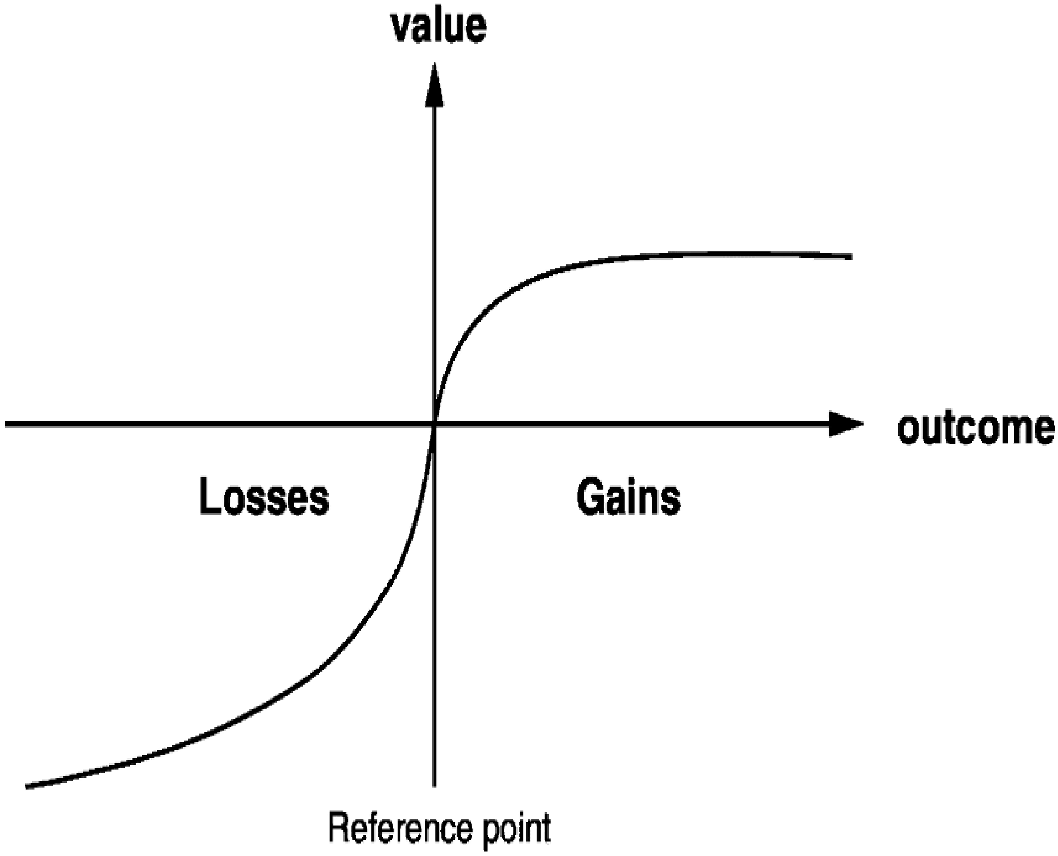

Fig. 1: *The value function in Prospect Theory*
(Kahneman and Tversky 1979).

The weighting function, instead, allows to include two important aspects linked to subjects’ perception of probabilities: smaller probabilities are overvalued while higher ones are undervalued. Probabilities follow a cumulative distribution function and value functions for gains and losses are not equal.

This function represents the weight attached to the value of each single result, which means that the outcomes which have less probability to occur are overvalued with respect to the conviction of not obtaining them, while most probable results are undervalued compared to the certainty of obtaining them (subjective evaluation of probabilities, Fig. 2).

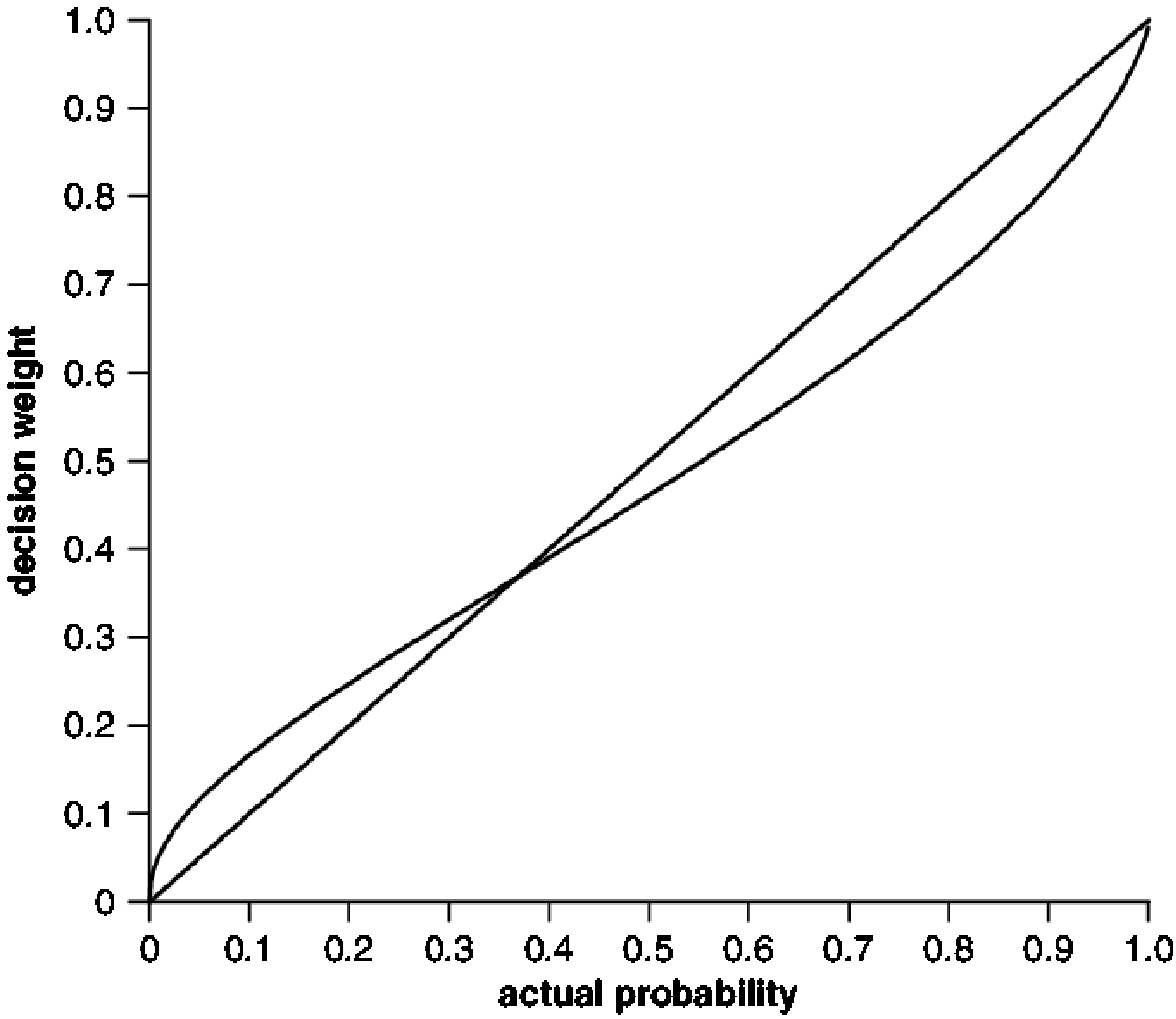

Fig. 2: *The probability-weight function in Prospect Theory*
(Kahneman and Tversky 1979).

This function even explains the certainty effect. When there is a switch from a certain win to a highly probable one, the attractiveness degree of the uncertain one falls down: the high probability is undervalued. In the opposite case, when the switch is from a 100% loss to a highly possible, but not certain loss, the attractiveness degree of the unsure loss increases: the reduction in the probability to lose is overvalued.
In conclusion, it is possible to notice, in investment terms, how agents in the prospect theory context structure their expected utility function relying on their potential gains and assumed loss, instead than on what should be considered the maximum level of wealth. For example, an unexpected gain of $1000 and an equivalent loss are not proportionate to the total wealth of the individual, but on the value function. Such function is different for each individual and provides for a reference point for wins and losses which is different form the total wealth. Therefore, utility does not depend on the maximum level of utility anymore, but depends on how the individual perceives losses and gains.
Moreover, we saw how decision makers do not value probabilities linearly, which means that they do not value these probabilities how they actually are. They create distortions.

Furthermore, according to what we analyzed, the individual has a variable risk aversion, which means that most of the times individuals feel worse for a loss than how much they feel happy for a gain of the same size. Lastly, individuals often take choices influenced by the way the problem is introduced to them because he is not capable of taking complex decisions.

5. Heuristics in the individual's decision-making process

The studies of Kahneman and Tversky in 1979 have been the firsts to show the errors in humans' mental processes, finding the so-called heuristics, which are the real cognitive rules. Heuristics, even defined as shortcuts in decision making, are rules resulting from approximations that allow to (apparently) simplify complex problems. Heuristics tend to monopolize the decision-making process, as they facilitate both the search for a solution to a problem and its evaluation. This way, they save mental activity by reducing the cognitive load in the decision-making phase, but lead to an undervaluation of complementary elements to the point that they could actually work out well in some circumstances but they might be even source of significant systematic errors.

The situations in which heuristic processes are used in decision-making, even if involuntary, are very dangerous in finance. In fact, the partial and simplified vision of the problem, leads to fast and immediate answers, which are likewise incomplete.

From the vast literature on heuristic strategies, we derive three principal cognitive errors, which are: representativeness, anchoring and availability. Then, follow other judgement errors, called bias, which characterize in particular individuals' investment decisions: overconfidence and mental accounting.

5.1 Representativeness and Overconfidence

The representativeness heuristic implies the use of stereotypes in the decision-making of the economic agent. The individual associates the probability of an event to the probability of similar events without looking at specific features. For representativeness, in fact, is meant a similar event. In finance, a common error affected by representativeness is the winner-loser effect. De Bondt and Thaler support that financial operators, even if they are professional investors, operate according to representativeness. So, investors, making medium- and long-term predictions, tend to be more optimist toward those stocks performing well in the past period rather than towards those securities that did not performed significantly well. Anyway, the evidence from the field shows something else: De Bondt and Thaler (1984)[8], documented that the stocks with a negative trend in a three-year period, tended to have better trends in the following three years than those stocks which previously had positive trends.

Representativeness, in the decision-making process, implies an underestimation of the mean reversion[9] process in financial markets. In other words, financial operators which are subject to this heuristic tend not to consider possible the phenomenon of price trends returning toward the mean, wrongly assuming that there is an ongoing between past and future trends.

The representativeness heuristic is often associated to behaviors such as overconfidence, which means that is associated to all those behaviors driven by excessive evaluation of own decision-making capabilities. An example of an overconfidence attitude, regards students interviewed about the probability to have answered correctly to a test having the tendency to say that they answered correctly to all the answers.

This might generate what is called "better than the average effect", which is caused by a high trust in yourself and consists in considering yourself to be above the average in what you do. This may lead to an illusion of control when the agent believes to have absolute mastering of the phenomenon without taking into account randomness.

Moreover, this is connected to the belief of having "magical skills", which means believing that your own actions are able to indirectly influence events not connected to them. For example, an investor who acquires a security beating the market, might just have been lucky without being particularly skilled. He believes to own some skills which are able to affect events, which actually he does not have.

5.2 Anchoring

A second heuristic behavior is anchoring. With this term is meant the economic agent's attachment to an "anchor", which is a reference phenomenon fundamental to solve an economic issue. The subject begins the reasoning process straight from this starting point, or reference point, which he believes to be salient. The starting point might be an important information, a well-known event or news coming from a reliable source. Such anchor can be extrapolated from how the problem is set or from a random information. Many times, even if the reference point is reviewed more than once, the individual always tends to focus his attention on is, such that his final decision is still oriented towards the starting point.

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[8] De Bondt W. e Thaler R., *Does The Stock Market Overreact?,* The Journal Of Finance, Vol. 40, N. 3, (Dallas, TX.: Wiley for AFA, 1984), 796-805.

[9] Mean reversion is the assumption upon which in the long run stock prices tend to stabilize around the mean value.

The heuristic behavior of anchoring, is helpful to the understanding of conservative actions operated by the agents in the market. Kahneman and Tversky (1974)[10] describe how financial agents are oriented to a more conservatism form. Consider, for example, the problem of analyzing a firm. We know that investors focus mainly on the characteristics of the firm itself to determine future profits. If there are interesting news about the firm in exam, the economic agent will tend to evaluate them according to its previous knowledge about past profits and performance of the firm. For example, if the firm recorded a non-particularly positive performance in the last period, but then we had very positive news, the analyst will still trust the starting hypotheses and continue to have a negative expectation about the firm making substantial profits is the future. Together with the representativeness heuristic, even anchoring recalls the problem of overconfidence that has been previously analyzed.

Anchoring may lead to another conservative form, known as "status quo bias", which consists in the individual assessing to a possessed good a value which is higher compared to the one assessed when he did not own it.

Often, in real life, it happens that cognitive errors coexist, for example, when a subject uses at the same time elements coming from both representativeness and anchoring in his everyday thoughts. Because of a distorted vision of information, the individual creates an erroneous construction of the phenomenon.

In this regard, it has been carried out an analysis by Amir and Ganzach (1998)[11], who have studied the combined effect of the representativeness heuristic, the anchoring heuristic and the optimism bias. In decision terms, representativeness implies more excessive reactions than anchoring. Optimism bias has the ability to affect the intensity of predictions. If the evaluation is positive, it will probably be amplified; if it is negative, the intensity will be reduced.

5.3 Availability

The availability heuristic refers to the easiness of recovering information from memory in the processes of data collection and formulation of the decision. Thus, the probability of a given event might be distorted by notoriety, by familiarity or by the ability to associate independent events[12].

In line with the cognitive model of availability, individuals attribute to probabilities a weight according to the numerosity and the accessibility of information regarding similar events. The subject estimates the frequencies and the causes of such phenomenon relying on the availability of information to his memory. An extraordinary event, which has captured the attention of the subject, is more alive and available to memory than other less

[10] Kahneman D., Tversky A., *Judgment under Uncertainty: Heuristics and Biases*, Science, New Series, Vol. 185, N. 4157, (American Association for the Advancement of Science, 1974), 1124-1131.

[11] Amir E., Ganzach Y., *Overreaction and underreaction in analysts' forecasts*, Journal of Economic Behavior & Organization, Vol. 37, (Columbia University, New York, USA and Tel Aviv University, Tel Aviv, IL, Elsevir, 1998), 333-347.

[12] It is called easy to recall bias: the most recent and emotively impactful events are the easiest to recall.

relevant events which become more difficult to remember. Most of the times, the availability heuristic allows to take the right decision. How Kahneman and Tversky (1974)[13] affirm, the link with the most frequent events allows to solve any matter in an easier way. Anyway, even if it may look effective to follow the pattern of experience, the availability of an information is not exclusively connected to its frequency but is subject to other factors from which wrong outcomes arise.

Based on the studies conducted by Kahneman and Tversky, the probability to mistake because of availability is high. In fact, the mind associates an event to similar phenomena previously happened and available to the memory. If, for example, we witness a theft, our perception of risk will increase more than if we read it on a newspaper.

In the financial market, the availability heuristic appears to be connected to the choice of investors in the selection of assets to keep in the portfolio. Investors acquire securities upon measurable parameters, such as liquidity, inclusion in indexes, and even the quantity of available information. This is why, the most publicized stocks are even the most traded. Such behavior implies high volumes of trade and subsequent high fluctuation in prices. Barber and Odean (2011)[14] define these investors as "attention-based buyers", that are those investors who acquired securities promoted by the media.

