FUNDAÇÃO GETULIO VARGAS

ESCOLA DE ADMINISTRAÇÃO DE EMPRESAS DE SÃO PAULO

ANYA BOUDAOUI

A STUDY OF BEHAVIORAL FINANCE:

BACKGROUND, THEORIES AND APPLICATION

SÃO PAULO

2011

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Dissertação apresentada à Escola de Administração de Empresas de São Paulo da Fundação Getulio Vargas como requisito para obtenção do título de Mestre em Gestão Internacional

Campo do conhecimento: Finanças

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SÃO PAULO

2011

Boudaoui, Anya.
A Study of Behavioral Finance: background, theories and application / Boudaoui, Anya.
- 2011.
98 f.

Orientador: Rafael Felipe Schiozer
Dissertação (mestrado) - Escola de Administração de Empresas de São Paulo.

1. Finanças. 2. Finanças - Aspectos psicológicos. 3. Investimentos - Aspectos psicológicos. 4. Mercado financeiro - Aspectos psicológicos. I. Schiozer, Rafael. II. Dissertação (mestrado) - Escola de Administração de Empresas de São Paulo. III. Título.

CDU 336.767

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Data de aprovação:

15 / 06 / 2011

Banca examinadora:

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RESUMO

Finanças comportamentais, ou economia comportamental,consiste em um campo teórico que justifica que existe importantes variáveis psicológicas e comportamentais que estejam envolvidos em actividades financeiras, tais como decisões de finanças corporativas e de investimentos (alocação de ativos, gestão de portfólios e assim por diante).

Este campo tem experimentado um crescente interesse de acadêmicos e profissionais da área financeira desde episódios de várias bolhas especulativas e crises financeiras. Na verdade, incoerências entre os eventos observados no mercado real e a teoria financeira tradicional estão levando mais e mais pesquisadores a olhar para modelos e teorias novos e mais abrangentes.

O objetivo deste trabalho é fazer uma revisão do campo de finanças comportamentais, ainda pouco conhecido pela maioria das pessoas. Este trabalho apresentará as suas origens e suas principais teorias, contrastando-as com as teorias tradicionais de finanças.

A principal questão que orienta o trabalho é identificar se esta área é capaz de fornecer melhores explicações para os fenômenos reais de mercado. Para esse efeito, o documento vai relatar algumas anomalias anomalias de mercado que não são explicadas pelas teorias tradicionais, que foram atualmente abordadas pelos estudiosos de finanças comportamentais. Além disso, o estudo faz uma aplicação prática para a atividade de gestão de carteiras, comparando a alocação de ativos resultante do modelo tradicional de Markowitz à obtida do modelo de Black e Litterman, que adiciona algumas questões de finanças comportamentais.

Palavras-chave: finanças comportamentais, preconceitos, aversão à perda, excesso de confiança, o enquadramento, o comportamento de manada, a carteira de baixa volatilidade, anomalias do mercado, o modelo Black-Litterman, o modelo de Markowitz.

ABSTRACT

Behavioral finance, or behavioral economics, consists of a theoretical field of research stating that consequent psychological and behavioral variables are involved in financial activities such as corporate finance and investment decisions (i.e. asset allocation, portfolio management and so on).

This field has known an increasing interest from scholar and financial professionals since episodes of multiple speculative bubbles and financial crises. Indeed, practical incoherencies between economic events and traditional neoclassical financial theories had pushed more and more researchers to look for new and broader models and theories.

The purpose of this work is to present the field of research, still ill-known by a vast majority. This work is thus a survey that introduces its origins and its main theories, while contrasting them with traditional finance theories still predominant nowadays.

The main question guiding this work would be to see if this area of inquiry is able to provide better explanations for real life market phenomenon. For that purpose, the study will present some market anomalies unsolved by traditional theories, which have been recently addressed by behavioral finance researchers. In addition, it presents a practical application of portfolio management, comparing asset allocation under the traditional Markowitz's approach to the Black-Litterman model, which incorporates some features of behavioral finance.

Keywords: behavioral finance, heuristic-driven biases, loss aversion, overconfidence, framing, herd behavior, low volatility portfolio, market anomalies, the Black-Litterman model, the Markowitz model.

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Chapter I

Introduction

Definition and Historical Background

This introductory chapter to this paper has for objective to present the field of study that constitutes behavioral finance. It will introduce the field's historical background through the research conducted by its main partisans.

I. What is Behavioral Finance ?

"*Behavioral finance is the study of the influence of psychology on the behavior of financial practitioners and the subsequent effects on market*." (Sewell, 2005)

"*I think of Behavioral finance as simply "open-minded" finance*". (Thaler, 1993)

"*This area of enquiry is sometimes referred as "behavioral finance" but we call it "behavioral economics". Behavioral economics combines the twin disciplines of psychology and economics to explain why and how people make seemingly irrational or illogical decisions when they spend, invest, save and borrow money*." (Blesky and Gilovich, 1999)

"*The objective of behavioral finance is to discover and remedy to the constated deviations from rational decision making in the investment process*." (Mahmood, Zohidkhan, Ahmad & Anjum, 2011)

Behavioral finance, or behavioral economics, seeks to understand and quantify the impact of emotions, psychology and general individuals' behavior on investing activities and financial decisions. It represents finance from a broader social sciences perspective including psychology and sociology. This field had known an increasing interest since its inception in the 1970's. Its theories had been mostly elaborated in contraction of the dominant theories proposed by the traditional finance researchers. The anomalies and incoherencies of this field's theories pushed behavioral finance researchers to look for new models. Its main contraction with traditional finance is about the Efficient Market Hypothesis. The later hypothesis argues that speculative assets prices always incorporate all the information about fundamental values and prices only change because of sensible information. The main proponent from this theory is the economist Eugene Fama, who published in 1970 a defense of this theory called "*Efficient market: a review of empirical work*".

II. Historical Background

« *We suffer more…when we fall from a better to a worst situation, than we ever enjoy when we rise from a worst to a better* ». This citation, representing in some ways the "*loss aversion*" theory, is from Adam Smith, economist of the 18th century. However, Adam Smith is not even the first one mentioning theories close to the behavioral field that we know, which started to grow exponentially since 1980's. Indeed, more than a century before him, Gustave Le Bon published "*The Crowd: a study of the popular mind*" (1896) which is still a reference among the literature about social psychology. Moreover, the belief that prices' movements on the exchanges were dependent to an important degree on the mental attitudes of the investors was first presented as early as 1912 by Selden in his book "*The psychology of the stock market*".

The theories of cognitive dissonance emerged in 1956 thanks to Lean Festinger. These theories describe the fact that, when an individual is subject to two cognitions that are inconsistent, this will produce a state of "*cognitive dissonance*". As this is an unpleasant experience, most people will try to decrease it by altering their beliefs.

1970's and the beginning of constatation of anomalies

In 1973, Tversky and Kanheman performed several studies about the "*availability heuristic*". They describe it as a "*judgmental heuristic*" with which individuals evaluate the frequency of a class, or the probability of an event, by their availability. It means that they evaluate them by the ease with which the relevant information concerning them comes to mind. In 1974, the same researchers described two other heuristics that are employed when making judgment under uncertainty: the "*representativeness heuristic*" and the "*anchoring-and-adjustment heuristic*". The first one represents the fact that people tend to rely too much on stereotypes when judging the probability that an event belongs to a certain class. The second one is characteristic of the fact that people, when making estimates, tend to start from an initial value that they then adjust to yield a final answer. The main conclusion they drew from their studies concerned the effects of these heuristics, and of numerous others that we will study later on, on individuals' investing behavior. Indeed, people tend to make decisions impacted by systematic biases because of these heuristics.

In 1979, Kanheman and Tversky criticized the "*expected utility theory*", used by traditional finance as a descriptive model of decision making under risk. They developed an alternative model which they called the "*Prospect Theory*" and that we will study in another chapter. Their findings permitted them to obtain the Nobel Prize of Economy in 2002. Principally, under the prospect theory, value is assigned to gains and losses separately instead of being assigned to the final wealth position of final asset holdings. The theory (confirmed by experiments) predicts a distinctive pattern of risk attitude: risk aversion for gains of moderate to high probability and losses of low probability; risk seeking for gains of low probability and losses of moderate to high probability. According to Kahneman and Tversky, investors' attitude is not consistent when dealing with the prospect of gains and losses. In reality, their attitude will be representing the opposite of these prospects. It diverges from traditional finance as it states that investors' behavior is actually consistent in profits and losses' prospects. The basic difference between the prospect theory and traditional finance theories is that investors who expect profits or gains tend to become risk adverse in order to stabilize their gains, but become risk seekers in the prospect of losses. On the contrary, traditional finance states that investors are consistent, and that they are risk adverse all the time.

These theories concerning heuristics and biased irrational investors are totally in contradiction with traditional finance theories and mostly with the Efficient Market Hypothesis. Indeed, according to its main artisan, Eugene Fama (1970), investors are rational and efficiently respond to new information regarding the stock market. Any decision they make fully reflect any information available. There is thus no chance of abnormal return event in the long run. Even if assets prices are not properly valued, the hypothesis said that they will come around to rational price level through the process of arbitrage.

<u>1980's literature and the evidence of excess volatility</u>

Behavioral finance theories mainly emerged in their most elaborated form in the 1980's. Thanks to empirical testing concerning investing patterns, it appeared that the market was not as efficient as described by the Efficient Market Hypothesis. The existence of certain anomalies such as the "*small firm effect*" or "*January effect*" was proof of some inconsistencies between the theory and the reality. According to behavioral finance theorists, the main reason for this discordance between models and reality was that traditional finance was not taking into consideration the importance of investors' behavior in decision making processes.

Several reasons were exposed by the researchers in order to justify the lack of rationality of investors. First, in 1980, Thaler argued that there were multiple circumstances when consumers act in a manner that is inconsistent with the traditional economic theory and proposed that the prospect theory be used as the basis for an alternative theory. He discussed also several other topics such as: the "*underweighting of opportunity costs*", the "*feeling of regret*" and the "*issue of self-control*" plus an introduction to his "*mental accounting theory*". Mental accounting is principally a set of mind operations that people use to organize, evaluate and keep track of their financial activities.

In 1981, Tversky and Kanheman introduce the notion of "*framing*". It is a psychological principle that rules the perception of problems, the evaluation of probabilities and that can produce shifts of preferences when the same problem is framed in different ways. On another subject, the same year, Schiller argued that the stock price volatility was far too high to be attributed to new information about future real dividends.

In 1985, De Bondt and Thaler gave an official start what is nowadays known as behavioral finance through their article "*Does the stock market overreact?"* Their main argument was that people tended to systematically overreact to unexpected and dramatic news. This phenomenon resulted in creating a weak form of efficiency in the stock market.

Moreover, a year later, Simon argued that sometimes investors made irrational decisions because they had a limited capacity to process the information available or revealed to them.

In 1988, Campbell found evidences of excess volatility in the stock market. The phenomenon of excess volatility implies that changes in prices occur for no fundamental reason. Behavioral finance argues that it happens because of things such as "*animal spirits*" or "*mass psychology*" phenomenon. His work confirmed the hypothesis that stock prices had more volatility than the efficient market hypothesis could explain. Indeed, the volatility of the overall stock market seems to not be explainable with any variant of the efficient market model in which stock prices are formed by looking at the discounted present value of future returns.

1990's and the blossom of behavioral finance

In 1991, Kanheman, Knetsch and Thaler discussed three anomalies that do not fit in the efficient market hypothesis model: the "*endowment effect*", "*loss aversion*" and "*the status quo bias*". Thaler published the following year "*The winner's curse: paradoxes and anomalies of economic life*" dealing with these anomalies and how they are in contradiction with traditional finance theories. Following the trend, Plous discussed the social aspects of decision making processes in "*Psychology of judgment and decision making*" (1993) and Grinblatt, Titman and Wermers studied the behavior of mutual funds in 1995. The three researchers found evidence of momentum strategy and herding behavior.

In 1996, Chan, Jegadessh and Lakonishok found evidence that price and earnings momentum strategies were profitable. It implies that the market only responds gradually to new information, which represents a phenomenon of under-reaction to new information, in contradiction with efficient market theories.

In 1997, Basu studied and revealed evidences asserting the existence of the "*conservatism*" principle which he interprets as earnings reflecting bad news more quickly than good news. One year later, Barberis, Shleifer and Vishny elaborated a model of investors' sentiment that displayed under-reaction of stock prices to news such are earnings' announcements and overreaction of stock prices to series of good or bad news.

In 1998, Eugene Fama defends the Efficient market hypothesis; he claims that the apparent overreaction of stock prices to information is about as common as their under-reaction. Therefore, he argues that there is no particular behavioral attitude that is responsible for any of the comportment as they are as common as the other. This argument is judged unconvincing by behavioral finance researchers as the two phenomena seem to occur in different circumstances and time intervals.The same year, Odean made tests and found evidences for the "*disposition effect*", which represents the tendency of investors to sell winning investments too soon and to hold the losing ones for too long. Meanwhile, Daniel, Subrahmanyam and Hirshleifer developped a theory of the security market based on investors' overconfidence about the accuracy of private information, and about biased self-attribution. The later tend to cause changes in investors' confidence as a function of their investments' outcomes. Both phenomenons can lead to events of market under-reaction and overreaction.