Like in the previously illustrated cases, the availability heuristic is a consequence of a simplified reasoning which may lead to wrong behaviors and incorrect choices.

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[13] Kahneman D., Tversky A., *Judgment under Uncertainty: Heuristics and Biases*, Science, New Series, Vol. 185, N. 4157, (American Association for the Advancement of Science, 1974), 1124-1131.

[14] Barber B. M., Odean T., *The Behavior of Individual Investors*, (University of California, Davis and University of California, Berkeley, 2011), 1-46.

REPRESENTATIVENESS	
Mean reversion	Investors tend to forget that a stock's price will tend to move to the average price over time.
Overconfidence	Individuals have the tendency to hold a false and misleading assessment of their skills, intellect, or talent.
ANCHORING	
Conservatism	Agents keep their old beliefs without updating their views on the base of new information.
AVAILABILITY	
Familiarity	Individuals refer to the events which recur to their mind in an easier way, because they are more important or more recent with respect to those which are more difficult to trace.
Recoverability	Memory plays a key role in deciding which information to store, even causing mistakes
Association	If an investor associates two events, then it is possible that he overestimates the frequency of the two events.

Tab. 1: *Heuristics and Bias*
(personal elaboration)

CHAPTER 2

Inefficient Markets and new evolutionary perspectives

1. The Efficient Market Hypothesis

The Efficient Market Hypothesis, carried out by Fama in the 60s, bases its considerations on the concept of efficient markets, meaning that the stock market is characterized by the absence of asymmetric information and that all information is equally available to market players.

If the real value is defined as the market price, which takes into consideration the influence of asset's supply and demand, and if the fundamental value, or fair value, is defined as the theoretical reference value, then: the price of securities is the expression of the real value, and corresponds, instant by instant, to the fundamental value. This is due to the competition among market players who properly and equally evaluate the price of the traded assets so as to maintain the efficiency of the market. This theory assumes the absence of risk-less arbitrages, which means that there are no unexploited extra return opportunities because securities immediately adjust by including all new information.

When the investor is rational, he considers the security as the expression of the fundamental value, which is equivalent to the value of future dividends discounted with the risk-adjusted discount rate.

Defined the price of the security in time t with Pt, the expected dividend in time t+1 with D^e_{t+1}, the interest rate in time t with r_t and the risk premium with ε, then:

$$P_t = \frac{D^e_{t+1}}{(1+r_t+\varepsilon)} + \frac{D^e_{t+2}}{(1+r_t+\varepsilon)+(1+{r^e}_{t+1}+\varepsilon)} + \cdots + \frac{D^e_{t+n}}{(1+r_t+\varepsilon)(1+{r^e}_{t+n-1}+\varepsilon)}$$

If the investor receives positive news about the security's fundamental value, he will raise his offered price, while if he receives a negative information, he will lower his offer and so the price. Should the investor receive a positive information on a Company's profits, he will then expect the dividends to increase, being consequently ready to sell the security only at a higher price; in case the investor wants to buy the security, he will be willing to pay more to purchase the security.

Considering the assumptions of the existence of efficient markets:

- Information on securities is complete, available to everybody and costless.
- There are no transaction costs.
- Individuals are rational subjects: they are able to estimate the correct value of securities as new information come by.

A market is efficient when, through the purchase and sale of securities, it is not possible to obtain abnormal returns by relying on available information alone.

Since information, being by definition available to everybody, is already integrated in the price, and since only subjects having at their disposal additional information could obtain an advantage from buying and selling activities, this theory assumes the absence of riskless arbitrages, which means that there are no extra return opportunities.

Considering that both investors' expectations and prices are based upon available information, then the market is efficient and rational subjects' expectations reflect market quotes.

Relying on the assumption that information is reflected on the price of financial securities, the literature (Frankfurter 2007)[15] offers three different forms of market efficiency: the weak form, the semi-strong form and the strong form.

1. The weak form occurs when all information included in the time-series of prices, in the exchange volumes and in the interest rates are fully reflected in the price in a specific moment. This form of market efficiency provides that there is no possibility, through any buying or selling strategy, to obtain a return higher than the market one by relying only on the information included in the time-series. If time-series had incorporated significant information for the forecast of future prices, these would have been already available to all market operators.
2. The semi-strong efficiency occurs when prices reflect both information incorporated in the time-series and business information available to the public, deriving, for example, from balance sheets and income statements or from earnings and dividends forecasts. This form of efficiency provides that prices immediately re-equilibrate after new information is disclosed, thus eliminating the possibility for speculators to earn abnormal profits by exclusively relying on public information.
3. The strong-form efficiency occurs when prices reflect all the existing information, both public and private. In this specific market efficiency context, prices capture all private information possessed by investors and so avoid arbitrageurs to exploit any riskless profit opportunity.

The strong form implies the semi-strong form which itself involves the weak form.

Market efficiency is also described in reference to the behavior of individuals who operate in the market:

1. There are a lot of irrational investors who trade without any specific logic, but still cannot affect prices thanks to the operations of rational subjects.
2. Some of the agents are irrational and, even if they trade without a specific logic, they do not affect the price level since their expectations are uncorrelated and so the sum of their actions is null. Through the presence of arbitrageurs who identify errors, the price is immediately corrected.
3. All market operators are rational and evaluate each stock for its fundamental price.

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[15] Frankfurter G. M., *Market Efficiency cum Anomalies, or Behavioral Finance?*, Homo Oeconomicus, Vol. 24, N.1, (Munich: Accedo Verlagsgesellschaft, 2007), 81-93.

In all these situations, market efficiency is guaranteed and any operation which alters prices is prevented.

2. Introduction of the Behavioral Finance and current thoughts about the EMH

The various financial crises, including the most recent one started in 2008, have pointed out a discordance between the empirical data and the theories about efficient markets operated by perfectly rational individuals, moving last decades' academic discussions to the validity of financial models.

Events like the crash of the US Stock Exchange of 1987, known as "Black Monday", which led to a drop in prices of over 20% in a single day, strongly undermined the efficient market hypothesis. Such important variations in listed stocks price could not be the result of changes in fundamental values alone.

It has been important the contribution of the behavioral finance, which has allowed to amplify the vision of the classical financial theory and describe the phenomena observed in the reality, like loss aversion, overconfidence and regret aversion. For instance, bubbles in financial markets find an explanation in the excessive exuberance of investors who overvalue the traded securities until their slightly rational expectations are proved to be wrong and the market collapses. Noise traders, which are those operators who follow the buying and selling activities of other market agents, create an "investor sentiment" (a general feeling), which rises expectations and reflects the errors in judgement of market operators.

The errors and the anomalies in prices, observed in specific historical periods and source of predictability of stock prices in the short term, would exclude market efficiency. As a consequence, in response to the empirical evidence and through the application of psychology to finance, even the efficient markets idea has been re-examined over time.

If we assume, as Malkiel (2003)[16] affirmed, that it is difficult to beat the market obtaining excess returns without being exposed to equally high risks, markets can be considered efficient even if anomalies exist. Prices do not always represent their fundamental value, but still are not source of systematic errors since they get corrected over time. Malkiel believes that, as time goes by and technology improves, other market anomalies will pop out and the efficient market hypothesis will keep being challenged even in the future.

The author's final consideration is that at the end no one will leave this theory, Malkiel describes the anomalies as exceptions confirming the rule and claims that "If any $100 bills are lying around the stock exchanges of the world, they will not be there for long" (2003) [17], it is quite improbable that any anomaly in prices will persist in the long term.

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[16] Malkiel B. G., *The Efficient Market Hypothesis and Its Critics,* Journal of Economic Perspectives, Vol. 17, N. 1, (Princeton University, 2003), 59-82.

[17] Malkiel B. G., *The Efficient Market Hypothesis and Its Critics,* Journal of Economic Perspectives, Vol. 17, N. 1, (Princeton University, 2003), 15-34.

Also Shiller (2003)[18] argues that, even the most popular of the anomalies, like the excessive volatility of stocks, will be hardly disproved with the improvement of technology in empirical studies. In contrast, as years go by, he believes that volatility in the market will increase. Moreover, the only fact that the anomalies cancel out with time, and so are considered temporary, is not sufficient to state that agents are rational.
The same author claims that it is difficult to support the statement that listed securities which are overpriced or underpriced, at first, then converge to their respective fundamental value. This is because if we consider that the fundamental value is difficult to estimate, it would be even more difficult to estimate it after a long period in which prices were not in equilibrium.
In future studies, it will not be possible to support the efficient market theory in its purest form (according to Shiller it is the representation of an "ideal world"), but it will be necessary to adopt a detached perspective knowing that the theory will not work correctly in every situation and that information does not always completely affect stock prices.
In conclusion, a quote of the author is summarizing: "The challenge for economists is to make this reality a better part of their models." (the author refers to the behavioral finance and its support to the comprehension markets' dynamics).

2.1 From the principles of financial evolution to the Adaptive Market Hypothesis

Through his studies, Lo (2005)[19] pointed out that the emotional component of man's behavior is the natural complementary constituent of logical reasoning. Emotivity and instinct are integrating parts of the rational investor's behavior in a financial market context; instinct, is crucial even in the decision-making behavior of the most expert and rational market operators.
From an evolutionary point of view, the emotional component is essential for the comprehension of human evolution. It is considered to underpin the acknowledgement and the evolution of the survival instinct, resulting from the fact that man, by nature, acts emotively and instinctively to survive and adopt to environmental changes.
The irrationality of man is explained by neurosciences under the evolutionary theories; every side of human brain has its own function which corresponds to a specific behavioral process (Sloman 1996)[20].

[18] Siller R. J., *From Efficient Markets Thoery to Behavioral Finance*, Journal of Economic Perspectives, Vol. 17, N. 1, (Yale University, 2003), 83-104.
[19] Lo A. W., *Reconciling Efficient Markets with the Behavioral Finance: The Adaptive Market Hypothesis*, The Journal of Investment Consulting, Vol. 7, N.2, (IMCA, 2005), 1-24.
[20] Sloman S. A., The empirical case for two systems of reasoning, Psychological Bulletin, Vol. 119, N.1, (Washington, DC: APA, 1996), 3-22.

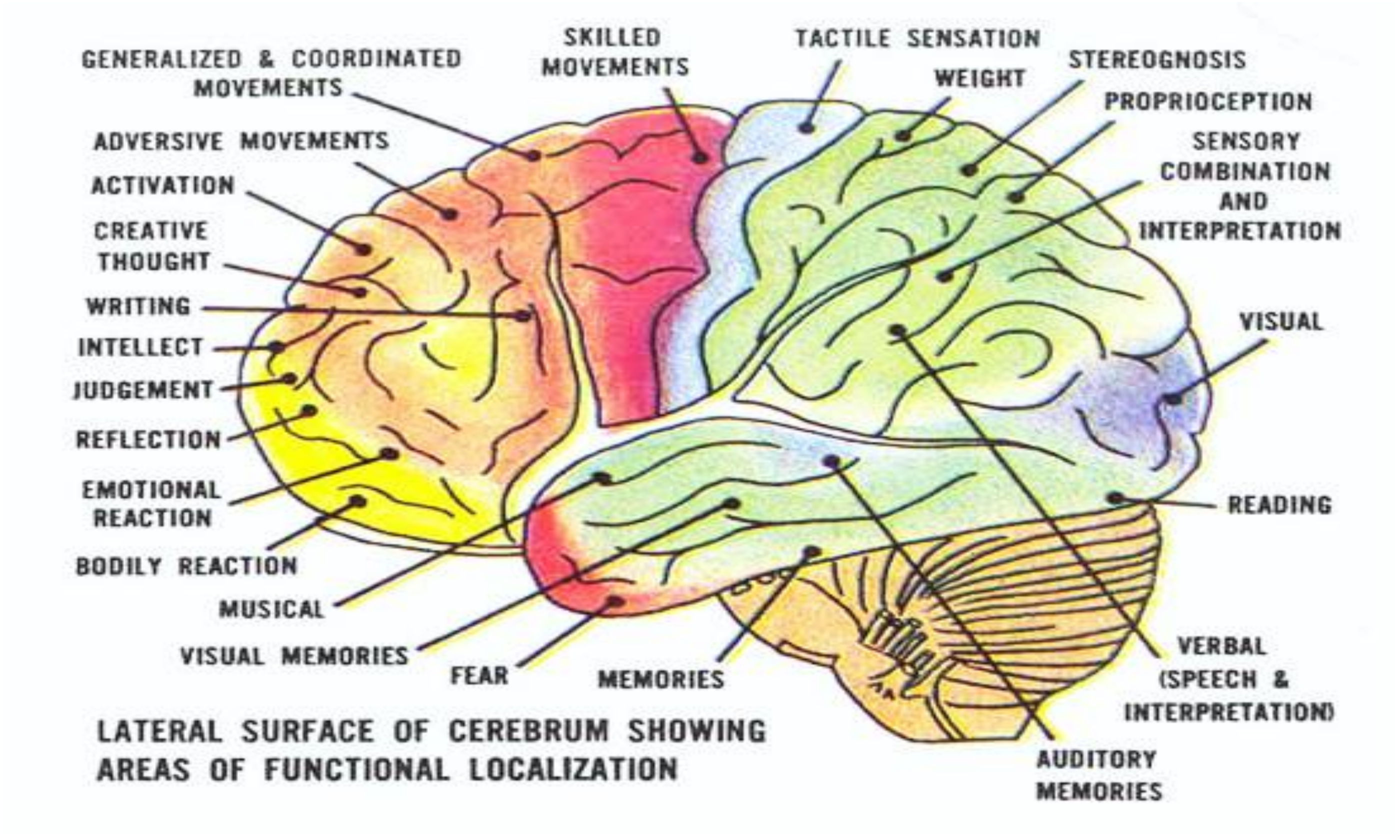


Fig. 3: *The jobs of the brain*

Source: Brain Made Simple, https://brainmadesimple.com/left-and-right-hemispheres/

The studies of Lo (2005)[21] lead to understand, through the evolutionary theory perspective, the preferences of individuals and the critics to the Efficient Market Hypothesis.

Natural selection is defined as the process that intervenes in the decision-making process of the individual, which affects the final result in two different ways: through the probabilistic calculation of alternatives (expected utility function) or, through a resort to past experiences (heuristics and biases). Whenever the choice has led to a positive or to a negative outcome, the subject will have a better understanding of whether the information selection process he adopted, or the subsequent interpretation was correct. When a new similar event occurs, the agent knows if using the same process will be the right choice.

It is important to consider the case in which environmental circumstances change. Investors' behavior and their shortcuts in decision making are not suitable anymore, since do not fit in the new context. According to Lo's theory, it is exactly in this case that distortions in the decision-making process of individuals, observable through empirical evidence, originate. When the decision-making process and the expectations of investors are not revamped after a change in the market context, it is observable that choices made by individuals are not optimal and are less suitable to the new market configuration. Cognitive biases are the result of behaviors not fitting the new financial context which is source of changes external to the individual that often imply choices less convenient with respect to the optimal ones. The competition

[21] Lo A. W., *Reconciling Efficient Markets with the Behavioral Finance: The Adaptive Market Hypothesis*, The Journal of Investment Consulting, Vol. 7, N.2, (IMCA, 2005), 1-24.

among individuals operating in the market is expression of the fight for survival caused by the changes in the economic context.

Lo came up with an interpretation which joins together the efficient market hypothesis with the behavioral finance, giving an explanation to the observed empirical evidence (heuristics and behavioral biases). The Adaptive Market Hypothesis is an alternative version to the efficient market hypothesis, studied through the lenses of the evolutionary theory. The AMH mainly provides for the following concepts:

- Every individual acts according to its preferences.
- Every individual can make some mistakes and for this he cannot be completely rational in the decision-making process.
- Every individual adapts to the surrounding environment only after having learned from previous experiences.
- Every individual fights to survive, leading to an improvement of the adaptability and of the innovation of society (in a highly competitive environment, every investor tries to do its best to avoid losses, thus keeping improving its strategies from time to time).
- Every individual is subject to natural selection, which is what determines the reference market.
- The market is subject to a constant renovating process depending on the evolutionary process.

Differently from the efficient markets theory, the adaptive markets hypothesis sees the possibility that individuals fall in errors since the market is not stable nor safe, as stated in the classical theory, but is subject to the dynamics of the evolutionary process. The AMH does not describe each single behavior on the basis of a stable economic context but focuses on contextual and environmental changes which lead to the choice of different attitudes, and so to not fully rational behaviors. Behaviors, which are adopted in a different way depending on market conditions, are not to be considered as rational or irrational, but rather as behaviors which adapt in a stronger or weaker way to new conditions.

Considering investors' behavior as an expression of the financial market, the hypotheses of perfect efficiency and inefficiency of the markets are extreme and slightly represent the reality. Instead, if we consider the last point of the AMH, the change in markets' circumstances leads to the evolution and adaptability of investors, with the consequence that the behavior of individuals results to be dependent to the reference context. The relationship between these subjects is dominated by natural selection, and so even the market is dominated by the same dynamics.

The degree of efficiency of the markets, is measurable by the amount of available resources and the respective species[22] involved in the fight to get them. The market will be highly efficient when there are a lot of operators who fight to possess a scarce and poorly available resource, because here prices are completely affected by information available to all operators. Instead, the market becomes inefficient when there are few operators contending a lot of highly available resources. Here, prices reflect the scarcity of available information.

Differently from the efficient market hypothesis, the AMH does not include the possibility that the evolutionary process will get to a permanent and stable equilibrium but believes that there is a constant evolution in every aspect of the system. The efficiency of financial markets, however, is not limited to the previous definition, but depends on the circumstances which arise every day in financial markets and on the interactions between individuals and the rest of society. The bigger the market is, the more numerous and complex the factors needed to explain it will be.

[22] For species who participate to financial markets, it is meant those subjects who have common characteristics among themselves, like for example: retail investors, pension funds managers or hedge funds managers.

2.2 The Adaptive Market Hypothesis: implications and empirical evidence

There are different ways to apply this alternative theory to financial markets (Lo 2005)[23].

1. The first implication of the AMH sends back to preferences and choice trends of investors. Heuristics, which influence the decision-making process, can bring to decisions which differ from the optimal one, and that are underproductive with respect to the desired wealth of the individual. Then, it turns out to be important to have a deep study of client's preferences with the scope to structure an adequate solution to his preferences and needs. Some of the technologies which measure the preferences of individuals are, for example, psychology which through tests and surveys studies how the characteristics of each individual affect his choices, and marketing which studies the attitude that individuals show towards changes in products characteristics. Through the joint analysis of these two methodologies and through the findings in the field of the neurosciences, it is possible to improve the estimate of the preferences of the individuals. The behavior of the client in the financial decision-making process is affected by the goals that the subject wants to achieve, by his future expectations and by his personality. For this reason, the figure of the financial advisor is necessary. This figure has the duty to understand and plan the targets with the aim to find a strategy which better suits the needs of the individual. Financial advisors and other financial intermediaries use to offer to their clients some tests that verify not only the financial knowledge and risk aversion of the consumer, but even his personality, his character and his emotional status in different circumstances. Theses analyses help to study those situations of mental irrationality of individuals; through the comprehension of the causes of irrationality and verifying its effects, it is possible to build up strategies which are more correct for the investment of the single individual, taking into account his risk aversion and other preferences. The classical financial theory sees the preferences of individuals without comparing them to the risk preference and other expectations of the investor. By contrast, Lo's alternative approach does not consider the preferences as unchangeable, but rather as the result of the interaction between various cerebral and emotive components of the individual.

2. The second implication of the AMH is about resource allocation strategies and especially the relationship between risk and return, which cannot be considered as fixed and stable anymore, but is subject to a constant change over time. Risk and return are determined by the size of the market, by the preferences of operators and by the different kinds of investors who operate in the market. As one of these elements varies, it will vary consequently even the relationship between risk and return. After a change in this relationship, the risk premium paid to investors will vary as well. The concept,

[23] Lo A. W., *Reconciling Efficient Markets with the Behavioral Finance: The Adaptive Market Hypothesis*, The Journal of Investment Consulting, Vol. 7, N.2, (IMCA, 2005), 1-24.

upon which a high risk is associated to a high return, is revised by the adaptive market hypothesis. Table 2, which reports the value of the means and standard deviations of returns over different categories of stocks and obligations from January 1926 to December 2010, allows to observe the positive relationship which exists between risk and return on different categories of assets. Instead, looking at Figure 4, which represents the returns on the CRSP index calculated for the period between March 19th, 1930 and December 31st, 2010, by using rolling windows[24] of 1250 days it is possible to notice the negative relationship between risk and return on the whole index. To have a better comprehension of this contradictory empirical evidence, consider the case in which it is registered an unexpected increase in the volatility of the stocks: investors will decide to reduce their investment in risky assets in order to increase their holding of safer securities. This behavior, called "flight to safety", is subjects to fear and risk aversion heuristics which control the decisions of the investor leading him to choose a less risky alternative. As a consequence, there is a temporary change in the relationship between risk and return which is caused by the decrease in the riskier shares price and an increase in the price of the safer ones. The variability of preferences, and consequently the variability in the risk premium, is described even in the classical financial theory but in the AMH version, the concept of preferences of the individual and its inclinations keep changing because of the natural selection. It results that price trends and returns change over time, affecting instant by instant the risk premiums independently by the fact that pries reflect all available information in the market.

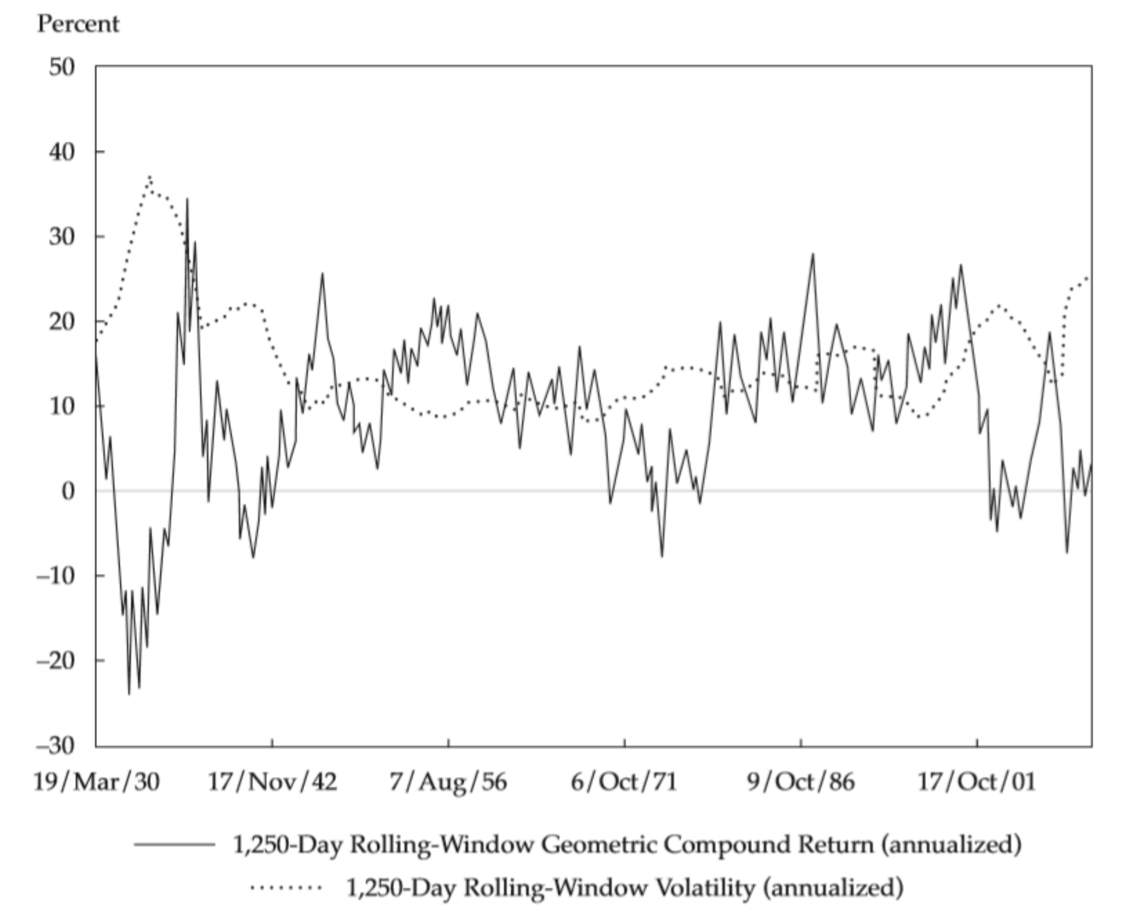
Asset Class	Geometric Mean (%)	Arithmetic Mean (%)	Standard Deviation (%)
Small-company stocks	12.1	16.7	32.6
Large-company stocks	9.9	11.9	20.4
Long-term corporate bonds	5.9	6.2	8.3
Long-term government bonds	5.5	5.9	9.5
Intermediate-term government bonds	5.4	5.5	5.7
U.S. Treasury bills	3.6	3.7	3.1

Source: Ibbotson (2011, Table 2–1).

Tab. 2: *Historical Means and Standard Deviations of Stocks and Bonds, January 1926 – December 2010*

(Lo, Adaptive Markets and The New World Order 2012)

[24] The rolling window is a technique used to for the analysis of financial time-series. It is mainly used to verify the consistency of a parameter in a model, by using a fixed time interval.



Sources: CRSP and author's calculations.

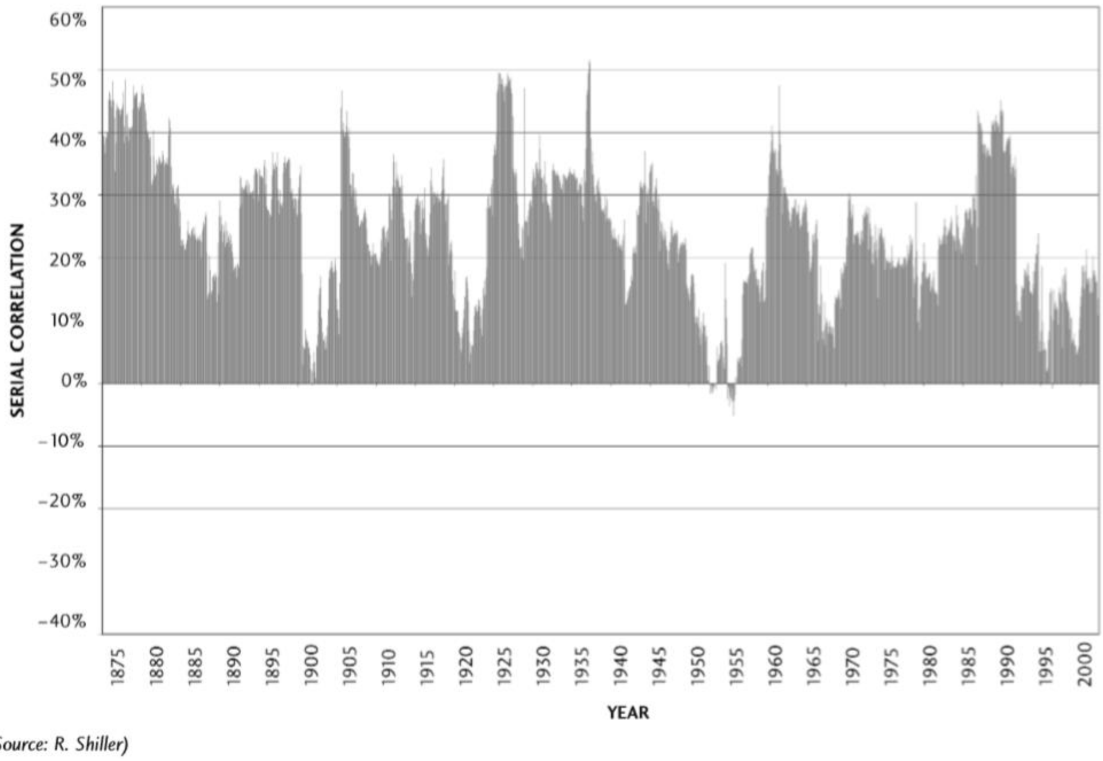
Fig. 4: *Geometrically Compounded Returns and Standard Deviations of Daily CRSP Value-Weighted Index Returns Over 1250-Day Rolling Windows, 19 March 1930 to 31 December 2010*

(Lo, Adaptive Markets and The New World Order 2012)

3. The third implication of the AMH considers that in the market riskless arbitrage opportunities occur, differently of what was stated in the classical theory where arbitrage does not exist. In a liquid market, where securities are highly tradable because there are a lot of buyers and sellers, there will always be some unexploited profit opportunities which are leveraged by those investors, in this case arbitrageurs, who better adapted to the new logics of the market. In other terms, if the market is characterized by a constant natural selection and evolutionary process, then there will always be some investors who adapt better than others to the changes in financial terms. This implies the mispricing of securities and subsequent arbitrage opportunities.

4. The fourth implication is linked to investment strategies. Considering the financial market as a market with constantly changing features, even investment strategies must be in constant change. If in a specific moment a strategy results to be effective, in another time, the same strategy could result

counterproductive. In relation to the study of Lo (2005)[25], the author examines, through 5-year rolling windows, the first-order autocorrelation coefficients of monthly returns on the S&P 500 Index from January 1871 to April 2003 (Figure 5). According to the efficient market hypothesis, the correlation coefficient ρ should be higher in the first phase of the analysis and decrease as the time frame increases. If at first, since it is new, the market is not stable enough to be considered efficient, it should stabilize as the time frame enlarges. This concept is connected to the random walk theory, according to which the return on securities is not correlated to their past return and so the coefficient ρ should be null. The graph shows how the level of efficiency varies in a cyclical way and does not follow the random walk hypothesis. The highest values of the coefficient (where the market is unstable) are registered in the years previous to the crisis of 1929, while the coefficient is close to zero in the post-war years (50s). The empirical evidence does not confirm the random walk but emphasizes the cyclicality and the seasonality existing in the markets, which diverge from the stability of the financial system. It should be paid particular attention to investors' constant adjustment to changes in market conditions, to the extent that investment strategies should take it into account.



(Data Source: R. Shiller)

Fig. 5: *Rolling 5-Year Serial Correlation Coefficient of the S&P Composite Index.*
(Lo 2005)

[25] Lo A. W., *Reconciling Efficient Markets with the Behavioral Finance: The Adaptive Market Hypothesis,* The Journal of Investment Consulting, Vol. 7, N.2, (IMCA, 2005), 1-24.

5. The fifth application of the AMH sees innovation as the key to survival. From an adaptive market theory point of view, the profit and utility maximization of the individual is less important than survival which is considered as the ultimate objective. The natural selection process, which with its dynamics alters the market and determines the choices of individuals instant by instant, forces the society to focus on the non-elimination of the ecosystem. Investment managers have the necessity to enlarge their skills and knowledge in order to better and faster adapt to the continuous changes in the market caused by natural selection. Innovation and capability to promptly adapt result to be essential skills to survive in a highly competitive context.