In 1999, Camerer and Lovallo experimentally found that overconfidence and optimism led to excessive businesses' creations. The same year, Odean argued that overall trading volume in the equity markets was excessive. He thought that this fact can possibly be explained by investors' overconfidence. He also found evidences of the disposition effect which led to profitable stocks to be sold too soon and losers to be held too long. Meanwhile, Veronsi elaborated a dynamic, rational expectation equilibrium model of asset prices. Within this model, among other features, prices tend to overreact to bad news in good times and to underreact to good news in bad times.

2000's literature, confirmation and recent findings

In 2000, Hong, Lim and Stein found evidences that firm-specific information, and most particularly negative ones, were diffusing only gradually across the investing public, which was responsible for the momentum in stock returns. The same year, Shleifer published a comparison of behavioral finance and the Efficient market hypothesis in "*Inefficient markets: an introduction to Behavioral Finance*", while Shefrin publishes his book "*Beyond greed and fear*", a reference within the behavioral finance field.

In 2001, Barber and Odean performed a psychological research which showed that men were more prone to overconfidence than women, especially in male dominated areas such as finance. This overconfidence tends to lead them to trade excessively. Indeed, they found that men were trading on average 45% more than women, and thereby they were decreasing their returns compared to women. The same year, Grinblatt and Kolharju studied buying and selling activities. They found evidenced that past returns, reference prices effect, tax losses selling, plus the fact that investors were reluctant to realize losses, were all determinants of trading activities. Meanwhile, Huberman provided compelling proofs that people strongly tended to invest in the familiar while often ignoring the principles of portfolio theory.

In 2002, Gilovich, Griffin and Kanheman published "*Heuristics and Biases: the psychology of intuitive judgment*". They defined three different categories of heuristics. First, there are general purpose heuristics such as "*affect*", "*availability*", "*causality*", "*fluency*", "*similarity*" and "*surprise*". In addition, there are special purpose heuristics such as "*attribution*", "*substitution*", "*outrage*", "*prototype*", "*recognition*" and "*choice by liking or by default*". Finally, there are additional heuristics such are "*representativeness*" and "*anchoring-and-adjustment*".

In 2003, Barberis and Thaler publish their "*Survey of behavioral finance*", reference paper, widely utilized in this paper. Most recently, in 2008, Birnbaum elaborated a transfer of attention exchange model and in 2009, Harrison and Rutström attempted the reconciliation of the expected utility theory and of the prospect theory by using a mix model.

Conclusion

In order to study financial markets, researchers have adopted the use of behavioral theories and applications to overcome the shortcomings of neoclassical financial approaches.
Behavioral finance attempts to integrate various elements neglected by traditional finance theory. The field agrees that, when making investment decisions, investors choose products matching their risk tolerance level. They tend to make up their mind based on the information available to them through various channels and sources, public and private.

However, on the contrary to traditional finance assumption, behavioral finance argues that their knowledge and past experience contribute considerably toward their risk assessment process of an investment. After determining their risk profile and attitudes, they will look for a suitable return for this level of risk tolerance. The aim of behavioral finance is to analyze phenomena on the market place, while still keeping in view psychological factors involved in the common behavior of investors.

Chapter 2

Heuristic-driven biases

A heuristic refers to "*the process by which people find things out for themselves, usually by trial and error*" (Shefrin, 2001). Behavioral finance attempts to identify the principles underlying these subsequent processes or "rules of thumb". According to the theory, they tend to initiate systematic errors that impact the market and stocks' prices. Indeed, agents rely on these heuristics and draw inferences from them according to the information at their disposal. They are thus susceptible to make certain mistakes because the general principles they developed are imperfect.

These heuristics are the main responsible for the biases that people, and therefore, investors have and which provoke erroneous decisions. They may surface in different contexts such as analysts' forecasts, investors' evaluation of funds performances, corporate takeover decisions and types of portfolio selected by individual or institutional investors.

This chapter has for objective to present and describe the different heuristics and biases that investors are subject to have according to behavioral finance. We will study their effects on investors' behavior and on the market in the following chapters.

I. Beliefs based biases

1. Overconfidence

One of the main bias, presented by Shefrin, but also by Barberis and Thaler in their "*Survey of behavioral finance*", is overconfidence. According to them, people are generally overconfident in their judgment, which can be seen in two different ways. First, the "confidence intervals" that agent attribute to their estimate of general quantities (i.e. the level of the Dow Jones in a year for instance) is way too narrow compared to reality (Alpert & Raiffa, 1982). Secondly, agents are often badly calibrated when estimating probabilities. The events they are generally certain that will occur actually occur only 80% of the time and the ones they judge impossible to happen tend to occur 20% of the time (Fishhoff, Slovic, Lichtenstein, 1977). To sum up, this factor is responsible for people setting overly narrow confidence bands; they evaluate the highest score too low and the lowest score too high.

2. Optimism and wishful thinking

This factor is represented by the fact that people show unrealistically good opinion of their own abilities and prospects (Weinstein, 1980). Over his study, Weinstein performed a survey which shows that 90% of the person interrogated believed that they possessed above average capabilities in domains such as driving skills, ability to get along with people and sense of humor. In addition, people tend to display systematic planning fallacy, where they predict that diverse tasks (i.e. such as writing papers for instance) will be completed much sooner than they actually are (Buehler, Griffin & Ross, 1994).

3. Representativeness

When people try to determine the probability that a data set A was generated by a model B, or that an object A belongs to a class B, they often use the representativeness heuristic. It means that they evaluate the probability by the degree to which A reflects the essential characteristics of B to their opinion (Tversky & Kanheman, 1974). More generally, it means that people tends to refer to judgments based on stereotypes. Even if this method can be useful, it can also provoke some severe biases. One of them is called the "*sample size neglect*". It represents the fact that, when judging the likelihood that a data set was generated by a particular model, people tend to fail to take the size of the sample into account in their estimation. In the cases where people do not know initially the data generating process, they will tend to infer it too quickly on the basis of very few data points (Barberis & Thaler, 2003).This belief that even small sample will reflect the properties of the parent population is also sometimes known as the "*law of small numbers*" (Robin, 2002). In the cases where people do know the data generating process in advance, the law of small numbers generates a "*gambler's fallacy effect*". This phenomenon arises when people inappropriately predict a reversal in a gambling or investing situation. It goes against the "*regression to the mean theory*". Indeed, people tend to believe that when a stock has been over performing the market several times in the row, it will probably be underperforming in the next cycle. However, regression to the mean suggests that, when there had been above average performances, the future performance will be closer to the mean. It will not be below it, like most people think, in order to satisfy the "*law of averages*". De Bondt reports that, because of the gambler's fallacy phenomenon, general market predictions are consistently overly pessimistic after three years of bullish markets and overly optimistic after three years of bearish market.

4. Conservatism, belief perseverance and confirmation bias

The conservatism bias is responsible for people having the tendency to react too little to new information, and to rely too much on their prior opinion. Indeed, once people have formed an opinion, they tend to be clinging to it too tightly and for way too long (Lord, Ross & Lepper, 1979). Therefore, people are first reluctant to search for evidence that contradicts their existing beliefs. Then, if they happen to find such evidence, they tend to treat it with excessive skepticism. The confirmation bias can also enter in play in this scheme when people misinterpret evidence that goes against their hypothesis as actually being in their favor. They are so persistent in their beliefs that they try to obtain a justification for them, even if the justification is an irrational one. For instance, if agents start to believe in the Efficient Market Hypothesis, they will keep believe in it long after compelling evidence to the contrary had appeared.

5. Anchoring

The anchoring phenomenon appears when people, while forming estimations, start with some initial, and possibly arbitrary value of the results. Once the estimations formed, they will just adjust away from it (Kanheman & Tversky, 1974). Experiments show however that the adjustment is often insufficient and that people anchor too much on the initial value. A representation of anchoring is the analysts' reactions to earnings announcements. Indeed, Shefrin argues that they do not revise their own estimates enough after the announcement in order to reflect the new information. As a consequence, positive earnings surprises tend to be followed by supplementary positive surprises, and the same goes for negative surprises.

6. Availability bias, emotion and cognition

When judging the probabilities of an event, agents often search in their memories and experiences for relevant information that could help them form a decision. This process can produce biased estimates because not all memories are similarly retrievable or "available".

Indeed, the most recent or salient memories will weight more heavily and will distort the estimate (Kahneman & Tversky, 1974). Emotions also play an important role in the way people remember events, which traditional finance theories failed to recognize. Cognition, as defined as "*the way people think*", is another element that needs to be taken into account as it plays a part in people's decision making process.

II. Preference based biases

1. Framing and Problem description

A frame is a form used by people to describe a decision problem. If agents are "*frame independent*", therefore the form would be irrelevant to the problem and would not interfere to the decision making process. Traditional finance affirms that framing is transparent, and therefore, as rational investors, agents are not considering the frame of a problem when making a decision. However, behavioral finance assumes that some frames are opaque. As a consequent, behavior and decision making can depend on the particular frame that affects the individual, depending on its opacity (Shefrin).

Problem description reflects a certain kind of framing. Indeed, there are numerous demonstrations that reveal a 30% to 40% shift in agents' preferences depending on the wording of a problem or of a situation. This fact shows the importance of the problem's description and thus of the way it has been framed. Traditional finance cannot explain such behavior as one of the main principle of rational choice is that the decision making process should be independent of the problem description or of its representation.

The framing heuristic concerns the way a problem or a situation is presented to the decision maker. The agents have a certain degree of flexibility in how they could think about a problem. In order to illustrate this fact, the Barberis and Thaler presented the following situation:

"A gambler goes to a race track and wins $200 in his first bet but then loses $50 on his second bet. Does he code the outcome of the second bet as a loss of $50 or as a recently won gain of $150?"

The process by which people formulate such problem for themselves is called "*mental accounting*" (Thaler, 1999). The important feature of mental accounting is the "*narrow framing*" phenomenon. Indeed, people have the tendency to treat individual gambles separately from other portion of their own wealth. When offered a gamble, agents often evaluate it as if it was the only gamble they face in the world rather than combining it with pre-existing gambles, to see if the new one is a worthwhile addition. Over a study, Tversky and Redelmeier (1992) showed the effects of framing and mental accounting through a survey. The following problem was proposed to a group of people:

"You are proposed the following bet: F (2000, 0.5; -500, 0.5). Questions:

- *Would you take the bet?*
- *Would you prefer to play F five times of six times?*
- *If you do not know the outcome of the five first times, would you be ready to play F a sixth time?"*

The results show that 57% of the subjects are not willing to take the bet; 70% would prefer to play F six times rather than five times; and 60% of the person surveyed rejected the possibility to play a sixth time if they do not know the gains and losses attached to the five first times. The results to the two last questions show a certain degree of reversal of preference according to what the agents know about the gains and losses. It suggests that some subjects are framing the sixth gamble in a certain way, by segregating it from the other gambles, as 60% of rejection is very close to the initial percentage of 57%. Therefore, the sixth gamble is almost taken separately as an individual gamble such as the very first one, considering the similarity of percentage of rejection.

2. Ambiguity aversion

People tend to have a strong aversion for ambiguity, as represented by uncertainty in results and situations for instance. Ellsberg showed this phenomenon by an experiment in 1961:

"*You are presented with two urns, 1 and 2. Urn 2 has 100 balls, 50 Red and 50 Blue. Urn 1 has 100 balls but the color mix is unknown. You are presented several gambles involving payment of $100:*

- *A: a ball is drawn from U1; you earn $100 if it is red and $0 if it is blue.*
- *B: a ball is drawn from U2; you earn $100 if it is red and $0 if it is blue.*

And then:

- *C: a ball is drawn from U1, you earn $100 if it is blue and $0 if it is red.*
- *D: a ball is drawn from U2, you earn $100 if it is blue and $0 if it is red."*

According to the results, the two gambles the most chosen were the B and the D. The persons surveyed had the tendency to avoid taking gambles with U1 which composition of colored balls was unknown. In this case however, the subjects make the assessment first that there is less than 50 red balls (thus more than 50 blue balls) in U1 by choosing the gamble B, and then they make the assessment that there is less than 50 blue balls (thus more than 50 red balls) in U1, which is impossible.

The experience suggests that people really dislike situations where are uncertain about the probability distribution of a gamble, that is why they tried to avoid to choose the urn with the unknown mix, even if it led to an impossible assumption. This phenomenon is representative of the "*ambiguity aversion*" heuristic. In their 1991 study, Heath and Tversky argued that in the real world, ambiguity aversion has a lot to do with how competent an individual feels about the way he can assess the accurate distribution. The opposite of ambiguity aversion is called "*preference for the familiar*" and is observed in situation where people feel especially competent in evaluating a gamble.

3. **Loss Aversion**

The role of loss is one of the starting points Kanheman and Tversky findings about frame dependency. They provided evidence that people strongly disliked loosing. They argued that a loss had about 2.5 times the impact of a gain of the same magnitude. This phenomenon is also responsible of what Shefrin called the "*get-evenitis*" syndrome. Indeed, investors are really reluctant to sell at a loss and have the strong desire to get "even" before getting out of a position.