3. Corrective measures for investors' cognitive and behavioral errors

In the last years studies, the behavioral approach has supplied answers to the solution of individuals' behavioral errors in investment choices.

The process called "debiasing", is a process put in place for the reduction of the effects of heuristics, emotional errors and biases showed up by investors during any financial decision-making process. Even financial education, financial advice and the role of institutions as guarantors of transparency and information disclosure, together with debiasing, are important means for the correction of financial errors. However, financial education is difficult to structure because it is also difficult to convey, in an effective way, complex and articulated concepts like, for instance, investment risk.

According to Dale's Cone of Experience (David B. 2014)[26], people remember only 10% of what they read, 20% of what they hear, 30% of the data they see, 50% of what they see and hear together, 70% of what they say and write and nearly 90% of what they do.

A first step towards the correction of the most frequent errors, is understanding the causes of the errors made. For learning, experience is extremely significant to understand a phenomenon. Therefore, it is easier to determine what caused the error when the individual refers to purely personal situations experienced in first person.

For instance, it is extremely functional to judge with a critical eye the reference points used, in order to understand if they are still valid instruments or if they need to be updated, especially when we talk about overconfidence. Overconfidence can be the cause of many errors and leads to the enhancement of own investment skills, also when these are minimal, enough to overestimate favorable options and underestimate unfavorable ones.

Thus, doubting is an effective tool for always questioning our point of view, so as to understand if the choices made and the perspective used in making decisions are correct.

[26] Davis B., Summers M., *Applying Dale's Cone of Experience to increase learning and retention: A study of student learning in a foundational leadership course,* (QScience Proceedings, 2014).

Financial education has a key role for the correct use of financial notions and for evaluating choices, just like debiasing is important to correct errors for a better behavior. Regarding education, it is recognized that a clear and fast learning process leads to immediate feedback together with a significant reduction of behavioral errors. However, due to the nature of financial choices, the learning process is slow and complex to be understood by human mind, especially when it is difficult to change already existing ideas or ideas deriving from other cognitive errors. There are many factors that determine the price of market securities, such that the investor does not even have an ex-post confirm of the choices made. Because of heuristics, in each situation that the investor faces, he will tend to take credit for the success of the choice made while he will blame unfavorable markets in case of unsuccess. For example, if an investor wants to check the successful outcome of a stock investment, he should wait for years since it is only then that is possible to evaluate it. Therefore, it is difficult to interpret the result and state whether the outcome is due to the investor's good financial skills or to favorable economic trends. In this way, the investor has neither clearness nor certainty of his investment choices, and so debiasing procedures end up being slow and difficult to apply.

To help investors understanding the choices to be made, comes into play an external figure, the financial advisor. This figure, as described by Kahneman and Riepe (1998)[27], has the task to help investors to implement decisions weighted according to their purposes, achieve their ambition avoiding them to make imprudent cognitive errors and, at the same time, amplify their view on available choices with the final goal to improve the return. In order to reach the goals of the individual, during the investment process, it is necessary to understand client's expectations together with the time and the means neede to reach them, so as to limit the changes in the investment strategy which would foreclose the established goals. Because the interest is mutual for both parties, a good relationship between the advisor and the investor is crucial.

Finally, since they aim to limit the opportunistic behavior of financial intermediaries on investors, also financial institutions play a key role.

Unfortunately, often investors are too much tied to the current state of things that also the simple option to leave the market or change intermediary is not easy to achieve; limited by the "*status quo*", the individual does not seek for better alternatives and is reluctant to change the current situation. Inertia explains the success of all those commercial offers which guarantee very favorable conditions for the initial period of the contract but that a few years later, or at the termination of the contract, change to the detriment of the consumer.

Institutions should ensure both fair transparency in the intermediary-investor relationship and investor's freedom of choice. Therefore, transparency on financial products takes on significant importance for behavioral finance in order to avoid that financial intermediaries take advantage from clients' mistakes.

In the end, it is important to create a right combination of financial education, clear and efficient institutional regulations and a customized financial consulting. This means that, relying on the guidelines of behavioral finance, investor education is of fundamental importance to encourage the spread of a basic financial culture

[27] Kahneman D., Riepe M. W., *Aspects of Investor Psychology*, The Journal of Portfolio Management, (1998), 52-65.

to make good investment choices and to have a good perception of the behavioral errors made. Secondly, institutional intervention must be the source of transparency policies on products' features in order to protect investors, and lastly, financial advice services, if appropriate to the investor's financial knowledge and to his future expectations, complete the correction process of improper conduct in investments.

CHAPTER 3

Intraday anomalies: empirical evidence and market efficiency

1. Intraday anomalies in stock prices

The main consequence of the EMH lies in the fact that investors should not be able to beat the market and gain abnormal returns. However, through a deeper study of the literature it is possible to notice the existence of some market anomalies which, if exploited by adequate trading strategies, would lead to profitable opportunities. The presence of such anomalies is justified by the behavioral finance. Anyway, it would be appropriate to analyze whether they allow investors to obtain returns high enough to allow them to make riskless profitable trades.

In this chapter, through several studies conducted across different stock exchanges, we will focus on the evidence of recurring patterns in stocks' prices within the same time interval of the trading session across several days. This anomaly would allow riskless profit opportunities thus being inconsistent with the classical financial theory thought about market efficiency. They are called "intraday anomalies" and include the "half of the day effect" and the "time of the day effect": the former consists in the tendency of returns to be very low at half of the trading day while the latter sees the first 45 and last 15 minutes of the trading day as the periods where the returns are at their highest value.

1.1 Empirical evidence of intraday effects in stock prices: the Athens Stock Exchange

In a study conducted by Niarchos and Alexakis[28] (2003), it was tested whether it was possible to profit from the statistical relationship between intraday stock returns in the Athens Stock Exchange (ASE). The ASE trading hours start at 10:45a.m. and end at 1.30p.m. with a half hour pre-opening period (10:15a.m.-10:45a.m.) used to set the opening price on the base of orders received in this time interval.

Data were taken from 01/06/1998 to 10/09/1998, mainly because this period did not show any particular price characteristics. Returns were calculated as the difference of the logarithmic prices over 15-minute time intervals by using intraday stock prices of the Banking, Industrial, Construction and Second Tier (Parallel) market indexes.

To test the existence of patterns in stock returns it was used an econometric model in which stock returns were set to be time dependent:

$$R_t = \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \dots + \alpha_{12} D_{12} + \sum_{i=1}^{k} \beta_i R_i \qquad (1)$$

[28] Niarchos N. A., Alexakis C. A., *Intraday stock price patterns in the Greek stock exchange,* Applied Financial Economics (Athens: 2003), 13-22.

where R_t is a series of actual stock returns and D_1, D_2 , D_3, ..., D_{12} are dummy variables which refer to the stock returns of the 15-minute time intervals (1-12) during the trading day. In case of serially dependence of intraday returns, which may be caused by thin trading or slow reaction of the market to incoming news, in order to avoid bias to the statistical findings were introduced R_i which are lagged intraday returns employed as explanatory variables to take into account the Autoregressive Conditional Heteroscedasticity (ARCH) effects. Anyway, if the EMH holds, $\alpha_i = 0$.

Table 3 shows the autocorrelation function of the four indexes for the first five lags. In particular, we can notice how the Construction index presents significant positive autocorrelation at the first lag and, therefore, for this index it will be applied the full model equation (1) comprehending lagged returns.

Tab. 3: *Index return autocorrelation function*

Lag	Banks	Industrials	Constructions	Parallel
1	0.061	0.031	0.113*	−0.076
2	−0.053	−0.043	−0.007	0.027
3	0.039	0.026	0.054	−0.006
4	0.031	0.032	0.024	0.011
5	0.038	0.029	0.043	−0.035

Note: * denotes significance at 95% confidence interval.

Tab. 4: *Regression results*

Variable	Coefficient	t statistic
Bank index		
D1	0.0011	1.22
D2	−0.0001	0.003
D3	−0.0021	2.20**
D4	0.00012	0.13
D5	0.00042	0.45
D6	−0.00068	0.72
D7	−0.00022	0.23
D8	0.00015	0.16
D9	0.00078	0.83
D10	0.00016	0.17
D11	−0.00062	0.66
D12	−0.00037	0.39

Regression statistics:

$R^2 = 0.01$ $Q_1 = 3.36$ $Q_5 = 8.52$

$Q_{(sq)1} = 1.29$ $Q_{(sq)5} = 0.24$

Variable	Coefficient	t statistic
Industrial index		
D1	0.0008	1.12
D2	−0.002	2.63**
D3	−0.002	3.08**
D4	0.0002	0.28
D5	−0.0006	0.77
D6	−0.0006	0.78
D7	0.0002	0.33
D8	0.0005	0.66
D9	0.0006	0.77
D10	−0.0004	0.05
D11	−0.0002	0.26
D12	0.0009	1.17

Regression statistics:

$R^2 = 0.02$ $Q_1 = 0.56$ $Q_5 = 4.38$

$Q_{(sq)1} = 6.96$ $Q_{(sq)5} = 7.52$

Variable	Coefficient	t statistic
Construction index		
D1	−0.001	0.93
D2	0.001	0.98
D3	−0.003	3.62**
D4	−0.001	1.58
D5	−0.0007	1.09
D6	−0.00002	0.03
D7	−0.0008	1.04
D8	0.0006	1.16
D9	0.001	1.56
D10	0.0008	1.47
D11	−0.0001	0.20
D12	0.004	7.11**

Regression statistics:

$R^2 = 0.05$ $Q_1 = 0.37$ $Q_5 = 7.33$

$Q_{(sq)1} = 1.93$ $Q_{(sq)5} = 4.67$

Variable	Coefficient	t statistic
Parallel market index		
D1	−0.001	1.79
D2	0.001	0.55
D3	−0.03	3.30**
D4	−0.0007	0.80
D5	−0.0009	1.33
D6	−0.001	2.31
D7	−0.0009	1.18
D8	−0.0006	0.97
D9	0.0005	1.02
D10	0.0005	0.80
D11	0.0003	0.47
D12	0.005	6.56**

Regression statistics:

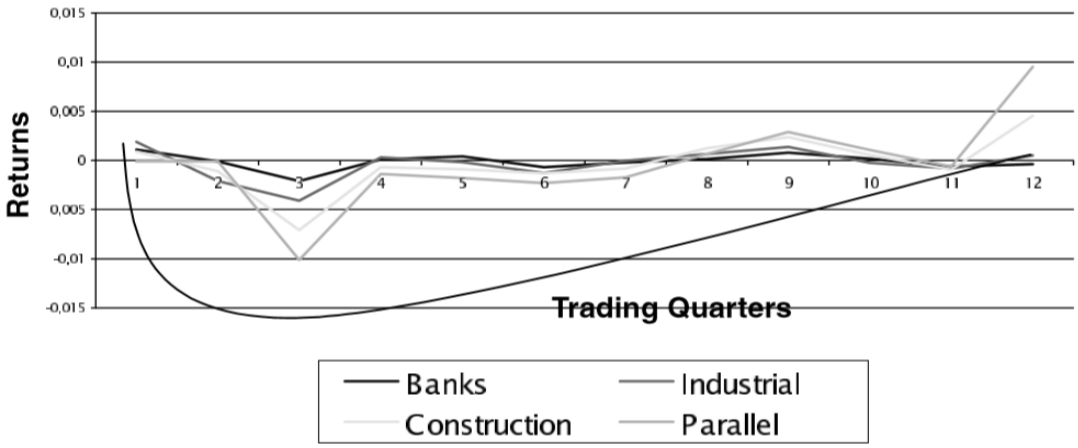
$R^2 = 0.06$ $Q_1 = 5.33$ $Q_5 = 6.26$

$Q_{(sq)1} = 0.60$ $Q_{(sq)5} = 0.98$

In Table 4 are presented the results of the tests for intraday regularities. We can notice that for the Construction and Parallel indexes there is strong statistical evidence of positive returns in the last 15 minutes of the trading day ("end of the day pattern"), and that at the half of the trading day, in the time interval going form 11:15a.m. to 11:30a.m., there is a statistically significant negative return in all cases ("half of the day effect"). More in general, returns form a U-shaped pattern as it is shown in Figure 6. The R^2 , which measures the explanatory power of the model setting the stock return to be time dependent, is very low for the Industrial and the Bank indexes while it is very high for the other two indexes. Moreover, the statistics Q and Q_{sq} for the residuals did not indicate any econometric problem which would have biased the results of the estimated equations.

It would be obvious at this point to think about a trading strategy which would exploit these patterns: buy at 11:30a.m. when the return is expected to be negative and then sell at the end of the trading session which is when returns are expected to be the highest possible. Remember that in the ASE short selling is not allowed. In Table 5 are shown the results of the trading strategy compared to a simple and passive "buy and hold" strategy. The trading rule generated positive returns in all cases except that for the Bank index where, like for the other indexes, the trading strategy still beat the "buy and hold" strategy. As risk is expressed by the standard deviation, the trading rule is not only more profitable, but it is even safer.

Fig. 6: *Intraday stock returns by quarter*



Tab. 5: *Trading rule evaluation*

	Average return	Standard deviation
Bank index		
Buy and hold	−0.00010	0.0079
Trading rule	−0.000039	0.0040
Industrial index		
Buy and hold	−0.00020	0.0067
Trading rule	0.000079	0.0041
Construction index		
Buy and hold	−0.000081	0.0079
Trading rule	0.00021	0.0051
Parallel market index		
Buy and hold	−0.000086	0.0076
Trading rule	0.00016	0.0053

1.2 Empirical evidence of intraday effects in stock prices: the New York Stock Exchange

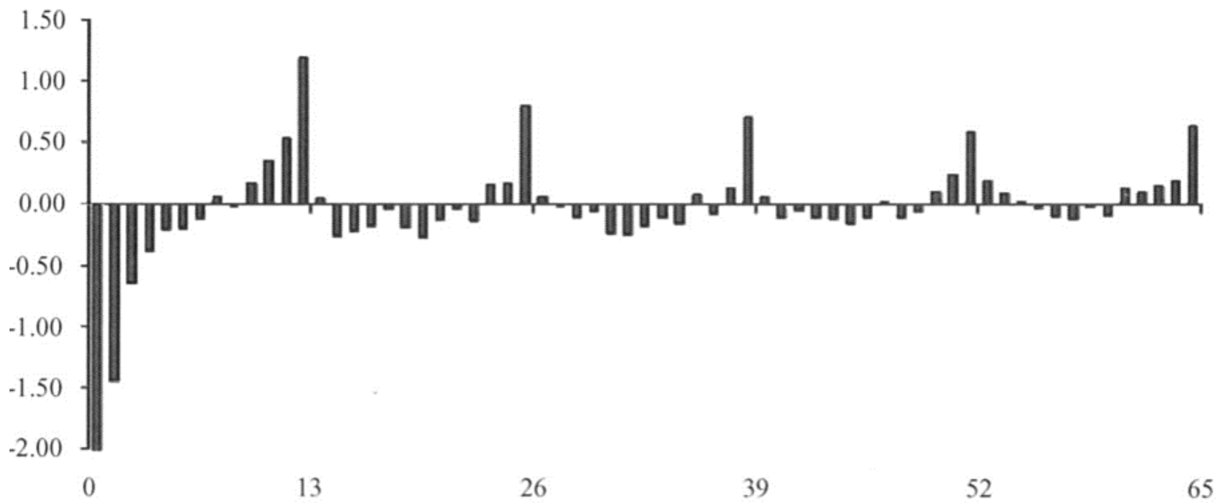
Even the researchers Steven L. Heston, Robert A. Korajczyk and Ronnie Sadka[29] (2010) conducted a study over the NYSE in order to study intraday periodicity in stock returns. Differently from the previous paper, they divided the trading day (9:30a.m. - 4:00p.m.) into 13 half-hour intervals. The sample includes data taken from the TAQ[30] database only for assets that were listed in the NYSE from January 2001 to December 2005 and that whose CRSP codes were 10 or 11.

Intraday stock returns were analyzed running cross-sectional regressions of half-hour stock returns on returns lagged by *k* half-hour periods,

$$r_{i,t} = \alpha_t + \gamma_{k,t}\, r_{i,t-k} + u_{i,t}$$

where $r_{i,t}$ is the return on stock *i* in the half-hour interval *t* and the slope coefficients $\gamma_{k,t}$ represent the response of returns at half-hour *t* to returns over a previous interval lagged by *k* half-hour periods, the "return responses". To calculate the pattern of return effects they averaged return responses over time for half-hour lags *k*. In Figure 7 are presented the average return responses across different lags for one week (5 trading days), estimated by using multiple regressions. So, 13 half-hour intervals per day for 5 trading days, gives 65 lagged intervals.

Fig. 7: *Estimates of cross-sectional regressions*



The most evident pattern is that return responses reach the highest positive value at intervals of one trading day (13 half-hours) and that in general they experience a reversal period since the first return responses are negative and then become positive. This is a clear evidence that returns follow a periodicity at daily intervals. In fact, in Table 6 we see how returns on portfolios made of securities which performed well in the same time

[29] Heston S. L., Korajczyk R. A., Sadka R., *Intraday Patterns in the Cross-section of Stock Returns*, The Journal of Finance, Vol. 65, N.4, (Wiley for AFA, 2010), 1369-1407.
[30] NYSE Trade and Quote database containing intraday transaction data.

interval on the previous day (strategy labeled as "Daily") are quite pronounced in the first and last half-hours of the trading day, namely they follow a U-shaped pattern. These price distortions may be caused by opening and closing procedures which might produce predictability in stock prices only for those specific time intervals. In conclusion, the periodicity at daily intervals of return strategies has a similar shape but different intensity at different times of the trading session. In particular, the patterns are mainly driven by trading near the opening and closing of the trading day. There is stronger magnitude at the beginning and at the end of the trading day while it is weaker, but still existent, in the intermediate intervals: it exists at all times.

Tab. 6

Returns of Strategies Based on Past Performance in Different Half-Hour Intervals of the Trading Day

We divide the 9:30 to 16:00 trading day into 13 disjoint half-hour return intervals. We analyze equal-weighted strategies with holding periods of one half-hour (i.e., one interval). Every half-hour interval, stocks are grouped into 10 portfolios (with an equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13. The portfolios are formed every half-hour. The average returns of the top-minus-bottom decile portfolios (per half-hour, in basis points) for each half-hour interval of a trading day for the period January 2001 through December 2005 (there are 1,255 observations for each half-hour interval of a trading day) are reported below, as well as the corresponding *t*-statistics (in brackets). The analysis uses NYSE-listed stocks.

Strategy	1 (First) [9:30 to 10:00]	2 [10:00 to 10:30]	3 [10:30 to 11:00]	4 [11:00 to 11:30]	5 [11:30 to 12:00]	6 [12:00 to 12:30]	7 [12:30 to 13:00]	8 [13:00 to 13:30]	9 [13:30 to 14:00]	10 [14:00 to 14:30]	11 [14:30 to 15:00]	12 [15:00 to 15:30]	13 (Last) [15:30 to 16:00]	2-12 [10:00 to 15:30]
Day 1	11.48	5.02	2.66	1.20	1.38	1.35	1.53	0.76	1.19	0.81	0.89	2.46	8.42	1.75
[lag 13]	[12.58]	[7.97]	[5.01]	[2.87]	[3.71]	[3.92]	[4.69]	[2.16]	[3.72]	[2.12]	[2.45]	[6.48]	[14.90]	[14.06]
Day 2	10.48	2.59	1.32	0.51	−0.06	0.35	0.84	0.06	0.27	0.22	1.35	1.10	6.52	0.78
[lag 26]	[12.32]	[4.22]	[2.67]	[1.21]	[−0.17]	[1.08]	[2.61]	[0.20]	[0.80]	[0.62]	[3.99]	[2.91]	[11.43]	[6.45]
Day 3	6.32	1.55	0.23	0.34	0.40	0.38	0.65	−0.18	0.57	0.06	1.19	0.56	5.57	0.52
[lag 39]	[7.59]	[2.70]	[0.46]	[0.80]	[1.06]	[1.14]	[2.07]	[−0.58]	[1.76]	[0.17]	[3.76]	[1.56]	[10.46]	[4.44]
Day 4	5.64	1.52	0.84	0.90	0.25	0.10	0.06	0.04	0.65	0.53	0.95	0.54	4.32	0.58
[lag 52]	[6.86]	[2.51]	[1.67]	[2.26]	[0.69]	[0.31]	[0.19]	[0.14]	[2.06]	[1.52]	[2.86]	[1.56]	[7.98]	[4.95]
Day 5	4.98	1.37	−0.68	0.89	0.18	0.45	0.34	0.88	0.64	0.62	0.25	0.78	3.50	0.52
[lag 65]	[6.13]	[2.34]	[−1.27]	[2.21]	[0.46]	[1.37]	[1.06]	[2.75]	[2.04]	[1.69]	[0.72]	[2.25]	[6.97]	[4.35]

From these results it seems possible to exploit return periodicity to implement profitable trading strategies, but what happens if transaction costs, such as the bid-ask spread, are included?

To test this, they ran a test by applying the Daily strategy, buying at the ask and selling at the bid to get immediate execution and profit from the periodicity. The test was conducted over different types of stocks sorted into three groups based on market capitalization. They made this distinction to test whether this periodicity in return premiums was due to the compensation for illiquidity of small stocks which should be theoretically more difficult to trade at efficient prices and so investors would ask higher returns. Test's results are reported in Table 7 and include the round-trip transaction costs of two different long-short strategies. The average returns are negative for all size categories at all times of the day, thus indicating that the periodicity previously found does not indicate a pure profit opportunity. Moreover, we can see how small stocks incur in higher losses than medium and large stocks confirming the theory that small stocks face higher transaction costs. This suggests that many investors have a demand for immediate execution and are not willing to shift their trade in order to take advantage of the current periodicity.

In conclusion, the patterns in returns do not represent a profit opportunity because strategies that attempt to take advantage of the daily periodicity lose money after paying the spread.

The fact that periodicity in returns is wiped out by paying the bid-ask spread may be explained by the fact that bid-ask spreads may follow the same pattern as returns on induvial stocks.

Tab. 7

Controlling for Size, Time of Day, and Bid-Ask Spreads

We divide the 9:30 to 16:00 trading day into 13 disjoint half-hour return intervals. We analyze equal-weighted strategies with holding periods of one half-hour (i.e., one interval). Every half-hour interval, stocks are grouped into 10 portfolios (with an equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13. The portfolios are formed every half-hour. The table reports long-short portfolio strategies: the daily strategies are calculated as top-minus-bottom decile portfolios. The average returns of the different strategies (per half-hour, in basis points), after accounting for transaction costs, for the period January 2001 through December 2005 are reported below, as well as the corresponding *t*-statistics (in brackets). The strategies are performed separately for three equally sized groups sorted by firm market capitalization at the end of the previous calendar year. The post–transaction cost return of buying a stock is calculated as the return from the first quoted offer price of a half-hour interval to its last quoted bid price. The post–transaction cost return of selling a stock is calculated as the negative of the return from the first quoted bid price of a half-hour interval to its last quoted offer price. The returns are reported using all half-hour intervals of a day, as well as only the first, the last, and the rest of the intervals. In each given interval, only firms with the first quoted relative bid-ask spread (spread divided by the midpoint of quotes) no larger than 10 basis points in a given interval are used for the calculations. The analysis uses NYSE-listed stocks.

	Small				Medium				Large			
Strategy	1-13 (All)	1 (First)	2-12	13 (Last)	1-13 (All)	1 (First)	2-12	13 (Last)	1-13 (All)	1 (First)	2-12	13 (Last)
Day 1	−23.78	−28.26	−23.68	−24.41	−18.58	−11.49	−19.03	−15.07	−13.25	−13.43	−13.91	−5.84
[lag 13]	[−28.37]	[−0.72]	[−27.43]	[−8.75]	[−49.79]	[−1.34]	[−52.11]	[−12.10]	[−46.50]	[−4.24]	[−61.05]	[−8.96]
Day 2	−24.49	−84.59	−24.31	−23.41	−19.38	−11.39	−19.83	−15.99	−13.46	−11.02	−14.07	−8.79
[lag 26]	[−29.41]	[−2.89]	[−28.20]	[−8.37]	[−53.34]	[−1.46]	[−54.83]	[−13.54]	[−49.00]	[−3.61]	[−63.68]	[−14.60]
Day 3	−24.29	−35.03	−24.61	−21.30	−20.31	−16.53	−20.64	−17.49	−13.77	−8.75	−14.48	−10.02
[lag 39]	[−30.68]	[−1.03]	[−30.07]	[−7.62]	[−54.89]	[−1.79]	[−57.42]	[−15.04]	[−52.27]	[−3.15]	[−65.83]	[−17.25]
Day 4	−23.77	−15.34	−23.44	−26.96	−20.38	−20.71	−20.43	−19.76	−14.13	−13.56	−14.50	−10.52
[lag 52]	[−28.87]	[−0.46]	[−27.75]	[−9.26]	[−56.52]	[−2.44]	[−57.60]	[−18.08]	[−53.48]	[−4.85]	[−65.71]	[−18.27]
Day 5	−25.92	−21.21	−25.63	−28.77	−20.27	−22.00	−20.37	−18.85	−13.66	−8.08	−14.28	−11.40
[lag 65]	[−32.58]	[−0.64]	[−30.95]	[−10.51]	[−56.64]	[−2.96]	[−56.85]	[−16.12]	[−35.73]	[−1.58]	[−61.98]	[−18.29]

2. Empirical evidence of intraday patterns in bid-ask spreads in the NYSE and LSE

From several studies conducted over different stock exchanges was found evidence of periodicity in intraday returns which, if exploited, would allow profit opportunities. Anyway, once transaction costs were included in the tests, returns were not profitable anymore, they were negative. The researchers Thomas H. McInish and Robert A. Wood, and then A. Abhyankar, D. Ghosh, E. Levin and R.J. Limmack, in two different studies conducted over the NYSE and the LSE respectively, tried to find evidence of intraday patterns in bid-ask spreads analogous to those in returns which would outweigh strategies exploiting periodicity in returns.

The data for the former study[31] (McInish T. M. 1992) comprise every bid and ask entered into the CQS[32] by NYSE specialists for the first six months of calendar year 1989. These data reflect the behavior of all market participants. For the use in this regression analysis, the trading day was divided into one 31-minute interval and twelve successive half-hour intervals. Then, for each of them was calculated the time-weighted percentage bid-ask spread (BAS) for any security. Here, the time-weighting was based on the number of seconds the quotation was outstanding during the 30-minute interval, and for every quotation was computed the percentage bid-ask spread:

$$BAS = \frac{(ask\ -\ bid)}{(ask\ +bid)/2}$$

Now, suppose that for every interval *T* - *T'*, where $T = t_0$ and $T' = t_{N+1}$, there are N quotation updates occurring at times t_i with spreads BAS_i. For each interval, measured in seconds, the time-weighted spread is:

$$\sum_{i=1}^{N} \frac{BAS_i\ (t_{i+1} -\ t_i)}{(T' - t_1)}$$

This paper wants to analyze whether some variables found in previous researches are significant in determining the bid-ask spread by formulating four different hypotheses:

- Hypothesis 1: There is an inverse relationship between spreads and trading activity.
- Hypothesis 2: There is a direct relationship between the level of risk and spreads.
- Hypothesis 3: There is a direct relationship between spreads and the amount of information coming to the market.
- Hypothesis 4: There is an inverse relationship between spreads and the level of competition.

To test these hypotheses was used a linear regression model seeing the BAS regressed against a variety of independent variables for which were used the respective square roots in order to avoid that outliers could dominate the results since the distribution of the variables was highly skewed.
Hypothesis 1 was tested using two different activity variables, one for the number of transactions for each stock *i* in interval *t* labeled as "$TRADES_{i,t}$", and one for the average number of shares per trade for each stock *i* in interval *t* labeled as "$SIZE_{i,t}$".

[31] McInish T. M., Wood R. A., *An Analysis of Intraday Patterns in Bid/Ask Spreads for NYSE Stocks*, The Journal of Finance, Vol. 47, N. 2, (Wiley for the AFA, 1992), 753-764.
[32] The Consolidated Quotation System is an electronic system that records quotation information for securities listed on major US stock exchanges

Hypothesis 2 was tested adopting risk measures based on variability of the mid-point of bid and ask quotes which are not affected by bid-ask bounce, rather than measures of total risk and systematic risk which instead are significantly affected by the bid-ask bounce. Even here are used two variables, the first is labeled as "$RISK1_i$" and captures differential risk from one stock to another while the second measure of risk is labeled as "$RISK2_{i,t}$" and captures the differential risk from one interval to another for the stock. Defined the standard deviation of the time-weighted average bid-ask spread for each stock i in interval t as $V_{i,t}$, its mean as M_i and with S_i the standard deviation of $V_{i,t}$, $RISK1_i$ is equal to M_i and $RISK2_{i,t}$ corresponds to $\frac{(V_{i,t} - M_i)}{S_i}$.

Hypothesis 3 was tested using the variable labeled as $NSIZE_{i,t} = \frac{(SIZE_{i,t} - X_i)}{D_i}$ where $SIZE_{i,t}$ is the volume per trade for stock i over interval t, X_i is its mean and D_i its standard deviation. NSIZE captures the effects of unusually large or small trades relative to the mean size of trades during a given interval for a trading stock since previous evidence showed that periods during which there are relatively more abnormal large transactions, are more likely to have greater information flow.

Finally, Hypothesis 4 was tested by including the variable $REGIONAL_{i,t}$ which is the ratio of the number of shares of stock i traded on regional exchanges to the number of shares traded on the NYSE during interval t. This variable captures the competition in the variables used in previous studies, such as the number of dealers, which are not suitable when using transaction data since they do not change over time.

Moreover, it is included as a control variable $PRICE_{i,t}$, as previous studies found an inverse relationship between a stock's listing price and its spread.

The final linear model including all the variables is:

$$\mathbf{BAS}_{i,t} = b_0 + b_1\, TRADES_{i,t} + b_2\, SIZE_{i,t} + b_3\, RISK1 + b_4\, RISK2_{i,t} + b_5\, NSIZE_{i,t} + b_6\, REGIONAL_{i,t} + \\ + b_7\, PRICE_{i,t} + 12 \text{ Interval Dummy Variables (numbered 1-9 and 11-13)} + \\ + 4 \text{ Weekday Dummy Variables} + e_{i,t}$$

where b_0, …, b_{23} are parameters to be estimated and $e_{i,t}$ is a random error term. The interval dummy variables are used to assess whether the relationship between BAS and the explanatory variables is the same at all intervals, while the weekday dummy variables are used to capture potential day-of-the-week effects.