The vast majority of models assume that investors evaluate gambles according to the "*Expected Utility framework*". However, it has been shown that people tend to violate this framework when choosing among risky gambles (Von Neuman & Morgenstern, 1947). The expected utility model constitutes a good approximation to how people evaluate a risky gamble like investing in the stock market. However, it can difficultly to explain basic facts about the same stock market. Other models have thus been proposed in order to improve the current model such as the "*Weighted Utility theory*" (Chew & MacCrimmon, 1979), the "*Implicit Expected Utility theory*" (Chew, 1989), the "*Disappointment Aversion theory*" (Gul, 1991), the "*Regret theory*" (Bell, Loomes & Sugden, 1982), the "*Rank Dependent Utility*" theory (Segal, Yoari, 1987), and finally the "*Prospect Theory*" (Kanheman & Tversky, 1979 and 1992).

The Prospect theory represents the most promising of the above propositions for financial applications. It revealed itself as being the most successful at capturing experimental results. The theory tries to understand and explain people's attitude towards risky gambles. According to the two researchers, people tend to make choices impossible to justify based on rational grounds. Moreover, when choosing between different gambles, they tend to pick the one with highest value. This theory has several important features:

First, within the theory, utility is defined over gains and losses rather than overall final wealth position (Markowitz, 1952). There is a thus a violation of the expected utility theory by this focus on only gains and losses. To illustrate their assumptions, the authors performed a survey with the following problems:

Problem 1: "In addition to whatever you own, you have been giver $1000. You have now the choice between these two gambles: A (1000; 0.5) and B (500; 1)."

Problem 2: "In addition to whatever you own, you have been giver 2000. You have now the choice between these two gambles: C (-1000; 0.5) and D (-500; 1)."

When presented to a group of people, the choices B and C were the most popular. The interesting fact about this experiment was that the two problems offer the same situation in terms of final wealth position. A rational group of agents would be expected to choose the same, but yet they chose differently. It showed that they only focused on the gains and losses factors, and not on the final wealth position as should do rational agents.

Secondly, people tend to be risk adverse over gains and risk seeking over losses. They appear to have a greater sensitivity to losses than to gains, which is representative of the "*loss aversion*" heuristic.

Finally, the prospect theory explains people's preference for insurances and for buying lottery tickets by a process of overweighting a small probability (i.e. accident or winning the lottery), which leads to risk seeking. The same phenomenon of overweighting small probabilities introduces risk aversion over gambles which have a small chance to provoke a large loss.

The theory main goal is to explain why people make different choices in situation with identical final wealth level. It can also accommodate the effects of problem description or of framing.

4. Hedonic editing, cognitive/emotional aspects and self-control

According to Gross (1982), investors prefer some frames to others. This fact represents the principle of "*hedonic edition*". For instance, to encourage reluctant investors to sell loosing assets, the hedonic edited version would be to advise him to "*transfer his/her assets*".

The "*cognitive aspect*" concerns the way people organize their information whereas the" *emotional aspect*" concerns the way people feel as they register the information (Shefrin).

"*Self-control*" refers to the capacity of people to control their emotions. The lack, or perceived lack, of self-control that people tend to have is a reason for the "*do not dip into your capital*" heuristic (Shefrin). Indeed, investors are always happier to receive dividends than to not any, even when the issuance of dividends would not be the most rational decision, on a tax basis for instance. However, dividends are labeled as income rather that capital. They are "framed" as income. Investors feel thus more comfortable choosing a portfolio of stocks that feature high dividends streams. Spending these dividends for living expenses without dipping into their capital respects the general rules of self-control that people impose to themselves.

5. Regret & Money illusion

"*Regret*" is defined as the emotion felt for not having done the "right" thing or made the "right" decision (Shefrin). It is something more than the sole pain of loss; it is a pain associated with the feeling of being responsible for it. It can impact investors' actions as people who feel regret with more intensity do not have an important tendency to like variety, and thus portfolio diversification. Moreover, in order to diminish regret, some investors tend to use dividends instead of selling stocks to finance their consumption expenditures, which can leads to keep unprofitable stocks in their portfolios.

"*Money illusion*" is another framing aspect that impacts the way people consider and deal with inflation. According to Shefrin, even if people could figure out how to adjust for inflation, it would still not be a natural way of thinking for them. The normal way of thinking for most people is in terms of nominal values, which is something that investors still do.

III. <u>Conclusion</u>

To sum up, frame dependency deals with the difference between form and substance (Shefrin). The frame dependency bias holds that the differences in form can also become substantive. It reflects a mix of cognitive and emotional factors. The main emotional issue affecting investors' behavior seems to be the loss aversion. People tend to feel loss more acutely than gain of the same magnitude. Therefore, people tend to frame obscure losses and engage in hedonic editing in order to diminish the pain. In addition, they tend to feel a pain even stronger when they feel responsible for it, and this sense of responsibility leads to regret. Framing also help agents to deal with self control issues.

When confronted by these different findings described in this chapter - the heuristics and biases that can impact investors' rational decision making process - traditional finance economists defend that these beliefs do not have the impact that behavioral finance researchers give them. First, they argue that, through repetition, people will learn their way out of these biases and thus that they will not be recurrent problems. Then, they also state that experts in a field, and thus professional money managers, will be less prone to these biases and make fewer errors. Finally, the presence of powerful incentives will provoke the disappearance of these effects.

According to behavioral finance researchers, these factors pre-cited can effectively decrease the strength of the biases. However, there is little evidence that they are powerful enough wipe them out completely. It is accurate that repetition can have an effect. However, even when one is explained a bias and understands it, there is a good chance that he will still violate it later on. Concerning expertise, this factor can be responsible of more overconfidence from experts than from other investors, especially when they receive limited feedbacks about their prediction. Finally, while incentives can reduce the biases people display, there is still "*no replicated study has made rationality violations disappear by purely raising incentives*" (Camerer & Hogart, 1999).

Chapter 3

Study of market inefficiencies: limits to arbitrage and other anomalies

In addition to the heuristics and biases we studied in the preceding chapter showing that the rational investor hypothesis is not representative of the reality, there are other elements making behavioral finance researchers discuss the Efficient Market Hypothesis and some traditional finance theories.

In this chapter, two main blocks will be presented: the limits to arbitrage theory and anomalies unexplained by traditional finance theory. The subject of the existing limits to arbitrage has also been discussed by some traditional finance researchers such as Eugene Fama. However, this phenomenon had been exhaustively examined by behavioral researchers in order to contradict the efficient market hypothesis. The list of anomalies presented is not exhaustive but they are representative of the gaps in rational finance models and theories. Behavioral approaches and models elaborated in order to solve or explained these incoherencies and anomalies will be presented in Chapter 4.

I. The limits to arbitrage

1. The theory

One traditional objection from classical finance to behavioral finance theories is to say that, if some investors are irrationals, or less rational than others, the fully rational agents will prevent them by their actions to influence security prices for a very long period through the process of "*arbitrage*". On the contrary, behavioral finance shows that the actions of irrational investors can have a consequent and long term impact on prices.

According to classical finance theory, the price of a security should reflect its fundamental value. The latest is equal to the discounted sum of its expected futures cash flows. They are calculated when investors form accurate expectations while processing all available information, concerning the cash flows and the discount rate altogether. One of the cornerstones of traditional finance is that no investment strategy can allow the performer to earn “excess risk-adjusted return”, or an average return greater that is warranted for its risk. Therefore, the “*No free lunch*” saying is possible as mispricing cannot persist on the market without being corrected by the rational agents; they will quickly undo any deviation caused by the irrational ones (Friedman, 1953). Friedman illustrated his argument by the fact that if a share’s price is pushed down, relatively to its fundamental value, then the rational investors, sensing the opportunity to buy an undervalued stock, will buy it and thus push the price up. This buying pressure will quickly bring back the share to its fundamental value according to him. On the contrary, in the case of an overvalued stock, the selling pressure will push the price downward to reach its fundamental value as well. The main argument is that any mispricing event represents an attractive investment opportunity. Therefore, any rational investor will take advantage of the opportunity and by this way correct the mispricing.

On the contrary, behavioral finance argues that deviation from fundamental values can exist and be persistent, brought about by investors and traders who are not fully rational. One of main arguments is that correcting the mispricing can be both costly and risky and therefore trying to take advantage of the opportunity can be unattractive. The mispricing could thus remain unchallenged. Therefore, according to the Barberis and Thaler (2003), the “no free lunch” state of things could be true even in an inefficient market. Indeed, it can happen that there is not enough compensation to take advantage of a mispricing opportunity, but it does not mean that the prices are “right”. As a consequence, even if many researchers keep pointing out the inability of professional money managers to beat the market as a proof of its efficiency, this fact does not tell us if the prices really reflect the stocks’ fundamental values (Rubinstein, 2000; Ross, 2001).

2. Fundamental and noise traders’ risks

In order to study the limits to arbitrage, Barberis and Thaler examined the different risks and costs that may exist and prevent the strategies designed to eliminate mispricing events.

First of all, there always is some fundamental risk that the investor needs to deal with. Indeed, if he decides to buy an undervalued stock, there is still a risk that a bad news will push the price further down, which would result in a loss. As arbitrageurs are rational and well aware of this fact, they tend to short a “substitute” security (i.e. a security that is very similar to the first one, with similar cash flow) are the same time as they buy the first one. The problem however is that substitutes are rarely perfect, and even often highly imperfect. It thus makes it impossible to remove all fundamental risk thanks to this strategy. It can only protect the arbitrageur to somewhat adverse news about the industry as a whole but will left him vulnerable to more specific news concerning this stock and its company.

Secondly, the existence of the noise traders risk can also cause some limits to arbitrage. Indeed, there is still a risk that the mispricing being exploited by the arbitrageurs can worsen in the short run due to noise traders, and thus causing them losses. Even if a perfect substitute security is found, there is still a risk that the security price will go further down, in the case of an undervalued security. If it happens, it can force the arbitrageurs to liquidate their position earlier than expected (De Long, 1990; Shleifer & Vishny, 1997).
There is also a certain agency feature that needs to be taken into consideration as the professional portfolio managers are not managing their own money (“*the separation of brain and capital*”, Shleifer & Vishny, 1997). As the investors only evaluate the manager’s strategy on his return, he might decide to withdraw his/her funds if the mispricing worsen and potentially brought losses. The managers will be then obligated to liquidate their positions prematurely, which makes their strategies less efficient in fighting the mispricing. They could also be obligated to liquidate their positions if the original owner of the borrowed security shorted wants it back, which would force them to close up their positions. For all the reasons above mentioned, the risk existing in correcting mispricing could make the arbitrageurs more cautious when envisaging of taking advantage of it.

3. <u>The implementations costs</u>

Another limit to arbitrage pointed out by the authors is represented by the existence of implementations costs. Indeed, factors like the commission fees, the bid-ask spread or the price paid for the security could make it less attractive to exploit mispricing events. In addition to these costs, the short sale constraints that can exist could also prevent investors to take advantage of the opportunity, as short selling is often essential in the arbitrage process. The short selling constraints are represented by the fees charged for borrowing a stock. These fees could be expensive, but the problem could be that sometimes one cannot find a stock to borrow at any price. In addition, there are legal constraints as short selling is not allowed for many categories of money managers such as pension funds or mutual funds.

The cost linked with finding and learning about a mispricing, and the cost of the resources necessary to exploit it can also be added to these constraints (Merton, 1987). Indeed, as Shiller pointed out in 1984, the cost of finding and learning about a mispricing could be consequent as, even with strong noise traders' demand causing large and persistent mispricing, it might be generated so little predictability in return as to be almost undetectable.

4. Effects of implementation costs and noise traders' risks

Moreover, Barberis and Thaler illustrated the limitations that can have noise trader risk and implementation costs on arbitrage. They presented the two following situations:

First of all, if a mispriced security does not have a close substitute stock, the arbitrageur is then exposed to fundamental risk. Arbitrage can be limited in this situation if arbitrageurs are risk adverse. Indeed, fundamental risk is systematic and cannot be diversified by taking many such positions. Moreover, if the mispricing cannot be wiped out by a single arbitrageur taking large position in mispriced security, or by a large number of arbitrageurs each adding small positions in the mispricing to their current holdings, arbitrage actions can also be limited.

Secondly, if a perfect substitute to the stock exists and can be found, and only noise trader risk remains (i.e. systematic risk wiped out), the first one can still be strong enough to limit arbitrage (De Long, 1990). Indeed, the arbitrage can be limited if the arbitrageurs are risk adverse and have in addition short horizons in their investments. Actually, the possibility of early forced liquidations that has been mentioned earlier signifies that many arbitrageurs possess effectively short horizons (Shleifer & Vishny, 1997). In addition, on the presence of implementation costs, arbitrageurs might think that it is not worth it to intervene and therefore correct the mispricing. Moreover, there is always the possibility that the arbitrageurs prefer to trade in same sense than the noise traders and thus worsen the mispricing. Indeed, this seemingly irrational behavior from arbitrageurs could be caused by the actions of "feedback traders". Feedback traders tend to buy more of an asset over the current period if it has done well the past period. Taking this fact into consideration, if noise traders push the price of a security above its fundamental value, the arbitrageurs might buy it instead of selling it by anticipating that it will go even higher the following period. They anticipate that the security will attract even more feedback traders the following period, leading to higher prices, at which point the arbitrageurs can exit at a profit despite the different noise traders and implementation costs mentioned earlier. Hedge funds are known for trying to take advantage of noise traders. However, firm managers can also obtain some profit from it. Indeed, if they think that the share's price of their company is overvalued, they can provide some benefits to their shareholders by issuing some extra shares at these attractive prices. Moreover, by issuing extra shares, the stock price will eventually be push back to its fundamental value. However, this action includes its own amount of costs and risks. They are always involved in the share issuing process in a certain measure (i.e. necessary time or underwriting fees for instance), and the manager cannot be totally sure that the share are overvalued. By doing so, he always risks to deviate from his target capital structure.