The results of the regression are showed in Table 8:

Hypothesis 1 is confirmed as the coefficients of TRADES and SIZE are significantly negative.

Hypothesis 2 is confirmed since the coefficients of RISK1 and RISK2 are significantly positive, meaning that differential spread across stocks can be explained in part by differences in a stock's risk, and that spreads are larger for intervals with greater risk.

Hypothesis 3 is supported by the fact that the coefficient of NSIZE, which measures the information flow reflected in trades of an unusual size, is significantly positive.

Hypothesis 4 is confirmed as well because the coefficient of REGIONAL is significantly negative and so greater trading activity on the regional exchanges is associated with smaller spreads.

Finally, the control variable PRICE, presenting a significantly negative coefficient, confirms that higher priced stocks have smaller spreads.

The coefficients of the dummy variables for each interval decline from interval 1 to interval 9 and then start increasing from interval 11 to interval 13, in other words they reveal a reverse *j*-shaped pattern being relatively high at the beginning and at the end of the trading day. Instead, the weekday dummy variables present a low level of the *t*-statistics indicating that weekday patterns are relatively weak compared to the strength of the intraday ones.

Tab. 8

Results for the Regression of Percentage Spreads Against Activity, Risk, Information, Competition and Control Variables

Each trading day during the first six months of 1989 is segmented into one 31-minute interval and twelve thirty-minute intervals (9:30 A.M. to 10:00 A.M., etc). Then, for each security i for each interval t, the mean value of the following variables is calculated: (1) the time-weighted percentage bid-ask spread $BAS_{i,t}$, (2) the square root of the number of trades ($TRADES_{i,t}$), (3) the square root of the number of shares per trade ($SIZE_{i,t}$), (4) $SIZE_{i,t}$ minus the mean of $SIZE_{i,t}$ for stock i over all t and then divided by the standard deviation of $SIZE_{i,t}$ for stock i over all t ($NSIZE_{i,t}$), (5) the square root of the number of trades on regional exchanges relative to the number on the NYSE ($REGIONAL_{i,t}$), and (6) the square root of the average price ($PRICE_{i,t}$). Define $V_{i,t}$ as the standard deviation of the time-weighted average bid and ask for each stock in interval t, M_t as the mean of $V_{i,t}$ for stock i over all t and S_i as the standard deviation of $V_{i,t}$ for stock i over all t. The first measure of risk ($RISK1_i$) is M_i and the second measure of risk ($RISK2_{i,t}$) is $(V_{i,t} - M_i)/S_i$. $BAS_{i,t}$ is regressed against TRADES, SIZE, RISK1, RISK2, NSIZE, REGIONAL, and PRICE plus dummy variables for each of the 13 intervals (with interval 10 omitted) and dummy variables for each day of the week (with Wednesday omitted).

Independent Variables	Coefficients	*t*-statistic
INTERCEPT	0.0158	849.12[a]
TRADES	−0.0005	−226.96[a]
SIZE	−0.0002	−82.28[a]
RISK1	0.0668	320.45[a]
RISK2	0.0004	137.23[a]
NSIZE	0.0005	80.98[a]
REGIONAL	−0.0002	−24.66[a]
PRICE	−0.0018	−673.17[a]
	Regression Results	
Interval 1	0.00065	49.12[a]
Interval 2	0.00042	32.35[a]
Interval 3	0.00030	23.46[a]
Interval 4	0.00021	16.09[a]
Interval 5	0.00016	11.97[a]
Interval 6	0.00009	6.58[a]
Interval 7	0.00001	0.05
Interval 8	−0.00005	−3.71[a]
Interval 9	−0.00038	−2.88[a]
Interval 11	0.00011	8.65[a]
Interval 12	0.00025	18.98[a]
Interval 13	0.00041	32.19[a]
Monday	0.00004	4.61[a]
Tuesday	0.00001	1.78
Thursday	0.00003	4.31[a]
Friday	0.00005	6.13[a]
R-square	0.4652	N = 871,954
F-statistic	32,983	

[a] Significant at the 0.01 level.

In Figure 8 is illustrated the examination of the mean BASs for every minute of the trading session and shows how spreads are relatively high at minute 3, then start declining at a decreasing rate until minute 293 and finally increase at an increasing rate until the end of the trading day. Figure 8 represents the graph confirming the reverse *j*-shaped pattern of BAS resulting from the regression in Table 8.

Fig. 8

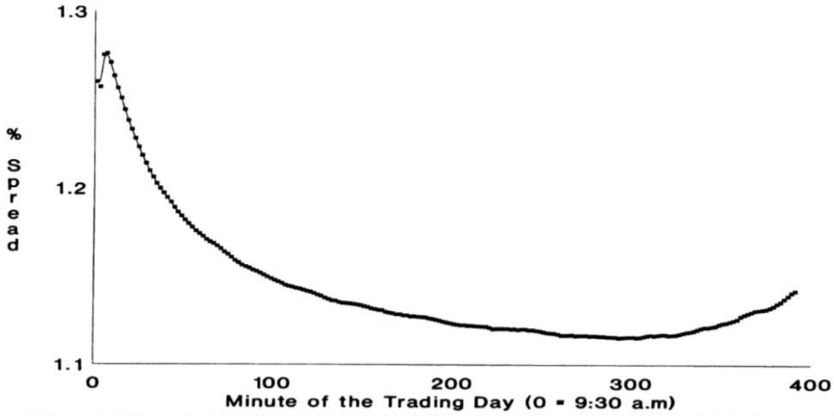


Figure 1. Mean Bid-Ask Spreads for Each Minute of the Trading Day. First, a time-series of second-by-second percentage bid-ask spreads is created for each stock. The time-series begins with the initial quotation each trading day. For a given stock for every second during which a quotation is outstanding a percentage bid-ask spread is calculated as (ask − bid)/((ask + bid)/2). The process is repeated for each stock. Then, for each trading second of the calendar year, all of the percentage bid-ask spreads are averaged to create a second-by-second time series of "market" percentage bid-ask spreads. The percentage bid-ask spreads are then averaged within each trading minute to create a time series of minute-by-minute bid-ask spreads.

After having documented the presence of a U-shaped pattern in spreads for stocks in the NYSE, researchers wanted to extend their analyses to non-US equity markets.

The economists A. Abhyankar, D. Ghosh, E. Levin and R.J. Limmack[33] (1997) extended the empirical work by taking a large sample consisting of 835 stocks traded during the first quarter of 1991 in what is one of the largest dealership stock exchange in the world: the London Stock Exchange. In their attempt to find evidence of intraday patterns in bid-ask spreads they contributed to the analysis of some variables which should be particularly relevant for market participants as well as for all those figures involved in the design of efficient markets such as regulators and policy makers.

The data used for this study consist of time-stamped and date-stamped intra-day bid-ask quotes and matched transactions prices from 01/01/1991 to 31/03/1991. Each trading day was divided into 44 fifteen-minute time intervals from before the SEAQ pre-market open to the close (7:00a.m - 6p.m.). The 15-minute time interval was chosen for a specific reason: since changes in the timing of the MPQ occur at thirty-minute intervals, 15-minute intervals provide a better indication of the variations within pre- and post-MPQ periods as well as allowing a meaningful interpretation.

Tab. 9: *Summary Information on the Trading Day*

	Post 26 March, 1990
SEAQ Pre-Market (Users may log on, receive down-load trade reports)	0715
SEAQ Open (Users may do all above plus enter quotes)	0800
Mandatory Quote Period (MQP)	
Start	0830
MQP End	1630
SEAQ Close	1645
Actual or SEAQ System Close	1715

[33] Abhyankar A., Ghosh D., Levin E., Limmack R. J., *Bid-ask spreads, trading volume and volatility: intra-day evidence from the London Stock Exchange*, Journal of Business Finance & Accounting, Vol. 24, N.3-4, (1997), 343-363.

For each stock *i*, for each trading day *j* in the sample, were taken the highest bid and the lowest ask at the end of each interval *t* and thereafter the proportional bid-ask spread was obtained as:

$$BAS_{i,j,t} = \frac{ASK_{i,j,t} - BID_{i,j,t}}{(ASK_{i,j,t} - BID_{i,j,t})/2}$$

then they were averaged for all trading days for each stock and then for all the stocks in the sample.
Moreover, it was calculated even a series of proportional bid-ask spreads for each stock for each trading day divided by the mean of the series for that day:

$$SBAS = \frac{BAS_{i,j,t}}{Avg\ BAS\ across\ N\ intra-day\ intervals}$$

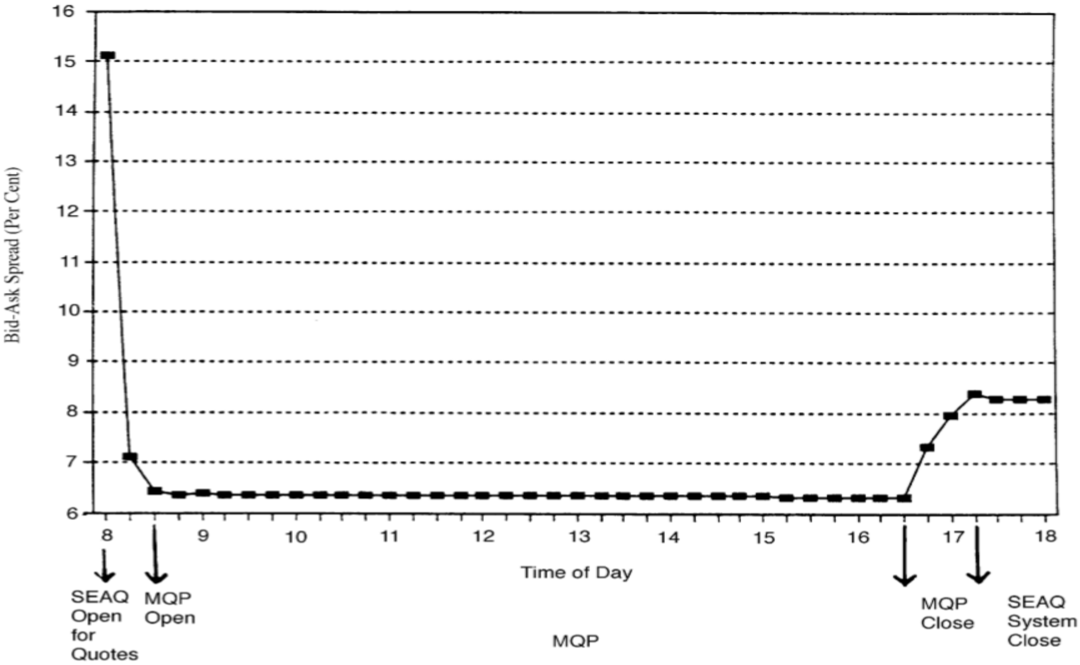
where *N* is the total number of fifteen-minute intervals (44).

The statistical significance of this variable was finally tested by running the regression:

$$SBAS_{i,j,t} = c_0 + \sum_{i=1}^{n} c_i D_i + \sum_{k=N-n}^{N} c_k D_k + e_{i,t}$$

where c_0 is a constant, c_i are the coefficients, *D* is the indicator variable taking the values (0,1) and *e* is the error term.
Particular attention is given to changes in the variable at the beginning and at the end of the trading day to verify whether what previous researches found applied even here, i.e. that the bid-ask spread follows a particular pattern in those specific time intervals.
It is tested, through an X^2 test distributed with 12 degrees of freedom, the null hypothesis that all the interval dummy variables are equal to zero. Remember that where there is a large X^2 it means that at least one of the dummies is different from zero and that the size of the coefficient measures the relative importance of that interval with respect to the mean.
The results of the regression are shown in Table 10 and then are represented graphically in Figure 9 which suggests that the BAS is at its highest value from 8:00a.m. to 8:30a.m., then it rapidly falls remaining constant throughout the day, till it starts to widen again from 4:30p.m. to 6:00p.m.. In other words, the spread is at its widest from the SEAQ open to when the MQP starts, then it narrows and finally widens again after the end of the MQP until the SEAQ close.
Figure 9 makes it easy for us to reject the null hypothesis at conventional levels of significance, suggesting that the bid-ask spread follows a U-shaped pattern during the trading day which supports previous literature.

Fig. 9: *Intra-Day Bid-Ask Spreads 1991 Q1: 8:00a.m. – 6:00p.m.*



Tab. 10: *Results of the Estimation of Intra-Day Variation in the Inside Bid-Ask Spread (SBAS)*

Variable	*1991 Quarter 1*
constant	0.0646
	(0.0005)
c_1	0.0877
	(0.0003)
c_2	0.0079
	(0.0013)
c_3	0.0007
	(0.0009)
c_4	0.0002
	(0.0009)
c_5	0.0003
	(0.0009)
c_6	0.0003
	(0.0009)
c_{36}	−0.0004
	(0.0009)
c_{37}	−0.0003
	(0.0009)
c_{38}	0.0062
	(0.0033)
c_{39}	0.0321
	(0.0104)
c_{40}	0.0339
	(0.0085)
c_{41}	0.0359
	(0.0087)
$\chi^2(12)$	109281
(p-value)	(0.0000)

Notes:
Values in parenthesis are standard errors adjusted for autocorrelation and heteroscedasticity using Hansens' (1982) correlation. $\chi^2(12)$ is the χ^2 statistic that tests whether the lag (lead) coefficients are jointly zero.

In conclusion, the daily behavior of many variables such as the bid-ask spread appears to be strictly connected to the mechanism by which the market absorbs news via order flows at the beginning and at the end of the day which subsequently affects the process of price discovery.

3. Intraday effects and Market Efficiency: analysis conducted by a trading robot

From the previously mentioned studies, we saw how actually there exists a cyclicality in patterns of returns and how it could be exploited through adequate trading strategies.

Anyway, when trading costs (variable and fixed) were included in the analyses, these strategies were not profitable anymore. It is like if there was a variable cost associated to transactions which was following the same pattern of returns. In fact, it was identified a cyclicality in the bid-ask spread pattern (variable transaction cost) having a shape similar to the one of the returns on the respective market.

G. M. Caporale, L. G-Alana, A. Plastum and I. Makarenko[34] (2015) gathered the results of the previous studies within a single analysis. Their analysis is based on a trading robot which simulates traders' actions incorporating spreads as transaction costs, with the aim to show that market anomalies by themselves do not represent evidence of market inefficiency because they might not be exploited in practice. They might be exploited only in the very short run using appropriate strategies, which, however, would have a corrective effect over these arbitrage opportunities.

They conducted the analysis over both a developed and a developing market in different phases of the economic cycle, to check if there was evidence of variables changing behavior depending on those aspects. In other words, were analyzed 27 companies included in the Dow Jones Index and 8 Blue-chip Russian Companies. For the US, the sample period is 2005-2011 which was then divided into three sub-periods: "normal" 2005-2006, "crisis" 2007-2009, "post-crisis" 2010-2011. Instead, for Russian companies was taken the period from 2011 to 2013 due to a lack of data.

This study is in line with the majority of its predecessors, using 15-minute intervals and focusing on the presence of anomalies in the first 45 minutes and the last 15 minutes of the trading session.

They looked at the intraday anomaly from the trader's viewpoint: is it possible to make profits from trading on intraday patterns? In particular, they tested the following three hypotheses:

Hypothesis 1: first 45 min up effect exists (H1):

- H1a—case of developed countries
- H1b—case of developing countries

Hypothesis 2: last 15 min up effect exists (H2)

- H2a—case of developed countries
- H2b—case of developing countries

Hypothesis 3: the results for different periods (pre-crisis, crisis, post-crisis) are statistically different (H3).

[34] Caporale G. M., Gil-Alana L., Plastum A., Makarenko A., *Intraday Anomalies and Market Efficiency: A Trading Robot Analysis*, (Springerlink.com, 2015).

Positive profits > 50% imply that H1 and H2 cannot be rejected, while for H3 were ran t-tests rejecting H3 if t < *t-critical*.

The trading robot was programmed to automatically open (at ask price) and close (at bid price) positions according to the time of the day effect, thus incorporating the variable part of transaction costs. In other words, long positions were opened at the beginning of the trading day and closed after 45 minutes. Then they were opened again in the last 15 minutes of the trading session and finally closed at the end. They used a program developed in MQL4[35] which is a language that allows to program trading robots that automate trade processes and that perfectly suits the implementation of trading strategies.

The test verifies first the 45 minutes up effect and then the last 15 minutes up effect.

First 45 minutes up in Dow Jones:

From Table 11, which summarizes the different time periods, H1a is rejected as the probability of a profitable trade is less than 50%, meaning that there is no evidence of a first 45 minute up effect in the US stock market. Table 12, which reports the t-test for profitable trades, shows that H3 is rejected in all cases.

Last 15 minutes up in Dow Jones:

From Table 13 we see how all periods were unprofitable, thus rejecting H2a since the probability of a profitable trade is less than 40%: there is no last 15 minutes up effect in the US stock market. Table 14 displays the results of the t-test for H3 which in this case cannot be rejected.

Russian stock market:

A summary for the Russian stock market is illustrated in Table 15 where we find evidence which allows to reject H1b and H2b even in this case, thus indicating the absence of any of the two effects even in a developing market such as the Russian one.

In conclusion, the three hypotheses have been rejected for both the Russian and the US stock markets, with the only exception being H3: the results for the last 15 minutes up effect demonstrated to be affected by the sub-period in which they are. Anyway, this analysis confirms the fact that it is not possible to profit from the predictability in returns pattern as it was suggested in many misleading studies not taking into account transaction costs. Therefore, intraday anomalies by themselves are not enough to represent inconsistency with the EMH.

[35] MetaQuotes Language 4 is a programming language for developing trading robots.

Tab. 11: *Summary of testing results for the "first 45 min up effect"*

Period	Average profit trades (% of total)	Average total net profit	Average net profit per deal
2005–2006	44	−174	−0.374
2007–2009	45	−336	−0.454
2010–2011	43	−142	−0.420

Tab. 12: *t test for profit trades (% of total)*

	Mean	Std.Dv.	*N*	Diff.	Std.Dv. Diff.	*T*	*df*	*p*
2005–2006	0.437129	0.047744						
2007–2009	0.446955	0.030631	27	−0.009827	0.043375	−1.17720	26	0.249781
2005–2006	0.437129	0.047744						
2010–2011	0.430666	0.047008	27	0.006463	0.051519	0.65187	26	0.520206
2007–2009	0.446955	0.030631						
2010–2011	0.430666	0.047008	27	0.016290	0.051128	1.65555	26	0.109834

Tab. 13: *Summary of testing results for the "last 15 min up effect"*

Period	Average profit trades (% of total)	Average total net profit	Average net profit per deal
2005–2006	26	−235	−0.538
2007–2009	35	−351	−0.512
2010–2011	31	−168	−0.544

Tab. 14: *t test for profit trades (% of total)*

	Mean	Std.Dv.	*N*	Diff.	Std.Dv. Diff.	*T*	*df*	*P*
2005–2006	0.256040	0.078941						
2007–2009	0.352451	0.058585	27	−0.096411	0.059926	−8.35981	26	0.000000
2005–2006	0.256040	0.078941						
2010–2011	0.313853	0.069267	27	−0.057813	0.082721	−3.63156	26	0.001213
2007–2009	0.352451	0.058585						
2010–2011	0.313853	0.069267	27	0.038598	0.043483	4.61237	26	0.000094

Tab. 15: *Summary for the Russian stock market*

Hypothesis	Average profit trades (% of total)	Average total net profit per deal
First 45 min up effect	41	−2
Last 15 min up effect	37	−1

4. First 45 minutes up effect and last 15 minutes up effect: a Dow Jones, NASDAQ Composite and S&P 500 analysis over May and June 2020

I verified whether the first 45 minutes up effect and the last 15 minutes up effect are occurring even in very recent times over some of the most famous and discussed stock market indexes in the world. The analysis is ran over the Dow Jones, the NASDAQ Composite and the S&P 500 indexes from May 4 and June 5, 2020. Unfortunately, this isn't the best period for an analysis of this kind as the world has been hit by a global societal and financial crisis triggered by the "Coronavirus Pandemic" caused by the spread of the virus "COVID-19" which distorted ordinariness in financial markets. However, I tried to make it the most ordinary possible by conducting the test in the last two months in which the world economy is starting to recover, as the pandemic had its epicenter in Wuhan, China, and then spread over the world between December 2019 and January 2020. The study wants to focus its investigation on the presence of intraday patterns in stock returns gross of variable costs, as bid-ask spreads are not included. To make the test, I have recourse to data from the website Yahoo Finance[36] where it is possible to find intraday data up to the last 30 days and real time quotes for multiple stock market indexes around the world.

The procedure has been the same for all the three indexes:

Once chosen the index to analyze, I set 15-minute time intervals in the website settings (Figure 13) in order to be able to test both anomalies without the need to adjust the interval at the beginning and at the end of the trading day, being 45 a multiple of 15. Then, I set up an Excel table for each stock (Table 16, Table 17, Table 18) where I entered the data taken from the graphs of the indexes to calculate the returns for each interval.

The tables summarize the outcomes of a buying and hold strategy which tries to exploit such anomalies. According to this strategy an investor opens a long position at the beginning of the trading day (9:30 a.m.), thus paying the opening price, and then closes the position after 45 minutes (10:15 a.m.) in order to exploit the first 45 minutes up effect. Instead, to exploit the last 15 minutes up effect it is used the same strategy but here the investor buys 15 minutes before the market closes (3:45 p.m.) and sells at the end of the trading day (4:00 p.m.) at the closing price.

For the trading session opening price it is used the opening price of the interval starting at 9:30 a.m. and for the price at 10:15 it is used the closing price of the 15-minute interval starting at 10:00. Instead, for the last 15 minutes up effect have been used the opening and the closing price of the interval starting at 3:45 p.m..

Returns have been calculated with the standard formula $R = \frac{P_1 - P_0}{P_0}$ where P_0 and P_1 are respectively the opening (buying) and the closing (selling) price of each interval.

[36] Yahoo Finance, https://it.finance.yahoo.com/.

Fig. 10 *(Yahoo Finance)*

Fig. 11 *(Yahoo Finance)*

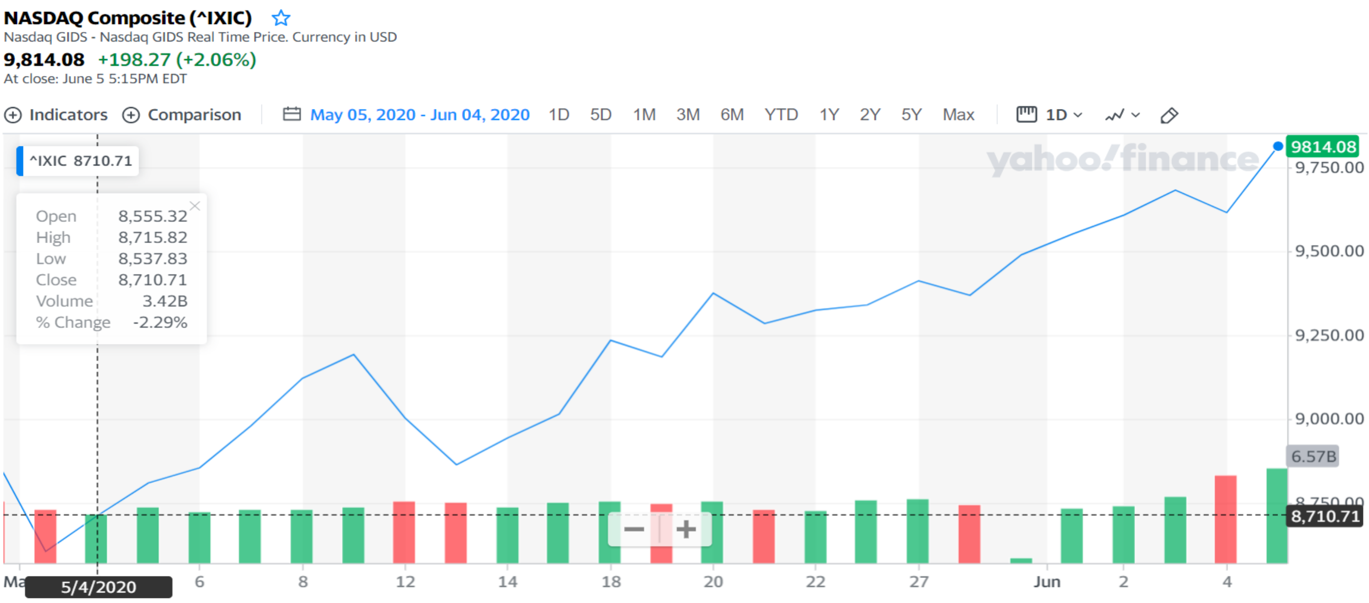
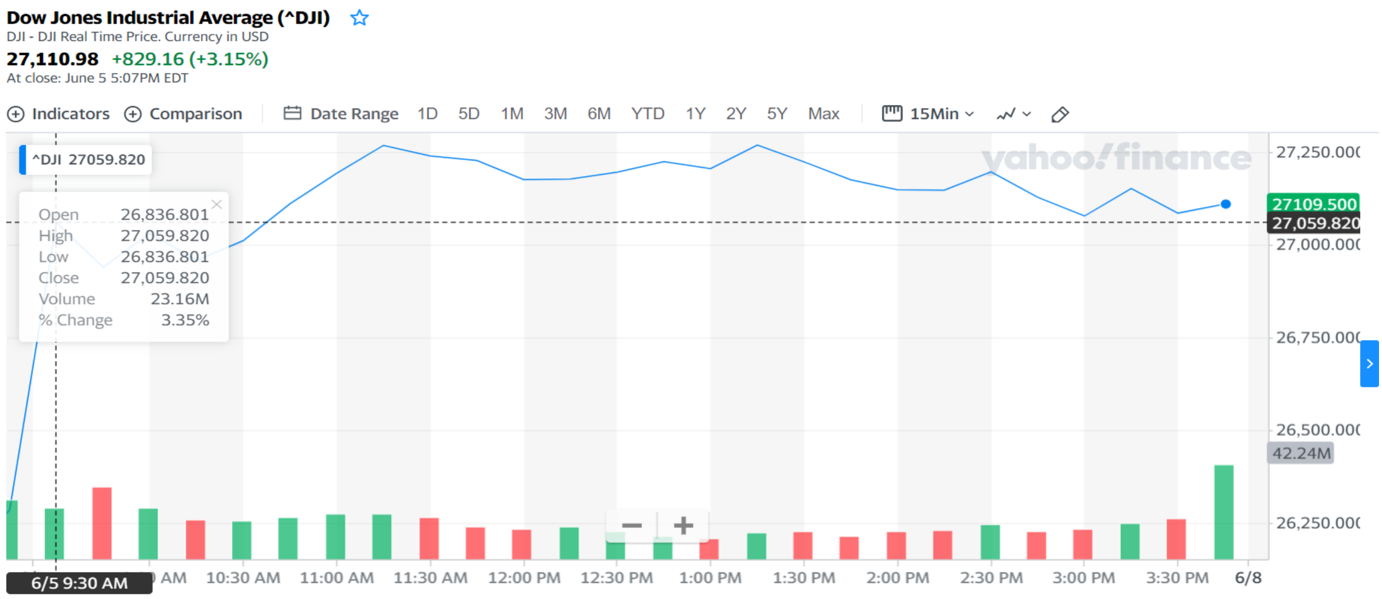


Fig. 12 *(Yahoo Finance)*

Fig. 13 *(Yahoo Finance)*



In Figures 10-11-12 are represented the patterns in stock prices for the whole sample period used for the study which goes from May 4, 2020 to June 5, 2020. It is possible to notice how there has been an overall increase for all the three indexes as stock markets are recovering from the global stock market crash began on “Black Thursday” February 20, 2020 which made Wall Street drop to the lowest levels since Black Monday in 1987: the Dow Jones presents an increase of 14,97%, the NASDAQ Composite has an increase of 14,71% while the S&P 500 shows an increase of 13,46%.

In Figure 13 it is represented the graph for a random trading day taken from the sample used in the analysis for the Dow Jones Index in which we have positive returns if we implement the previously described buy and hold strategy both at the beginning and at the end of the trading day. We see how prices go up from 9:30 a.m. to 10:15 a.m. and from 3:45 p.m. to the close, with a return of respectively 0,723% and of 0,094%.

Tab. 16 *(Personal elaboration)*

Dow Jones								
weekday (Monday-Friday)	Opening Price	Price at 10:15a.m.	Return after first 45 minutes	Price at 3:45p.m.	Closing Price	Return after last 15 minutes	first 45' effect (yes=1;no=-1)	last 15' effect (yes=1;no=-1)
04/05/2020	23.527,03	23.540,10	0,056%	23.755,21	23.755,11	-0,0004%	1	-1
05/05/2020	23.995,30	24.062,65	0,281%	23.923,60	23.884,17	-0,165%	1	-1
06/05/2020	24.024,70	23.804,30	-0,917%	23.753,12	23.655,04	-0,413%	-1	-1
07/05/2020	23.919,86	23.919,44	-0,002%	23.856,71	23.875,72	0,080%	-1	1
08/05/2020	24.107,82	24.216,08	0,449%	24.312,84	24.325,39	0,052%	1	1
11/05/2020	24.256,45	24.101,08	-0,641%	24.285,23	24.227,56	-0,237%	-1	-1
12/05/2020	24.292,84	24.289,34	-0,014%	23.891,14	23.762,58	-0,538%	-1	-1
13/05/2020	23.702,16	23.598,85	-0,436%	23.165,97	23.249,27	0,360%	-1	1
14/05/2020	23.049,06	22.897,36	-0,658%	23.521,46	23.443,63	-0,331%	-1	-1
15/05/2020	23.454,83	23.633,61	0,762%	23.599,28	23.687,06	0,372%	1	1
18/05/2020	24.376,37	24.356,03	-0,083%	24.680,87	24.580,55	-0,406%	-1	-1
19/05/2020	24.577,48	24.570,65	-0,028%	24.331,30	24.203,97	-0,523%	-1	-1
20/05/2020	24.455,94	24.509,67	0,220%	24.595,77	24.572,89	-0,093%	1	-1
21/05/2020	24.564,27	24.668,99	0,426%	24.516,72	24.475,55	-0,168%	1	-1
22/05/2020	24.461,98	24.307,65	-0,631%	24.427,95	24.466,12	0,156%	-1	1
25/05/2020	Meomorial Day	Meomorial Day	Meomorial Day	Meomorial Day	Meomorial Day	Meomorial Day		
26/05/2020	24.781,84	25.027,95	0,993%	25.017,26	24.996,14	-0,084%	1	-1
27/05/2020	25.298,63	25.275,05	-0,093%	25.443,06	25.544,20	0,398%	-1	1
28/05/2020	25.697,36	25.622,43	-0,292%	25.481,34	25.401,17	-0,315%	-1	-1
29/05/2020	25.324,15	25.273,51	-0,200%	25.382,09	25.421,34	0,155%	-1	1
01/06/2020	25.342,99	25.421,55	0,310%	25.471,44	25.476,41	0,020%	1	1
02/06/2020	25.582,52	25.633,99	0,201%	25.625,67	25.741,36	0,451%	1	1
03/06/2020	25.906,88	26.001,28	0,364%	26.321,35	26.272,27	-0,186%	1	-1
04/06/2020	26.226,49	26.248,98	0,086%	26.182,42	26.283,33	0,385%	1	1
05/06/2020	26.836,80	27.030,71	0,723%	27.083,99	27.109,50	0,094%	1	1
		Avg. Return	0,036%		Avg. Return	-0,039%	0	-2