5. Evidence of persistent mispricing events

Barberis and Thaler argued that the evidence of the limitation of arbitrage is seen through the presence of some persistent mispricing. However, only in a few cases the presence of these mispricing can be establish without a doubt according to them. This later fact is an argument of the Efficient Market Hypothesis partisan, Eugène Fama, used against some the results of behavioral finance. Indeed, what he calls the "*joint hypothesis problem*" makes it very difficult to provide a definitive evidence of mispricing and inefficiency. Indeed, any hypothesis of mispricing and market efficiency must assume an equilibrium model to which we can refer to, which would define normal security returns. Therefore, if efficiency is rejected and a mispricing is found, it could be or because the market is truly inefficient or because the equilibrium model used is itself incorrect (i.e. improper discount rate for instance). As a consequence, market efficiency as such cannot be totally rejected when finding a mispricing (Campbell, Lo & MacKinley, 1997). Despite these arguments, researchers found number of financial phenomenon that are almost certainly mispricing and which show the limits of arbitrage.

To illustrate the effects that can have implementation costs on the prevention of arbitrage, Barberis and Thaler used a study case performed by Thaler and Lamont in 2002 focusing on two shares part of the Internet industry. According to this study, implementation costs had a major role in the mispricing. The event persisted as investors looking for the overvalued shares to short were told that these shares were not available or were quoted at a very high borrowing price. The demand for shorting these shares was so high that there was no supply to meet the demand, which provoked a limitation to arbitrage and a persistence of the mispricing situation.

6. The index inclusion effect

Another theory presented by the studies of Harris & Gurel and Shleifer (1986), is the "*index inclusion effect*". Indeed, when a stock is added to an index, it tends to jump in price by an average of 3.5% according to the studies, and much of this jump is permanent, without any change of its fundamental value. For instance, Yahoo had a jump of 24% over one day when it joined the S&P 500. It is thus a clear evidence of mispricing as when stocks are selected by the S&P for inclusion, the analysts are just trying to make the index representative of the American economy. The index inclusion does not convey any information about the level of riskiness of the firm's future cash flows, or any information about its future prospects. In these situations, the noise trader risk is substantial, and the price can rise even further in the short run. In addition, there is the hypothesis that this rise is more important for stocks with the worst substitutes and for which the arbitrage process is the riskiest (Wurgler & Zhuravskaya, 2002). Their study also shows that it can be really difficult to find good substitute securities for individual stocks, which can lead to the conclusion that must securities will know a rise when they are included in an index.

II. Other anomalies

There are several phenomena inexplicable by the traditional finance theories in the behavior of the stock market. Behavioral finance researchers attempted to understand and explain them through new theories using cognitive psychology findings.

1. The aggregate market puzzles

The most striking facts about the aggregate stock market behavior are the equity premium, the volatility and the predictability puzzles.

The first one is issued from the observation that there had been historically high excess rate of return on the aggregate stock market. For instance, over the period of 1871 – 1993, it was found that the average log return on the S&P 500 was 3.9% higher than on commercial papers (Campbell & Cochrane, 1999).

The second puzzle consists of the fact that stock returns and price-dividend ratios are both highly variable. Over the same data set and period, Campbell and Cochrane found that the annual standard deviation of excess log return on S&P 500 was 18%, while the annual standard deviation of the log price-dividend ratio was 0.27.

The third one consists of the fact that stock returns can be forecasted. Over the period of 1941-1968, it was found that dividend-price ratios were able to explain 27% of the variation of the cumulative stock returns over the subsequent four years (Fama & French, 1988).

These three phenomena are labeled as puzzles as they are hard to rationalized using traditional finance models. Indeed, according to traditional economic models findings, the average log return on S&P 500 should be only 0.1% instead of the 3.9% found; the annual standard deviation of excess log return on the S&P 500 should be 12% instead of the 18% result found; and the price-dividend ratio is supposed to be constant so it could not possess any prediction power over the variation of cumulative stock returns.

According to Schiller, it is also very difficult to explain the historical volatility of stock returns with any model in which investors are rational and discount rates are constants. Indeed, over the previous decades, economists thought that discount rates were close to constant over time, implying that the stock market volatility could only be fully explained by the irrationality of investors. Nowadays, there is an understanding that a rational variation of discount rate can help explain the volatility puzzle. However, behavioral finance theory argues that models with the presence of irrational beliefs can also offer a plausible way to consider the data results.

2. <u>The cross-section of average returns</u>

When a group of stocks, defined by certain characteristics, earns average higher returns than another, they are known by traditional finance theorists as “anomalies” because this phenomenon cannot be explained through the CAPM theory. There are several anomalies of this sort found by traditional and behavioral finance researchers.

Size Premium

Over a stock sample between the period 1963 and 1990, Fama and French found in 1992 than the average return of the smallest stocks was 0.74% per month higher than the largest ones. Even if they have a higher beta to compensate their higher risk, it is not enough to explain this difference of returns.

Long term reversals

Over the period 1926 and 1982, De Bondt and Thaler found in 1985 that the average annual return (i.e. average calculated on a three year basis) of loser portfolios was higher than the one of winner portfolio by approximately 8% per year.

Predictive power of scaled-price ratios

Scaled-price ratios encompass several variables such as book-to-market ratio or earning-to-price ratio. Over the studied period of 1963 and 1990, Fama and French found in 1992 that the average return of "*value stocks*" (i.e. stocks with high book-to-market ratio) was 1.53% per month higher than the average return of "*growth*" or "*glamour*" stocks (i.e. stocks with low book-to-market ratio).This difference is much higher than can possibly be explained by the difference in beta between two portfolios composed respectively of these two kinds of stocks. When performing the same study with the same sample, but comparing earning-to-price ratio, value stocks were still 0.68% per month higher in average return than growth stocks.

Momentum

The momentum effect is a quite usual phenomenon by which asset prices follow a trend for a long time, creating a growing discrepancy between their prices and their fundamental values until the tendency is reverse.

Jadadeesh and Titman (1993) performed a study leading to the result that the biggest prior winners stocks tend to outperform biggest prior loser stocks by an average of 10% on an annual basis. When comparing this study with the result obtained by De Bondt and Thaler previously explained, one can see the importance of the period length studied. Indeed, De Bondt and Thaler used the three-year prior returns for the stocks whereas Jadageesh and Titman used a six-month prior return period. Here, the challenge would be to explain why the extension of the formation period switches the results found.

Moreover, there is evidence that tax-loss selling creates some seasonal variation in the momentum effect. The selling pressure is represented by the fact that losers keep loosing which enhances the momentum effect. On the other hand, the selling pressure eases off at the turn of the year allowing prior losers to rebound and thus weaken the momentum effect. Grinblatt and Moskowitz argue in 1999 that tax-loss selling can explain a part of the momentum effect. Indeed, while selling stocks for tax purpose is rational, a model of predictable price variation based on this kind of behavior is not. According to Roll (1983), investors would need to be very irrational or even "*stupid*", to not "*buy a stock in December if the prices can be anticipated to go up in January*".

Earnings announcements

According to a study performed by Bernard and Thomas in 1989, on average, 60 days after an announcement, stocks with surprisingly good news outperformed the ones with surprisingly bad news by an average of 4%. This phenomenon represents the "*post-earnings announcement drift*". However, it cannot be explained by a difference in beta once again. Similar results were obtained by the researcher in 1996 while calculating the "surprise" factor in a different way.

Dividend's emissions and omissions

The shares of firms that provide dividends to their shareholders tend to significantly outperform the market portfolio over one year after the announcement. On the contrary, the shares of firms that do not provide dividends tend to largely underperform the market portfolio over the same period (Michaely, Thaler and Womack, 1995).

Stocks' repurchases

Two different studies were conducted on this topic, one by Ikenberry, Lakonishok and Vermaelen and one by Mitchell and Stafford both in 1995. The first study focused on the period between 1980 and 1990 and the second on the period between 1960 and 1993. Both studies revealed that the shares of a firm which conducted a repurchase operation tend to outperform a control group of shares with the similar size and book-to-market ratio by a substantial margin over the four following years.

Primary and secondary offerings

The average return of shares over the five following years after an issue operation is significantly below the average return of shares from similar non issuing firms (Loughran & Ritter, 1995 – study of the period between 1970 and 1990).

Here, one can attribute importance to cross-sectional correlation. Indeed, if a firm announces a repurchase shortly after another one did, its four year post event return cannot be considered as totally independent from the other. A more general concern would be "*data mining*". If one lists or ranks stocks in different ways, one is bounded to discover cross-sectional differences in average returns, which makes the results of these studies pretty difficult to appear independent. However, there are ways to reduce the data mining factor. One can use only important announcements for the study, and not obscure or one with marginal characteristics which are more easily affected by other factors in the market. Moreover, it is also useful to perform study out of sample tests to see if the evidence found can be replicated in other data sets.

The Three-factor model

The challenge for traditional finance theorists is to be able to explain cross-sectional evidences emerging from a model with fully rational investors. As an attempt to do so, French and Fama elaborated in 1993 the "*three-factor model*". This model makes a good job at explaining the average return of formed portfolio based on size and book-to-market ranking. The factors used in this model are the return of the market portfolio, the return on a portfolio of small stock/large stocks (size factor) and the return on the portfolio of value stocks/growth stocks (book-to-market factor).

The problem with traditional approach is that it is the weightings or the betas that determine the average return, but there is not enough emphasis on the firm's characteristics. In his 1997 study, Titman shows that stocks with different weights or loadings but with same book-to-market ratio have the same average returns.

The other problem with the rational approach is that there is an issue on assessing correctly the riskiness of stocks. Indeed, the stocks with the lowest book-to-market ratios earn on average a return below the risk free rate. It is not easy to explain why then a rational investor would be willing to accept a lower return that a stable and safe T-Bond on a risky and volatile portfolio.

3. Closed-end funds and Commovement

Closed-end funds

A closed-end fund only issues a fixed number of shares. Investors can purchase the shares on the exchange from another investor at prevailing price. On the contrary, if an investor wants to buy a share from an open fund, the fund will create one and will sell it to him at the share's net asset value. Typically, closed-fund shares trade at a discount of the net asset value of 10%. The possible explanation is that a investor needs to make more researches about them at some costs and there are some tax liabilities.

Lee, Shleifer and Thaler (1991) performed a study about what they called the "*closed-end fund puzzle*". They found that the primary owners of closed end fund were noise traders, who have generally irrational swings in their expectations about future revenues. This phenomenon affects the difference between prices and net asset values. Therefore, rational investors demand compensation for the noise trader risk, hence the discount.

Commovement

This issue comes from the observation that closed-end funds' shares commove very strongly with one another, and that the class commoves as a whole with small stocks, without having any obvious explanation for it. Many examples of returns' commovement can be explained by the correlation between the securities' cash flows. However, "twin stocks", which have similar cash flows streams but are trading in different location commove strongly with their respective stock exchanges and less with each other.

According to Lee, Shleifer and Thaler, many investors choose to trade only a part of all available securities. It induces as a consequent a common factor between these securities they are holding, which is especially flagrant when their sentiment changes.

In addition, Barberis and Shleifer (2003) argued that, in order to simplify the portfolio allocation process, many agents start by dividing stocks into groups according to certain categories such as “small-cap stocks”. After that, they allocate their available funds across these categories. However, if the same categories are also adopted by noise traders, the price pressure from a possible coordinated demand will generate some common factors between the stocks. In the case where an asset is added to a category, it should thus begin to commove with it a lot more strongly than before.

Chapter 4

Application of behavioral finance theories

Section I: Some behavioral models

Section II: Behavioral explanations to financial anomalies

This chapter aims to introduce some models and approaches attempting to solve or explain the anomalies studied in the preceding chapter.

Section I

Some behavioral models

I. The feedback model

The price to price feedback theory is one of the oldest theories on the financial market. It argues that when speculative prices go up it creates on the meantime success for some investors but may attract attention and heighten expectation. This phenomenon leads to further prices' increase. The feedback keeps going, and if not interrupted, it may produce a speculative bubble after many rounds. These high prices are however not sustainable on the long term, as they are this high only because of expectations of further price increase. The bubble will eventually burst and the prices will crash. The feedback that created and sustained the bubble contained the seeds of its own implosion. Therefore, the end of a speculative bubble event can be unrelated to new information about the prices' fundamentals. In the same way, feedbacks can produce negative bubbles, creating a downward price movement. The pessimistic word of mouth will keep the prices on their downward trend until they reach an unsustainably low level.