Tab. 17 *(Personal elaboration)*

NASDAQ								
weekday (Monday-Friday)	Opening Price	Price at 10:15a.m.	Return after first 45 minutes	Price at 3:45p.m.	Closing Price	Return after last 15 minutes	first 45' effect (yes=1;no=-1)	last 15' effect (yes=1;no=-1)
04/05/2020	8.560,42	8.639,14	0,920%	8.696,62	8.711,28	0,169%	1	1
05/05/2020	8.804,48	8.849,27	0,509%	8.810,35	8.809,94	-0,005%	1	-1
06/05/2020	8.875,93	8.832,42	-0,490%	8.873,07	8.854,09	-0,214%	-1	-1
07/05/2020	8.974,89	8.942,72	-0,358%	8.962,42	8.978,85	0,183%	-1	1
08/05/2020	9.051,41	9.068,85	0,193%	9.119,46	9.119,90	0,005%	1	1
11/05/2020	9.057,73	9.127,83	0,774%	9.216,72	9.195,84	-0,227%	1	-1
12/05/2020	9.224,90	9.167,16	-0,626%	9.054,54	9.000,96	-0,592%	-1	-1
13/05/2020	9.010,94	9.031,74	0,231%	8.822,25	8.863,66	0,469%	1	1
14/05/2020	8.793,63	8.740,72	-0,602%	8.888,26	8.945,71	0,646%	-1	1
15/05/2020	8.841,38	8.929,09	0,992%	8.981,97	9.016,25	0,382%	1	1
18/05/2020	9.177,63	9.175,40	-0,024%	9.260,47	9.229,93	-0,330%	-1	-1
19/05/2020	9.227,86	9.297,48	0,754%	9.245,83	9.183,63	-0,673%	1	-1
20/05/2020	9.304,54	9.363,36	0,632%	9.380,23	9.375,07	-0,055%	1	-1
21/05/2020	9.372,87	9.346,74	-0,279%	9.312,02	9.289,60	-0,241%	-1	-1
22/05/2020	9.283,51	9.260,51	-0,248%	9.305,42	9.325,40	0,215%	-1	1
25/05/2020	Meomorial Day	Meomorial Day	Meomorial Day	Meomorial Day	Meomorial Day	Meomorial Day		
26/05/2020	9.497,99	9.452,94	-0,474%	9.342,90	9.340,69	-0,024%	-1	-1
27/05/2020	9.352,80	9.285,36	-0,721%	9.395,87	9.411,48	0,166%	-1	1
28/05/2020	9.392,26	9.441,76	0,527%	9.408,03	9.369,37	-0,411%	1	-1
29/05/2020	9.378,96	9.352,81	-0,279%	9.472,55	9.501,62	0,307%	-1	1
01/06/2020	9.466,79	9.521,79	0,581%	9.555,30	9.550,91	-0,046%	1	-1
02/06/2020	9.566,63	9.549,63	-0,178%	9.569,97	9.610,05	0,419%	-1	1
03/06/2020	9.649,03	9.647,10	-0,020%	9.698,75	9.681,11	-0,182%	-1	-1
04/06/2020	9.649,46	9.688,09	0,400%	9.589,20	9.615,57	0,275%	1	1
05/06/2020	9.703,81	9.777,19	0,756%	9.807,74	9.818,71	0,112%	1	1
		Avg. Return	0,124%		Avg. Return	0,015%	0	0

Tab. 18 *(Personal elaboration)*

S&P 500								
weekday (Monday-Friday)	Opening Price	Price at 10:15a.m.	Return after first 45 minutes	Price at 3:45p.m.	Closing Price	Return after last 15 minutes	first 45' effect (yes=1;no=-1)	last 15' effect (yes=1;no=-1)
04/05/2020	2.815,01	2.819,39	0,156%	2.842,79	2.843,41	0,022%	1	1
05/05/2020	2.878,75	2.882,62	0,134%	2.871,68	2.868,29	-0,118%	1	-1
06/05/2020	2.885,68	2.860,08	-0,887%	2.857,97	2.848,40	-0,335%	-1	-1
07/05/2020	2.878,26	2.879,89	0,057%	2.878,15	2.881,09	0,102%	1	1
08/05/2020	2.908,83	2.916,21	0,254%	2.928,61	2.929,22	0,021%	1	1
11/05/2020	2.906,69	2.912,20	0,190%	2.937,02	2.930,51	-0,222%	1	-1
12/05/2020	2.939,50	2.927,17	-0,419%	2.884,28	2.869,76	-0,503%	-1	-1
13/05/2020	2.856,86	2.859,43	0,090%	2.807,45	2.820,26	0,456%	1	1
14/05/2020	2.790,15	2.780,43	-0,348%	2.838,55	2.852,63	0,496%	-1	1
15/05/2020	2.829,95	2.836,56	0,234%	2.851,82	2.864,05	0,429%	1	1
18/05/2020	2.913,86	2.933,45	0,672%	2.965,82	2.952,65	-0,444%	1	-1
19/05/2020	2.948,59	2.957,94	0,317%	2.937,74	2.922,41	-0,522%	1	-1
20/05/2020	2.953,63	2.974,32	0,700%	2.974,13	2.975,45	0,044%	1	1
21/05/2020	2.969,95	2.970,61	0,022%	2.955,04	2.949,06	-0,202%	1	-1
22/05/2020	2.984,05	2.934,91	-1,647%	2.950,43	2.955,42	0,169%	-1	1
25/05/2020	Meomorial Day	Meomorial Day	Meomorial Day	Meomorial Day	Meomorial Day	Meomorial Day		
26/05/2020	3.004,08	3.007,91	0,127%	2.994,92	2.991,83	-0,103%	1	-1
27/05/2020	3.015,65	3.005,32	-0,343%	3.027,38	3.065,60	1,262%	-1	1
28/05/2020	3.046,61	3.046,09	-0,017%	3.039,05	3.029,71	-0,307%	-1	-1
29/05/2020	3.025,17	3.018,60	-0,217%	3.039,85	3.047,84	0,263%	-1	1
01/06/2020	3.038,78	3.048,15	0,308%	3.056,57	3.055,83	-0,024%	1	-1
02/06/2020	3.064,78	3.064,00	-0,025%	3.067,17	3.080,95	0,449%	-1	1
03/06/2020	3.098,90	3.105,50	0,213%	3.128,67	3.122,81	-0,187%	1	-1
04/06/2020	3.111,56	3.119,54	0,256%	3.101,49	3.112,41	0,352%	1	1
05/06/2020	3.163,84	3.184,37	0,649%	3.191,10	3.194,15	0,096%	1	1
		Avg. Return	0,020%		Avg. Return	0,050%	8	2

Taking these tables, we can see how there result positive average returns after the first 45 minutes of trading in all the cases, while after the last 15 minutes of trading there are positive average returns only for the NASDAQ Composite and the S&P 500 indexes and a negative average return in the Dow Jones Index. Moreover, in the rightmost columns it is shown the spread between the number of times there is evidence of the anomalies and when there is not. The only case where there are positive spreads, meaning that the anomalies showed up more than 50% of the days, is in the S&P 500 Index.

So, by implementing the buy and hold strategy every day for the sample period, we would have gained positive returns in all cases except that for when purchasing and selling in the last 15 minutes interval of the trading day in the Dow Jones Index. However, we cannot say that there is evidence of these anomalies as they happen not more than 50% of the times except that for the S&P 500 Index where there is stronger evidence of the first 45 minutes up effect happening the 66,67% of the trading days (16/24), and slightly weaker evidence of the last 15 minutes up effect happening the 54,17% of the days (13/24).

In conclusion, if we link the findings of this analysis with previous literature we find discordant evidences which may be caused by the general change in financial markets' environment over time or more specifically by the period of the sample in exam which sees a distorted version of reality. It could be said that, even if without strong evidence, these anomalies exist in the S&P 500, but it is not possible to say whether those strategies exploiting the periodicity in returns patterns would have been profitable as bid-ask spreads are not included in the analysis.

Summary and Conclusions

Economists realized that classical financial theories, by themselves, are not sufficient to explain reality. Theories such as The Expected Utility Theory and The Efficient Market Hypothesis need the support of further tools to comprehend the psychological factors which affect investors in their decision-making process, especially in conditions of high uncertainty.

Knowledge in economic and financial fields has been developing, allowing economists to better understand what happens in the surrounding environment. It is demonstrated how men adopt shortcuts, even called heuristics, when they reason in order to ease the decision-making process in front of a difficult problem. Some common heuristics see individuals affecting each other's behavior, individuals having excessive confidence in themselves or individuals giving different weight to gains and losses.

The explanation to such anomalies was provided by the behavioral finance, which after the conduction of different psychological studies, also suggested several guidelines to correct the same errors resulted from previous analyses such as financial education, transparency in information, disclosure policies and the assistance of intermediaries like the financial advisor.

Instead, due to neurosciences trying to explain individuals' behavior, it has been highlighted a similarity between financial markets and natural ecosystems: the processes of information selection and decision structuring are not only analytic but are influenced by elements external to individuals, like the environment for example, which are subject to changes caused by natural selection dynamics.

Thanks to the combined work of psychologists, neuroscientists and economists studying cognitive errors of investors in financial markets, it was possible to find, analyze and comprehend many anomalies.

Obviously, the main objective of investors is to make profits out of their investments, and the easiest way to achieve it is to find some errors or anomalies which would allow riskless profitable opportunities.

The financial market is characterized by many anomalies of different kinds, one of them is the periodicity in the daily pattern of some economic variables like stock returns and bid-ask spreads. So, researchers, through econometric and statistical tests over stock indexes, tried to find evidence that these anomalies actually exist.

The first analysis reported in this thesis was conducted with data from 1998 over the Athens Stock Exchange which was divided into four different sub-indexes grouping stocks according to their business sector. In all sub-indexes it was found evidence that returns followed a U-shaped pattern during the trading day, meaning that returns were high at the beginning and at the end of the trading session, touching the bottom in the middle of the session. Furthermore, it was tested whether a trading strategy exploiting this anomaly was more profitable than a passive "buy and hold strategy". The result was that not only it was more profitable, it was even safer. The U-shaped pattern produced evidence of both "middle of the day effect" and "time of the day effect" which is line with many other studies.

In fact, similar outcomes were provided in the second paper which is a study like the previous one but carried out in this case over the New York Stock Exchange. With data taken from 2001 to 2005 it was documented a significant continuation of returns at intervals of one trading day. Moreover, this was not the only anomaly documented, it was found evidence of a daily periodicity in bid-ask spreads of the same order of magnitude. Even here, for returns as for spreads, the continuation had a U-shape being more pronounced at the beginning and at the end of the day. In fact, investors who tried to profit from this predictable pattern in stocks lost money after paying the bid-ask spread.

For this reason, economists found reasonable to examine whether if there exists a periodicity in returns why shouldn't there exist a cyclicality in bid-ask spreads as well, and why not even in non-US-based stock market indexes.

In the third study it was found evidence which confirmed the fact that bid-ask spreads in the NYSE in 1989 were higher at the beginning and at the end of the trading day, and then, the same analysis was conducted in the fourth reported empirical test over the London Stock Exchange during the first quarter of 1991. Even here, evidence supports the theoretical model suggesting that spreads are U-shaped, they are at their highest value at the market open, constant throughout the day and then widen again slightly before the close of the trading session.

The case studies that have been discussed in this thesis are conducted over different typologies of stock markets located across different countries. This choice is not accidental, it is intentional. It is important that the predictions of theoretical models are tested in a variety of institutional settings so as to examine their strength. The behavior of market variables appears to be closely linked across different markets especially at the open and at the close of the trading day. The similar patterns in returns and bid-ask spreads seem to outweigh each other, wiping out any apparent profit opportunity. This was tested in the last, concluding and gathering analysis conducted over both the NYSE and the Russian stock market. The data used for American stocks are relative to the period going from 2005 to 2011, then divided into three sub-periods representing different economic cycles. Instead, for Russian stocks were used data taken from the single period going from 2011 to 2013. In this study, have been tested, for both markets, the most common hypotheses suggested by previous literature: there exists a first 45 minutes up effect and a last 15 minutes up effect which are profitable if exploited, and finally that these anomalies are influenced by the economic cycle in which they are.

The difference with previous studies is the inclusion of variable transaction costs, namely bid-ask spreads. Evidence from this test suggests that all the hypotheses are rejected for both markets, with the only exception being the third one as the results for the last 15 minutes up effect vary depending on the sub-period.

In other words, this analysis suggests that previous studies supporting evidence of exploitable profit opportunities resulting from market anomalies are erroneous because do not take into account bid-ask spreads. In fact, the presence of these anomalies, taken by itself, does not represent a significant evidence of market inefficiency since risk-free profit opportunities do not exist when coming to practice, thus being consistent with the EMH.

The final part of the thesis has been dedicated to a study I personally elaborated over the Dow Jones, NASDAQ Composite and S&P 500 stock market indexes between May and June 2020. The analysis wanted to find evidence of the last discussed phenomena in the present situation which unfortunately happened to be distorted from ordinariness because of the uncertainty caused by the “Coronavirus Pandemic” which made stock markets crash on February 20, 2020.

The results report returns gross of variable costs represented by bid-ask spreads in previous analyses. So, they are not a proper indicator of whether it is possible to make profits by exploiting such anomalies, but they just show whether there exists such periodicity in stock returns pattern.

It resulted that in the sample period going from May 4 to June 5, 2020 the investigated stock market indexes did not show evidence of a first 45 minutes up effect nor of a last 15 minutes up effect, except that for the S&P 500 index.

In conclusion, joining the results found in previously analyzed studies with the results of the last study, the outcome is that by adopting trading strategies aimed at exploiting periodicity in patterns at the beginning and at the end of the trading session, it is not possible to make any profit. So, even if the last study contradicts what has been verified in previous literature, there is a common ground between them: intraday anomalies, whether exist or not, if taken by themselves are not enough to show evidence against the Efficient Market Hypothesis.

This means that from an intraday effect perspective markets are efficient as they do not allow any riskless profitable opportunity for arbitrageurs because it is like if markets self-regulate when these anomalies show up, by moving other market variables which make such profitable anomalies unexploitable. Anyway, it might be possible that with the development of new high frequency trading technologies, investors using such mechanisms could profit from such intraday patterns in returns in the very short run before other variables change. Even in the case this was true, the presence of arbitrageurs may be of fundamental importance to preserve efficiency in financial markets as they would have a corrective effect by increasing and decreasing the price of mispriced securities through their trading activity.

So, to have a better and wider understanding of financial markets it is needed that economists, researchers and scientists keep studying the behaviors, incentives and errors made by economic agents, and that they keep finding evidence to explain the phenomena recurring in the financial environment and how they evolve across time and different economic cycles while for now, we will have to embrace the idea that the aforementioned market anomalies are the exception that proves the rule: market efficiency.

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