The feedback model, also known as a "herd behavior" phenomenon, is mostly behaviorally based and inconsistent with traditional finance models of rationality. Its origins came from a long time ago. We can find evidence of the feedback theory in 1637 in an anonymous description in the middle of the "*Tulipmania*" (excerpt published by Shiller in

2002) and in the description of the same event by Charles Mackay in 1841. More recently, Schiller published the "*Irrational exuberance*" in 2000, at the pick of the internet stock market bubble. His main argument was that the word of mouth produced the bubble, which opened the possibility of downward feedback afterwards and gave dangerous outlooks for the stocks in the future. An experimental evidence of the feedback theory had been provided by the psychologists Andreassen and Kraus in 1988. They found that when people were shown real historical stock prices and invited to operate trade simulations they tended to extrapolate past prices changes when these prices appeared to exhibit a trend from one period to another. In addition, Smith, Suchonek and Williams (1988) created experimental markets in which bubbles were generated in concordance with the feedback theory.

Feedback can produce complicated dynamics and they can be source of apparently inexplicable phenomenon that we can see in financial markets. According to Daniel, Hirschleifer and Subramayan (1999), people are prone to a "*self-attribution bias*" that can also promote the feedback theory. It represents a pattern of human behavior whereby individuals attribute events that confirm the validity of their actions to their own high ability and attribute events that disconfirm their actions to bad luck or sabotage.

II. A psychologically-based investment model

More recently, Mahmood, Ahmad, Zahidkhan and Anjum (2011) attempted to elaborate a psychologically-based investment model in order to examine the role of different socioeconomic, demographic and attitudinal factors affecting investment decisions of investors in the market place. Their model has for goal to "*describe the impact of past investment experiences, of variation of regulatory policies and asymmetric information, of their marital status, gender and sensation seeking, on their reinvestment intention and their returns expectations through the mediating role of risk propensity and risk perception*". To sum up, the model aims mainly at knowing the mechanism underlying the investors' behavior in the stock market and to help understand investment expectations about returns through risk perception.

1. Foundations and Design

According to Warneryd (2001), new information is the cause of fluctuation of stock market's prices. Therefore, changes in investors' decision tend to happen on the basis of their expectations regarding expected future information. Different types of information act as "*external stimulus*" for the investors, due to their power to affect their investment decisions. For instance, a variation of regulatory policies can affect their investment strategies. A change of monetary policy on the exchange rate or on the rules of listed companies has an impact on agents' strategies as well. However, the phenomenon of asymmetry of information can become a problem in a model where information is the cause of prices' fluctuations. Indeed, due to a lack of proper disclosure of information, all of it is not always available to all investors. Therefore, some agents are more informed than others, which is a cause of irrational decision making.

Skihin and Pablo (1992) argue that past experience and the risk perception of investors are important factors for framing a problem. Perception of risk is defined by the assessment of risk in an uncertain environment. In these situations, investors tend to develop inferences about the result of their potential investment by drawing conclusion from those inferences. Concerning past experiences, they play a role in the sense that investors who have regular experiences of investing possess a higher level of risk tolerance compared to people who do not have a comparable experience. According to Cortor and Chen (2006), this factor is one of the reasons of the existence of high risk portfolios and low risk portfolios instead of more balanced ones. Moreover, Kathleen Byrn (2005) shows evidences that the investors' risk tolerance increases if they had successful investing past experiences, but decreases in the case of unsuccessful ones. This argument means that a positive correlation exists between investors' experiences and their risk tolerance level. This argument is actually in conflict with Kanhneman and Tversky's Prospect Theory. Indeed, the Prospect theory does not cover the aspect of past investing experiences' effects on future behaviors and only admits the effects of their attitudes towards future gains and losses.

Gender is also an important variable. Indeed, women tend to be more conservative and risk adverse than men (Fellner & Maciejovsk, 2007). According to Ronay and Kim's study (2006), attitudes toward risk by the two genders are the same at the individual level but at the group level, male group are found to be more risk-takers.

Another aspect to consider is the degree to which an individual is risk seeking. Eysenck and Eysenck (1978) argue that in the general life risk taking and adverse attitude are parts of the general traits of an individual's personality. Zuckerman (1983; 1984) confirms this finding and adds that this sensation-seeking attitude prevails in financial decision making. Sensation-

seeking is defined by the consent to accept various types of risk for the sake of making new and complex experiences.
In addition to gender and sensation-seeking personality types, individuals' marital status also plays an important role in determining the agents' risk perception. According to Grable's study (2000) and Chou and Chang's study (2010), married investors have less risk perception as they appear to be more experimented than unmarried investors. Moreover, among married investors, longer-time married individuals possess the most risk tolerance due generally to more disposable income.

2. The Proposed Model

Mahmood, Ahmad, Zahidkhan and Anjum choose a set of dependent and independent variables to build their model, based on the findings described above.
The dependent variables chosen are the investor's reinvestment intention and his/her return expectation. They are set as dependent due to their importance in stabilizing the stock market. On the other hand, the independent variables are the investor's experience, the changes of regulatory policies (about the stock market, the exchange rate or listed companies for instance), the information asymmetry, the marital status, the gender and the sensation seeking/avoiding attitude. Moreover, the researchers add two mediating variables to their model which are risk perception and risk propensity or risk tolerance.
The model will function by studying the effect of the independent variables on the dependent variable through the mediating effect of the mediating variables.The objective of this model is to present an expanded model which explains the risk perception characteristics of different variables and their effect on reinvestment intention and returns expectations of investors.

3. Model's hypothesis

Several hypotheses are meant to be tested through this model:

- The first hypothesis is to see if investors' past investment experiences and their risk propensity are positively correlated, and if risk perception and risk propensity are negatively correlated. Indeed, as we have seen earlier, past experiences are used to anchor values which can create overly optimistic investment behavior if the past experiences were good ones, and vice and versa. It shows that past experience and risk propensity are effectively positively correlated. Moreover, in the case of positive past experiences, it would provoke an overconfidence of the investor, and thus a high tolerance for risk and the engagement in high risky investment. Therefore, risk perception and risk tolerance seem to be negatively correlated as overconfidence tends to reduce risk perception of investors when the tolerance is high, and vice and versa.

- The second hypothesis is to see if changes or variations in regulatory policies relating to sources of risk (stock markets, exchange rate, listings) and risk perception are positively correlated. According to the authors, spontaneous changes of regulatory policies affect investors' risk perception. They argue that important or numerous changes of policies increase investors' risk perception, which shows a positive correlation between the two variables.

- The third hypothesis concerns the possible positive correlation between information symmetry and investors' risk perception. Information availability and symmetry play an important role in investment decisions. If the information about the market and listing are symmetric, it means that all investors have the same information. If not, there is a phenomenon of information asymmetry which could increase investors' risk perception. This shows the positive correlation between the variables.

- The fourth hypothesis is to see whether or not married investors have a lower risk perception than unmarried investors. According to the studies we have seen earlier, married investors believe that they tend to have more knowledge about the markets and life in general. This element tends to make them more risk tolerant and to have low risk perception, in addition to the fact that they generally possess more disposable income. Marital status seems then to have an effect on risk perception and tolerance, and married investors appear to effectively have a lower risk perception than unmarried investors.

- The fifth hypothesis concerns sensation seeking attitude and to see if it negatively correlated to risk perception. Indeed, it appears that investors with attitude to take on more risk have the tendency to accept high risk investment opportunities because of the general traits of their own personality, as compared to some other investors who are risk adverse by nature. Therefore, sensation seeking, or risk seeking attitude, seems negatively correlated with investors' risk perception.

- The sixth hypothesis is related to the risk perception differences between men and women investors. Risk perception of men investors is supposed to be lower than for women because men are generally more risk tolerant.

- The seventh and last hypothesis concerns the possible positive correlation between returns expectations and negative reinvestment intensions. Indeed, if the risk perception of investors is high, he will expect high returns or he will not be willing to reinvest, and vice versa.

4. <u>Discussion and problems</u>

All the hypotheses and results described earlier are presented within the model. Risk perception represents a key role in this model. However, this behavioral model still possesses some shortcomings. The main one is that it possesses limits in terms of empirical testing. Even if the hypotheses and solutions used to elaborate the model are based on earlier studies and tests done by other researchers, the model in itself lacks of an empirical feature to test these hypotheses themselves. It is more a useful representation and gathering of elements that investment professionals should take into account while performing investment decisions or designing portfolios for their clients. Nevertheless, this model illustrates in a pretty clear fashion the different effects and implications of some behavioral characteristics of investors on the financial markets and open the way for more empirical testing that could be done in the future.

Section II.

Behavioral explanations to financial anomalies

I. The aggregate stock market : the financial puzzles, a behavioral finance approach

The main issue of this puzzle is that even though stocks appear to be an attractive asset - they have high average returns and a low covariance with consumption growth – investors seem unwilling to hold them. It appears that they demand a substantial risk premium in order to hold the market supply.

Behavioral finance considers two approaches to this problem, both based on preferences: the Prospect Theory and the ambiguity aversion heuristic. Both approaches try to understand why investors seem fear stocks, leading them to require a high equity premium to hold them.

1. The Equity Premium Puzzle

A Prospect theory approach

The Prospect theory argues that when people are choosing between two gambles, they compute gains and losses for each one of them and they select the one with the highest prospective utility. Therefore, agents might choose a portfolio allocation by computing, for each different allocation, the potential gains and losses in the value of their holdings. They will then take the allocation with the highest prospective utility. As a consequence, a person that monitors his/her portfolio regularly, on daily basis for instance, may contract an aversion for stocks. Indeed, as stocks go up and down all day long, the loss factor is more salient. On the contrary, a person who monitors only once per decade will probably not contract any loss aversion. In reality, stocks offer a small risk of losing money at a 10 year-horizon, which makes the loss impact a lot less important.

In 1995, Benartzi and Thaler studied how investors with prospect theory type prefer allocating their financial wealth between T-Bills and the stock market. They evaluated how often investors would have to evaluate their portfolio in order to make them roughly indifferent between investing in stocks or in bonds. In another way, how often they would need to evaluate their gains and losses and still be satisfied in holding stockst. According to their experiment, investors would need to monitor their portfolio only once a year in order to become indifferent. The experiment also showed that the way people tend to frame gains and losses is plausibly influenced by the way the information is presented to them, confirming the "*problem description*" heuristic. When monitoring their financial wealth more than once a year, a combination of a loss aversion feeling and frequent evaluations provokes a phenomenon of "*myopic loss aversion*" according to Benartzi and Thaler. However, this explanation is only a suggestive one based on behavioral principles to the equity premium puzzle.

Barberis, Huang and Santos were the first ones to attempt to build a solution into a dynamic equilibrium model of stock return in 2001 in order to solve the equity premium puzzle. In this model, the investors get utility from consumption and from changes in the value of their holdings of risky assets in between a certain period of time. The researchers show that loss aversion can provide a partial explanation of the high price-dividend ratio on the aggregate market. However, this factor depends heavily on the importance of the second source of utility, the utility from changes of the value of their risky asset holdings. The results show that the psychological pain of losing an amount of $100 in the stock market is approximately equals to the consumption-related pain of having to consume $100 less.

Moreover, the studies assume that investors are prone to narrow framing. They get utility for changes in the value of one specific component of their total wealth: financial wealth for Benartzi and Thaler, and stock holdings for Barberis, Huang and Santos. And even if investors have long term investment horizons, they will still evaluate their portfolio on an annual basis. Barberis, Huang and Santos explore in addition the possibility of cross-sectional narrow framing that can be motivated for several reasons. Narrow framing in a cross-sectional context means that investors make each trading decision in isolation and are unable or unwilling to aggregate gains and losses of individual stocks in their portfolio (Kumar & Lim, 2008). As a consequence, they can feel regret from non-consumption, which represents the pain felt when one realizes that he could would have been better off if he had not perform a certain action or taken a certain decision in the past. As a consequence, if the stock holdings fall in value, the investors may regret the specific decision they made to invest in stocks. Such feelings are captured by defining utility directly linked over the changes in financial wealth or in value of holdings.

Another scenario would occur when investors are afraid of a decrease of their consumption below their habit level. The right thing to do would be to consider a stock market investment as a merger of the stock market risk with other pre-existing risks such as labor income risk, to see if the additional risk of the investment is worthwhile. They could then compute the likelihood of their consumption level falling below habit according to this new situation. However, as it is pretty complex to perform, they might just focus on the gains and losses in the stock market alone instead of considering the total wealth situation.

An Ambiguity Aversion approach

As we have seen before, there is evidence that people dislike ambiguity or situation where they are not sure of what the probability distribution of a gamble is. Ambiguity aversion is particularly relevant for finance as investors are often uncertain about the distribution of stock returns.

When faced to ambiguity, people tend to consider a range of possible probability distributions and act to maximize the minimum expected utility under any of these candidate distribution (Camerer & Weber, 1992). The agents always try to guard themselves against worst case scenarios. According to Anderson, Hansen and Sargent, the ambiguity aversion and minimum expected utility maximization framework can be used in pricing problems and portfolio choices. Maenhout, in 1999, tries to apply this framework to the equity premium puzzle, assuming that the fear of misspecification of the probability distribution lead to ask for substantially higher premium. However, he adds that to explain the 3.9% equity premium mentioned earlier, there will be a need of an unreasonable high concern about misspecification. Therefore, ambiguity aversion is only a partial solution to the equity premium puzzle.

2. The Volatility puzzle, a behavioral approah

The puzzle represents the fact that the volatility of returns appears to be higher than the volatility of dividends' growth. According to the rational approach, the gap should be made up for by introducing a variation in the price-dividend ratio. Campbell and Shiller show in 1988 two reasons why the price-dividend ratio can move around, by using a version of the Present Value formula. The two reasons are the changing expectation of future dividend growth and the changing discount rate. Both phenomena could be a cause for moving the ratio. The discount rate in turn can change because of changing expectation of the future risk free rate, changing forecast of risk or changing risk aversion sentiment.

Behavioral finance lead two different approaches of this problem, one through the beliefs system of investors and the other one using preferences, in order to find a solution to the puzzle.

A Beliefs approach

This approach examines the possibility that investors believe that the mean dividend growth rate is more variable than it actually is. When they see a surge in dividends, they tend to be too quick to believe that the mean dividend growth rate has increased as well. Their exuberance can have the consequence of pushing prices up relatively to the dividend, adding volatility of returns. The version of representativeness called "*law of small numbers*" can help explain this phenomenon. This law shows a situation whereby people expect that even small samples reflect the properties of the whole parent population. In this case, if investors see many periods of good earnings/dividends, they tend to believe that the overall earnings' growth has gone up and that it will continue to be high in the future.

Overconfidence about private information is another factor playing in this situation. People tend to overestimate the information they gathered by themselves. They put too much weight on it relatively to prior opinion they could have had, based on publicly available information. If the private information is "positive", the investors will act in a way that prices will be pushed too high relatively to dividends, which will thus add volatility. Another factor that can play in this increased volatility is the extrapolation of past returns by investors.

Fisher's 1928 money illusion theory can also be taken into account in this belief approach. Money illusion phenomenon is present when people confound real and nominal values. Fitter and War (2002) argue that part of the variation of the price-dividend ratio and stock return may be due to the fact that investors mix real and nominal quantities when forecasting future cash flow, and thus fundamental stock values. Indeed, the value of the stock market is determined by the discounted real cash flows at real rate, or by discounted nominal cash flows at nominal rate. It makes a difference as, if the inflation rate goes up, the nominal rate will go up as well. If investors make a mistake, and discount real cash flows at nominal rate, they take the risk to discount them at a higher rate that it should be. This kind of mistake could cause an excess variation of the price-dividend ratio and return. This factor is important in order to understand the low market valuation during high inflation period (1970's for instance) and high valuation over low inflation period (in the 1990's).

A Preferences approach

Benartzi, Huang and Santos (2001) show some experimental evidence about the dynamic aspects of loss aversion. They suggest that loss aversion is not the same in all circumstances but that it depends on prior gains and losses. According to Thaler and Johnson study (1990), people tend to make gamble they would normally do not after previous gains, and they do not make gamble they would normally do after previous losses. The "*house money effect*" reflects the first one, the gambler's increasing willingness to bet when he is ahead. The authors interpret it by the fact that losses are less painful after prior gains; they are cushioned. However, after being burnt a first time, they are not willing to endure the pain of another setback. This model can actually help explain the volatility puzzle. When some good cash news occur they push the stock market up, generating prior gains for investors. In return, the investors become less scared of stocks. They thus discount future cash flows at a lower rate (they make less conservative assumption), pushing the price up and as a consequence adding volatility.

II. The Cross-section of average return

1. Belief-based Models

Belief-based models try to explain anomalies using common beliefs and biases that were mentioned earlier in this paper.

According to Barberis, Shleifer and Vishny (1998), much of the above evidences and anomalies is the result of systematic errors that investors make when they use public information to form expectations on a stock's future cash flows. Therefore, they attempted to construct a model with two updating biases: conservatism and representativeness.

Conservatism represents the tendency to underweight new information relative to the prior ones the investors got. Here, representativeness is mostly assimilated to the "*law of small numbers*". The authors explain that, when a firm announces surprisingly good earnings, the conservatism bias enters in action causing investors to react insufficiently to the news. As a consequence, they are pushing the price up too little. The subsequent return will thus be higher than the average. This situation will thereby generate post-earnings announcement drift and momentum. On the other hand, after a series of good earnings announcements, the representativeness bias occurs. The investors tend to push the prices too high, thinking that the average return had gone up through the use of the law of small numbers. Therefore, the subsequent returns are low on average as the investors were to optimistic. It generates long-term reversals and scaled-price ratio effects.

Another study performed by Daniel, Hirshleifer and Subrahmanyan (1998; 2001) stresses the biases existing when investors interpret private rather than public information. Indeed, people tend to be overconfident about the information they gathered through their own researches. This fact tends to push prices up too far relatively to fundament values. Future public information will slowly pull back the prices and thus will generate long-term reversals and scaled-price effects. The self-attribution bias is also important to take into account. Indeed, the public news that confirms the investors own researches strongly increase the level of confidence he has on the research. On the contrary, disconfirming public news is given less attention and the investor's confidence on his own researches remains the same. As a consequence, the initial overconfidence feeling is generally followed by a greater level of overconfidence which will generate momentum.

Another study led by Chopra, Lakonishok and Riller (1992) shows evidence that investors tend to make irrational forecasts of stocks' future cash flows. According to Hong and Stein (1999), momentum is in part due to an initial under-reaction of the investors, followed by a correction. The diffusion of private information particularly slow among small firms and firms with low analyst coverage contributes to this phenomenon (Hong, Lim & Stein, 2000). Indeed, with firms with low coverage, momentum is almost entirely driven by prior losers which keep losing.

2. Belief-based models with institutional frictions

Institutional frictions are defined by the short-sale constraints. It includes direct cost of shorting (lending fees), the risk that the loan will be recalled by the lender at an inopportune moment, and legal restrictions (existence of a large amount of mutual funds which are not allowed to short).

According to Thaler and Barberis, when investors differ in their beliefs, the existence of short sale constraints can generate some deviations from fundamental values. It explains why stocks with high price-earnings ratio earn lower average returns. Bullish investors take long positions and bearish investors want to short but sometimes cannot because of the constraints. Therefore, the prices may only reflect the opinion of the most bullish/optimistic investors. They are generally too high, which will generate lower future returns (Miller, 1977). The short sale constraints also encourage the use of speculation-based mechanism where investors attempt to buy stocks for more than their fundamental values in the hope to sell them at an even higher price. This situation encourages deviations above fundamentals and the generation of lower future returns. This shows that stocks on which investors disagree the most will have higher price-earnings ratio and lower subsequent returns.

3. Preferences

Investors are loss averse over individual stock fluctuations. The pain of loss on some specific stocks depends on this very same stock past performance. If investors cause the prices to deviate away form their fundamental values, managers may try to time and follow these cycles. They will issue equity when they feel that the shares are overpriced and will repurchase them when they feel they are relatively cheap. Therefore, equity issuances will be indeed followed by low returns and repurchases operations will be followed by high returns.

III. Investor Behavior anomalies

Behavioral finance had known some success in explaining how certain groups of investors behave, what kind of portfolio they are likely to choose and how they are used to trade over time. However, explaining actions of investing does not mean necessarily claiming that these actions affect market prices. There are two factors of importance that we need to consider some characteristics of investors' behavior. First, the overall cost of entering the market went down. As a consequence, the number of individuals investing in equities went significantly up. Secondly, individuals are more and more responsible for their own financial well-being in retirement, which also encourage individuals' investments.

1. Diversification issues

Insufficient diversification

The first known cause for insufficient diversification is the "*home bias*" effect. Indeed, French and Porterba (1991) show that national investors have a strong tendency to invest in national companies. For instance, 94% for the United States, 98% for Japan and 82% in the United Kingdom of overall equity investment are made in domestic equities. Grinblatt (2001) found the same fact in a study of the Finnish market, where most equity investments are national but also close to home. The same is represented by a study of allocation of 401(k) by employees. They tend to have a strong bias toward owning their own company. In the United States, 30% of employees' allocations are invested in employer stocks in average.

Ambiguity and preference for familiarity are two simple factors that can help understanding the different examples of insufficient diversification. First, the investor's own company or national stocks are more familiar to most people. They seem thus more appealing to most investors. Secondly, investors try to avoid investing in ambiguous assets. It can provoke home bias but not necessarily. Thirdly, the search for information can be another reason. It is easier, less costly and less time consuming to make researches about local firms than about other national or foreign firms.

Naïve diversification

Benartzi and Thaler (2001) argue that when people do diversify, they do it in a naïve fashion. They often adopt a simple strategy like dividing their available income equally among all the propositions they have. This phenomenon is called the "1/n heuristic".

2. Trading issues

Excessive trading

According to rational models, there should be very little trading in the markets. However, the volume of trading on the world's stock exchange is very high. Individuals and institutions seem to be trading more than can be justified by traditional financial theories.

Barber and Odean (2000) argue that investors would do a lot better in average return if they were trading less. They say that underperformance is largely due to transaction costs. There is in addition evidence of poor security selection. Moreover, people who trade the most earn by far the lowest average return according to their study. There is also a marked difference between men and women. Women are trading less in average and earn thus a higher average return. Behavioral finance explains this phenomenon by the presence of overconfidence. Agents tend to think that the information they have is strong and reliable enough to justify a trade whereas it is often too weak. Barber and Odean (2002) also argue that the switch from phone based trading to online trading increase this overconfident state. Internet provides greater information and greater control.

Selling decision

Investors tend to be reluctant to sale assets currently trading at a loss relatively to the purchasing price. This factor is called the "*disposition effect*" (Shefrin & Statman, 1985). They are thus more likely to sell stocks that have relatively gone up. However, tax considerations would point on the selling of losers not of winners.

Grinblatt and Han (2001) argue that this disposition effect creates a momentum in stock returns. Investors will be willing to sell a stock which has earned them capital gains on paper. The subsequent selling pressure will contribute to a drop in price and thus to higher future returns. On the contrary, if the stock is a loser, investors will demand a price premium in order to sell it, according to the disposition effect. The price of this security will be thus inflated which will provoke lower returns.

Buying decision

According to Odean (1999), investors split evenly their resources when they choose to buy between big prior winners and big prior losers. These results concerning stock purchases are part due to an "*attention effect*". Investors tend to buy stocks that have caught their attention, which often occurs when there was extreme past good or bad performance. The difference between selling and buying decisions is that there are limits concerning selling. Investors can indeed only sell stocks they own because of the short selling constraints. There are on the contrary a way larger set of possibilities for buying. The main attention facts playing a role in influencing buying decision are high trading volume, high or low returns and new announcements.

IV. Corporate finance anomalies: a behavioral approach

1. Security issuance, capital structure and investment

Behavioral finance tries to see if irrational investors' behavior affects the financing and investment of a firm. The main question is how rational managers, interested in maximizing the firm's fundamental value, should act in face of irrational investors actions.

In 1996, Shein argues that, when a firm's stock price is too high, rational manager should issue supplementary shares in order to take advantage of the investors' apparent exuberance. On the contrary, when the stock's price is too low, the manager should undertake an operation of repurchasing. This strategy is called a "*market timing*" view on issuance.
There is evidence on the aggregate market level: the share of new equity issues among total new issues is higher when the overall stock market is more highly valued. This "equity share" factor is also an indicator of future stock revenues as the issue allows the stock's price to go back to its normal level.

At the individual firm level, the book-to-market ratio is a good cross-sectional predictor of new equity issuance. If the firm has its stock highly valuated, it should issue more. On the contrary, if the ratio is low, it should repurchase. There is some success of the market timing framework in predicting patterns of issuance. This framework could also be the basis for a successful theory of capital structure as a firm's capital structure can be represented by the cumulative financial decisions made overtime by the firm.

Irrational investors' sentiment affects financing decisions but should not affect firm's investment plans. However, sentiment might affect investment after all. Indeed, the argument made above is accurate only for non equity dependent firms, meaning firms that do not need equity markets to finance their marginal investments. For equity dependent firms, excessive investors' pessimism may distort investment plans. When they are too pessimistic, the firm may have to forgo attractive investment opportunities because it would be too costly to finance them with an undervalued equity and adverse market sentiment. However, when investors are overly optimistic, by refusing to make investment perceived as profitable by the market, the firm takes the risk that this action will depress the stock.

In addition, even if the firm's manager is rational, it does not necessarily mean that he will make the appropriate decision. Indeed, he might be willing to maximize other objectives such as the firm's size, in order to increase the company's prestige. He might thus make exuberant investments as a cover to do negative NPV "empire building" projects. Polk and Sapienza (2001) provide evidence of investment distortion. Overvalued firms tend to have high accruals (earnings – cash flows) in addition to issue more equity. They tend to earn low returns but they still have an overall investment activity higher than others, which means that sentiment does influence investment decisions. Their study shows that for some firms at least, sentiment may distort investment and it does mainly through the equity dependence channel.

2. Dividends

Stockholders who pay taxes would always prefer that the firm repurchases shares instead of paying them a dividend. Therefore, why investors seem happy to receive a substantial part of their returns in form of dividends? And why do firms choose to frame part of their returns as an explicit payment to stockholders and apparently make some of their stockholders worst off?

Shefrin and Statman (1984) argue that this obvious preference for dividend is representative of the notion of "*self-control*". Indeed, agents tend to themselves set rules in order to deal with their self-control issues. They thus make rule in to prevent an overconsumption of their wealth. And the rule is often to "*only consume the dividend but to no touch the capital*". Therefore, people may prefer dividends because it helps them surmount their self-control problems through the creation of rules as simple as this one. The second hypothesis is based on Thaler's "*mental accounting*" notion. With explicit dividend payment, the firms make it easier for their investors to segregate gains from losses and hence to increase their personal utility from their investment. Shefrin and Statman argue that by paying a dividend, the firm helps investors avoiding regret, which is generally stronger for errors of commission that for the ones of omission.

3. Models of managerial irrationality

The "*hubris hypothesis*" represents the fact that managers can be too quick to launch a bid on a company if they are overconfident in the accuracy of their analysis about its value. It leads to excessive takeover activity. The prediction of the hubris hypothesis is that the total combined gain to the bidder and the target will be zero. The announcement of the bid will provoke the increase in price and value of the target, but the bidder will fall of the similar amount.

Heaton (2002) analyzes the consequences of managerial optimism. He attempts to explain by it pecking order rules for capital structure. Indeed, when managers are optimistic relative to the capital market, he believes that the firm's equity is undervalued. Therefore, he is reluctant to issue unless he has no other choice. Managerial optimism can also help explaining the correlation between investment and cash flows. When the cash flows are low, there is a reluctance to use external markets as a financing mean. Therefore, the firm tends to forgo an unusually large number of projects and decrease its investments.

Chapter 5

The Case of Portfolio Management

Section I: The Black-Litterman model of Portfolio Management

Section II: The Case of Low Volatility Portfolio

The objective of this chapter is to introduce and apply the main behavioral finance concepts and theories we already explored to more concrete areas.

The first part consists of a study of portfolio management models, principally of the traditional finance Markowitz model and the Black-Litterman model. The Black-Litterman model, created from the Markowitz framework, uses some behavioral finance concepts. The goal of the study would be to determine what are the differences occurring when using one instead of the other in the context of portfolio or assets management.

The second part's objective would be to present and explain, thanks to behavioral finance concepts, a practical market anomaly which is the success of low volatility portfolio.

Section I

The Black-Litterman model of portfolio management

I. Presentation of the Markowitz model

a. Framework

In 1952 Markowitz published his research "*Portfolio selection*" which constitutes the origins of modern portfolio theory. According to Markowitz, it is not enough to consider the characteristics of individual assets when building a portfolio of financial securities. Indeed, the investor should take into account the co-movement of the assets with each other. This aspect is captured by the covariance of the assets. If they consider the covariance, investors could construct a portfolio that generates higher expected returns with a same level of risk, or even lower, than a portfolio that ignores the co-movement of its assets' returns. Therefore, within the Markowitz model, the risk is assessed as the variance of the portfolio, which depends on the variance of its assets and their covariance with one another.

The Markowitz model, or “mean-variance model”, constitutes the basis from which much researches within portfolio theory is performed. The model is a single period portfolio-building and decision-making technique that assumes that at least one of the two basic assumptions are true: first, that asset returns are multi-normally distributed, and second that economic agents have Von Neuman-Morgenstern quadratic utility function (increasing and concave. Markowitz showed that investors, under these and other assumptions (such as perfect asset divisibility and absence of restrictions for short sale), can build a portfolio that maximizes their expected return given a specified level of risk, or on the contrary minimize the risk given for a certain level of expected return. The objective of this initiative according to Sharpe (1967) is “*not to explain how people select portfolio but how they should*” select them.

The inputs needed to use the model and create an optimal portfolio are the expected returns of the each asset, the variances for all the assets and the covariance between every asset. The model focuses exclusively on risk and returns; it assumes that investors are looking for as high future expected returns as possible but with the lowest possible risk.

b. Issues of the Markowitz model

There are several researchers that discussed the shortcomings of the Markowitz model. For instance, Michaud published in 1989 “*The Markowitz optimization enigma: is “optimized” optimal?”*, exposing of its issues. His study discusses the practical problems encountered when using the model. The author claimed that it often led to irrelevant optimal portfolios. Some other studies also have shown that even portfolios with equal weighting of the assets can sometimes be superior in terms of risk and returns to Markowitz optimal portfolios.

There are five main problems concerning the use of the Markowitz model according to most researches on the subject.

First of all, according to Michaud, Black and Litterman (1990), the model has the tendency to maximize errors. To their opinion, since there are no correct and exact estimation of either expected returns or variances and covariance, these inputs are subject to estimation errors. The model tends to overweight securities with high expected returns and negative correlation,

and it tends to underweight those with low expected returns and positive correlation. However, according to Michaud, these securities are precisely the ones the most prone to be subject to large estimation errors.
Secondly, the habit of using historical data to produce a mean return and replace the expected return by this mean return is not an accurate method according to Michaud. The researcher claimed that this conduct contributes importantly to maximize errors within the Markowitz framework. Although Markowitz has not prescribed any particular procedure for estimating expected returns and variances, the use of historical data is common among practitioners.
The third issue concerns the fact that the model does not account for the assets' market capitalization weights. It implies that if assets with low level of capital have high expected returns and are negatively correlated to other assets in the portfolio, the model can possibly suggests a high portfolio weight for these assets. This fact constitutes a problem, especially in presence of shorting constraints that can provoke small stocks' prices to deviate from their fundamental values for a long period, as we have seen in the preceding chapters. Practically, the model actually often suggests very high weights in assets with low level of capital and that can be highly over or under valued relatively to their fundamental values.
The fourth issue is that the model does not make any differentiation between divergent levels of uncertainty associated with the estimated inputs used in the model. This is actually one of the main interesting additions made by the Black-Litterman model in order to take into account the fact that the inputs are mainly estimates, and thus are not a hundred percents accurate.
The fifth issue concerns the fact that the model seems to be particularly unstable. Indeed, a slight change in the inputs could completely change the portfolio assets' allocation (Fisher and Statman, 1997). The model is especially unstable relative to the expected returns inputs. A small change in expected returns on one of the assets might generate a radically different portfolio. This is an important issue as we have already seen that the expected returns are usually estimations based on the mean of historical data. As it is not an accurate input, errors can happen and thus produce a suboptimal portfolio.

One of the most striking empirical problems in addition of these five issues concerns the possible negative weighting. Indeed, when running the model without constraint, it almost always recommends portfolios with large negative weights in several assets according to a study of Black and Litterman (1992). Fund and portfolio managers are most of the time forbidden to take short position as we have seen previously. Therefore, shorting constraints are often added to the model. As a consequence, the model gives a solution with 0% weight in many of the assets and take large positions in only a few other assets. The large weights proposed in some assets are often unreasonable.

We can add to this aspect that the Markowitz model implies heavy calculations. Indeed, a portfolio of 50 assets will need to calculate 50 expected returns, 50 variances but 1225 covariance. With that many calculation based on estimates, the risk of error is relatively high and increases with the number of assets within a portfolio. As the approximations about future returns and risk are quite uncertain, and that the chance that it is absolutely correct is low, it seems reasonable that investors would wish to invest in a portfolio that would not be a total disaster in case of an incorrect estimation.

Therefore, all these disadvantages in using the Markowitz model constitute some of the reasons why fund and portfolio managers would not be inclined to use the model, and why Black and Litterman attempted to elaborate another one that would mitigate these problems. Indeed, the concept of maximizing returns, minimizing risk or having an optimal trade off between risk and expected return is so appealing that the search for better behaved frameworks such as the BL model had been encouraged.

II. The Black-Litterman model

The Black-Litterman model (BL model) consists of a financial portfolio model using a mathematical and a behavioral approach. As a consequence of using behavioral finance concepts, the BL model can appear more intuitive to fund managers than portfolios generated by the traditional Markowitz model.

According to behavioral finance, the actual utility function of investors is reference-based. An investor will estimate gains and losses in relation to a benchmark. Therefore, a point of reference, represented by a benchmark portfolio, is used in the BL model to evaluate the performance of the manager.

Another feature of the model is that the investor can attribute confidence levels to each of the assets constituting the portfolio in the form of confidence intervals. However, as behavioral finance shows that people tend to be poorly calibrated when it comes to estimates, this aspect could pose some issues to the accuracy of the model’s results.

The BL model encountered success in the practical finance industry as it is considered as a “*key tool in the investment management division and asset allocation process*” at Goldman Sachs (Litterman, 2006). Black and Litterman were indeed formerly part of this institution. Black and Litterman published in 1992 their research entitled "*Global portfolio optimization*" which constitutes a central contribution to the elaboration of the model. However, even if the theoretical project seems appealing, its practical use is often problematic. As the model demands to take actions based on judgments and estimates, it seems reasonable to search for explanations and new elements in the behavioral finance field.

This section will introduce the Black-Litterman model, along with the main theoretical differences that it has with the traditional Markowitz model. Then an application to a real portfolio example will be presented in order to illustrate these differences in practice and what using one or the other model could imply for the investor or manager.

a. Framework

The Black-Litterman model is constructed from the Markowitz model as a starting point and it aims at handling some of the practical problems it poses to financial professionals. Therefore, it is not a completely new model. It is mainly different from the Markowitz framework with respect to the expected returns calculation. Nevertheless, the BL model generates portfolios totally different from the Markowitz ones.

The optimization in the BL model starts from an equilibrium portfolio, often referred as the "benchmark weights" of the assets constituting the portfolio. Some adjustments from this equilibrium portfolio are then taken on the assets' weights. The model, on the contrary of the Markowitz model, takes into consideration the market capitalization weights of the asset within the portfolio. In addition, the investors assign views to each one of them, and to each view he attributes a level of confidence showing how confident he is on the accuracy of his view. Therefore, the level of confidence affects how much the weight of that particular asset in the BL portfolio will be different form the weight of the equilibrium portfolio.

There are two types of market views: "absolute" and "relative". Within each view, the investor needs to specify a confidence level showing how certain they feel about the accuracy of their views. Then, the views are combined with the equilibrium returns and the combination of these factors constitutes the BL expected returns for each assets. These returns are then optimized in a mean variance way, creating a portfolio where the gamble is taken on the assets on which the investors have opinions about future expected returns but not elsewhere. The size or the importance of the gambles, relatively to the equilibrium portfolio weights, depends on the confidence level determined by the user.

b. Equilibrium

Litterman determines the equilibrium as an idealized state in which supply equals demand. It never occurs in real financial markets but he argues that there are a number of attractive characteristics about the concept. At equilibrium, “natural forces” or the arbitrageurs act in order to eliminate deviation from the state. There is thus a tendency that mispricing will be corrected. Movements are also made in order to take advantage of the deviations. Therefore, there are actual forces that push toward that idealized equilibrium state. It is thus used a reference as a kind of ideal condition for the model. As a consequence, in order to apply the model to real practical investment situations, a reasonable approximation of this equilibrium state needs to be made. However, it poses some problems to use equilibrium weights as reference. Indeed, as this state is not possibly observable it has to be estimated. The solution would be to use a benchmark portfolio as the equilibrium portfolio such a capitalization weighted index. Within their model, Black and Litterman use the market portfolio as representing the equilibrium state. For the example that we are going to present, the index used will be the S&P 500.

c. Investors’ views and levels of confidence

Investors can express both relative and absolute views, which is an aspect that is not considered within the Markowitz framework. The absolute view specifies a precise percentage return that they believe a certain asset will provide (i.e. asset 1 will have a return of x %). The relative view compares one asset to another (i.e. asset 1 will have a yield higher than asset 2 by x %).

After expressing their views on each asset, they attribute them a certain level of confidence. It represents the standard deviation around the expected return on the view. If the investor is confident on the accuracy of his view, the standard deviation should be small and vice versa if he is less confident. The weaker the confidence, the least the view can affect the portfolio’s weights. It represents an attractive feature of the model as the views are most of the time erroneous. The views indicate on which assets the investor wants to take bets and on which direction the gambles are going. After setting up the views and their levels of confidence, we need to combine them with the equilibrium expected returns determined previously.

III. Behavioral finance and the Black-Litterman model

a. The effects of loss aversion

The Black-Litterman model is a mathematical model but it requires people to make estimations and judgments. Therefore, it is useful to consider the behavior of the people using the model and the context in which it is used.

The behavioral finance's researches concerning portfolio models focus mainly on how private investors invest and manage their own capital (Sheffrin and Statman, 1997). As we have seen previously, the utility function in behavioral finance implies that investors are prone to loss aversion. It means that individuals are risk adverse in the domain of gains but risk seeking in the domain of losses. However, a fund or portfolio manager rates his success relatively to a benchmark or a reference and not only considering losses and gains. Even if he encountered losses but his strategy outperformed the benchmark, he will not experiment pain from the loss, or at least to a much lesser extent.

Loss aversion has lots of consequence in the domain of portfolio management. The "*status quo bias*" and the "*endowment effect*" are two of them. First, as a consequence of loss aversion, individuals have a strong tendency to remain at status quo as the disadvantages of leaving it appear larger that the advantages (Knetsch & Sinden, 1984). Secondly, the endowment effect represents the fact that, once a person comes to posses a commodity or a financial asset, he or she will tend to value it more than previously (Robin, 1996). In addition, the "*herd behavior*" phenomenon is also source of issues. It happens when each decision maker considers first the decisions made by other decision-makers before making their own decisions. This tendency encourages passive investment strategies, which tend to be underperforming according to Shleifer (2000).

Since managers are often evaluated relatively to a reference point, they would probably appreciate working with a model taking this reference into consideration. Moreover, if they are status quo biased like most people, according to behavioral finance theories, they would probably be more comfortable working with a point of reference as they are willing to avoid regret. As a consequence of loss aversion effects, the expected return in relation to the risk might not always be high enough for investors to risk leaving the status quo, leaving the herd, falling behind the benchmark and feeling regret. Therefore, as deviations from the reference generate generally anxiety, it explains why fund and portfolio managers tend to stay close to the benchmark weights.

b. The Black-Litterman model and the overconfidence bias

As we have seen previously, when estimating probabilities, people have the tendency to exceed or to be below the accurate range. Then, they make judgments based on these estimates that are said to be overconfident. People tend to overweight information that captures attention and stands out (Kanheman & Tversky, 1973). Moreover, the overconfident investor trade a lot more than the rational ones (Odean, 1998). People tend to be more prone to overconfidence when judging the precision of their own knowledge or when performing very difficult tasks such as trading. Novice investors are also more overconfidence than experienced ones in their beliefs that they can beat the market. In addition, investors might overweight domestic assets in their portfolio because they feel more comfortable and familiar with them than with foreign assets. They also have more information, or they can get it more easily, information that they tend to exaggerate.

Overconfidence has implication on the BL model, especially on the attribution of the levels of confidence on the views given to the assets. Indeed, the estimation of future expected returns constitutes a very difficult task. Therefore, according to behavioral finance theories, the completion of this complex task can lead individuals to be overconfident in the process.

Conclusion: the contributions and omissions of behavioral finance to the Black-Litterman model

According to behavioral finance, investors are prone to loss aversion and its effects, and have difficulty in estimating their levels of confidence accurately. Hence, the behavioral researches regarding overconfidence and its implications do not encourage the use of the confidence levels in a portfolio management model, which is the most interesting addition of the BL model compared to the Markowitz framework. Moreover, the additions of behavioral finance focus mainly on the individual but it doest not take into consideration the social context in which the individual interacts. Behavioral finance ignores organizational and social contexts which are important shortcomings when one wants to be able to understand investors' actions and reasoning process.

As consequence, while the Black-Litterman model can still be considered as a progress toward the construction of better behaved and more intuitive portfolios, it still possesses some shortcoming s that need to be considered in order to use the model more efficiently

Section II

<u>The case of low volatility portfolios</u>

The violation of the risk and return tradeoff represented by the success of low volatility portfolios is one of the most striking anomalies within the stock market. This topic has been studied by several behavioral finance researchers such as Baker, Bradley and Wurgler within the recent years.

The interest for this topic comes from the ascertainment that, over the past forty years, high volatility and high beta stocks in the American stock markets have remarkably underperformed low volatility and low beta stocks. As a consequence, over this period of time, low volatility portfolios have known high average returns and small underperformances. This fact is in total contradiction with traditional finance theories. Indeed, according to the efficient markets theory, above average returns are possible to be obtained by taking above average risk. Risky stocks are thus supposed to have above-average future returns whereas safe stocks do not. However, this statement has appeared to be hard to prove over the history of stock markets.

Baker, Brendan and Wurgler (2009) performed a study using the last forty years of data from the Center for Research of Security Price (CRSP). They divided all the stocks in five groups according to their monthly trailing volatility. When comparing these groups considering their average returns and volatility, they found that $1 invested in the highest volatility (riskiest) stocks' group in January 1968 would be worth $0.61 at the end of December 2008, assuming no transaction costs. On the contrary, the same amount invested in the lowest volatility portfolio (safest) would be worth at the same period $56.38. The researchers also added that this group's path to this higher value was a lot smoother than for the riskier group. In addition, they noticed that much of this difference comes in recent years, after 1983 to be more precise. According to them, this period represents a time when institutional investment managers have become more and more numerous, better capitalized and more sophisticated.

The purpose of this part is to try to explain this portfolio management anomaly through the lens of behavioral finance principles, as traditional finance fails to provide a plausible answer. We will see the reasons underlying this phenomenon, the effects and what could be done in order to deal the best possible with this situation.

I. Explanation of the difference in return: the measure of risk

One of the first things to consider when studying this problem is the measure of risk. It would indeed be possible that this violation of the risk and return tradeoff could be explained by a wrong and inappropriate measure of risk. It may be that using volatility as a measure risk is not the good way to proceed. The standard deviation of returns would be a proper measure of risk only if at least one of the above mentioned assumptions – multi-normal districution, or quadratic utility function – hold. If not, this measure would not be an accurate measure of risk. Furthermore, individual securities are not typically held in isolation therefore the “right” measure of risk should not be the one on particular single stocks but on their own contribution to the overall risk of a diversified portfolio of securities. This is actually the logic behind traditional finance most famous model, the CAPM. The risk of a stock is represented by its Beta, which measures the contribution of this security to the risk within a broadly diversified market portfolio.

However, this reasonable assumption appears to be erroneous as well. Indeed, in order to consider this possibility, Wurgler, Bradley and Baker (2009) performed the same study with a refined definition of risk measurement. They found out that the highest volatility portfolio would then have provided a return of $8.07 (compared to the previous $.061) and the lowest volatility portfolio would still provide a much higher return of $54.78 (compared to the really similar result of $56.38). And once again, with exception of the internet bubble during the 1990’s, most of this difference in returns appeared after 1983. The renewed experience shows that the logic followed by the CAPM and traditional finance do not concord with the reality.

Following the same trend, the researchers Ang, Rodrick, Ying and Zhang (2006;2009) found out that high volatility stocks had "*abysmally low returns*" in both American and international markets, which shows that this phenomenon is a lot more general than an anomaly of the United States' stock market. The underperformances are especially salient in downturns periods such as 1972-1974, the crash of 1987, the burst of the internet bubble in 2000-2002 and the latest financial crisis of 2008.

Concerning the question of the appropriate measure of risk, in addition to the accuracy of the volatility parameter, using the stock's beta might be the wrong way to go as well. The CAPM is actually an equilibrium model of risk and returns based on punrealistic assumptions. The use of the beta might then be an erroneous measure of risk.

II. <u>A behavioral explanation to the difference in returns</u>

The behavioral explanation for this striking anomaly reposes on two phenomena different than risk: the presence of less than fully rational investors and the existence of limits to arbitrage.

Within inefficient markets, mispricing events come from the combination of two elements. First, the investors are not fully rational, on the contrary to traditional finance theories. Second, there must be some limits to arbitrage. The actions of arbitrageurs or "*smart money*" must be less than fully competitive in taking advantage of these mispricing events created by the noise trader group.

The main question is to understand what are the underlying psychological characteristics that lead to a preference for volatile stocks, making low volatility portfolio over-perform them. One could ask indeed why institutional arbitrageurs do not take action by overweighting low volatility stocks (and thus underweighting high volatility stocks) by just enough to offset the irrational demand. According to behavioral finance's views on these issues, investors' biases have an important role to play in this situation. Behavioral finance argues that there are three main biases creating this phenomenon: the preference for lotteries, representativeness and overconfidence.

a. <u>Preference for lotteries</u>

As a consequence as the loss aversion effects that we studied previously, investors should in theory shy away from volatile stocks, fearing to realize a loss as they are riskier.

However, empirical studies show that a different phenomenon takes place as the probabilities shift. Over the study of Wurgler, Baker and Bradley (2009), a group of individuals were presented two situations:

First situation: "*You have the occasion to play a game where you have 50% chance of losing $100 and 50% chance of winning $110. Do you play*?"

Second situation: "*You have the occasion to have a certain gain of $5 or to play a game with a 0.1% chance of a $5000 payoff. What do you choose?"*

When presented the first situation, most people refuse to play the game, despite the positive expected payoff. The possibility of losing $100 discourages participation, even when this amount is trivial compared to the individual income or total wealth situation. Therefore, when considering loss aversion phenomenon, people are expected to avoid volatility for fear to realize a loss. However, when considering the second situation, an interesting shift of preferences occurs. Indeed, most people rather take the gamble on the second situation rather than accepting a certain gain. This phenomenon illustrates clearly the appeal that people have for lotteries and fortune wheels.

From the statistical point of view, the researchers add that this phenomenon is more about "*positive skewness*", where large positive payoffs are more likely than large negative ones, than it is about volatility. Skewness "*describes the asymmetry from the normal distribution in a set of statistical data. Skewness can come in the form of "negative skewness" or "positive skewness" depending on whether data points are skewed to the left (negative skew) or to the right (positive skew) of the data average*". Skewness is considered as an important element in finance and investing activities. Indeed, the returns of most sets, including stocks, have either positive or negative skewness rather than a symmetric distribution. Therefore, by understanding on which way the returns are skewed, an investor more accurately estimates if a given or future data point will be more or less than the mean.

Mitton and Vorkink (2007) have pointed out that volatile individual stocks with limited liability happen to be positively skewed. Therefore, buying a low priced, volatile stock is like buying a lottery ticket. There is a small chance doubling or tripling the investor's value or much within a short period, but there is a much larger probability that a decrease in value will occur. However, as the size of the possible positive payoff is a lot larger than the more probable size of the decrease in value, a lot of investors are willing to take the chance.

b. <u>Representativeness</u>

To better illustrate the issue of representativeness, we are going to examine an experiment conducted by Tversky and Kanheman in 1983. Over the study, a group of individuals was presented the following situation:

"*Linda is a single, outspoken, very bright individual. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and she also participated in an anti-nuclear demonstration*".

<u>The question is</u>: "*What is the most probable?"*

A: *Linda is a bank teller.*
B: *Linda is a bank teller who is active in the women's movement*.

The results of the experiment showed that many subjects chose the statement B. However, it seems irrational as if B is true, than the statement A is automatically true as well. The mistake is thus made because the second proposition seems to better fit the description made of the young woman previously. It seems more "representative" of Linda.

A similar problem arises when agents attempt to define the main characteristics of an investment. From the success of Microsoft's IPO of 1986 (the company returned 70% per year in its five first years as a public company), they tend to draw the conclusion that small and speculative stocks in the new technology industry – and thus volatile stocks, were successful. The issue here however is that people ignores the large number of similar companies that failed. As a result, they can be inclined to overpay for volatile stocks, as an effect to the representativeness bias. On the contrary, a rational investor would probably examine an entire sample of similar stocks in order to fully assess the situation and the potential of their investment. They might conclude that, without an exhaustive knowledge allowing them to separate the successful from the losers, the overall group considered has performed too poorly on average.

c. Overconfidence

Numerous experimental evidences showed that most people tend to form confidence intervals far too narrow, as we have seen previously. They appear to show a certain overconfidence in the accuracy of their knowledge. Moreover, the more obscure is the question or the subject, and the more the calibration is deteriorating.

When valuing stocks, investors use the same kind of forecasting. However, their overconfidence will make them stick with some false previsions of their estimations. When they are in front of disagreements between overconfident agents, they will probably agree to disagree. The extent of the disagreement is usually higher for more uncertain outcomes. For instance, the stocks that are growing quickly or which are in distress (volatile stocks) will provoke a wider range of opinions, which will reinforce their volatility. If pessimistic investors act less aggressively that optimistic ones, because of short sales constraints for instance, the prices will be thus set by the optimistic group. Therefore, volatile stocks with wide range of opinions may sell for higher prices and will be generating lower future returns.

III. The limits to institutional arbitrage

a. The limits of contracted investment management

The fact that sophisticated and well capitalized institutions do not offset the irrational demand for high volatility stocks and capitalize on the return's differences constitutes a puzzle studied by Brendan, Bradley and Wurger (2009). Indeed, this irrational pattern has gained force over a period when the number institutional managers in the United States had doubled form 30% to 60% of the overall investment managers' population.

The first part of the puzzle presented by the researchers was to understand why institutional managers in the United States do not short the very poor performing top volatility stocks. According to them, the reason is that these stocks are generally small and costly to trade in large quantities. There are also difficulties in shorting them because of the low volume of shares available.

The second part of the puzzle consists in understanding why institutional managers do not overweight the lower risk and higher performing lowest volatility stocks' group. Here, what seems to come into play, are the limits to arbitrage coming from typical contracts ruling delegated investment management. Indeed, the vast majority of institutional managers are given implicit or explicit mandates aiming at the maximization of the "*information ratio*" relative to a specific fixed benchmark. For instance, if the benchmark is the S&P 500, this information ratio would represent "*the average difference between the return earned by the manager and the return of the index, scaled by the volatility on the tracking error*". The tracking error is "*the standard deviation of the returns' differences between the manager's obtained returns and the index returns*".

The advantage of this contract is that it makes it kind of easier to understand the skills of the investment manager and the risks he takes by examining the returns he obtained relatively to a benchmark. However, this mandate strategy has its costs. Indeed, Brennan (1993) considers that it has effects on stocks' prices. He argues that the benchmark make the institutional managers less likely to take advantage of observable patterns. His logic is that institutional managers who have fixed benchmarks will not be willing to exploit mispricing occurring because an irrational extra demand for high volatility stocks provoked by preference for lotteries, representativeness and overconfidence biases of investors.

To recapitulate, institutional managers with fixed benchmark are only suited to exploit mispricing that involves stocks with approximately the market risk, or a Beta almost equal to 1 (similar to the market portfolio Beta). There will however do very little to correct undervalued stocks with low Beta and overvalued stocks with high Beta.

The combination of an irrational extra demand, coming from a preference for lotteries, representativeness and overconfidence biases, and the presence of delegated institutional investment managers with fixed benchmarks causes the tradeoff between risk and return not to hold. High risk, volatile stocks do not earn a commensurate return, whereas low risk stocks have a tendency to outperform. However, despite this pattern, sophisticated investors are largely on the sideline because their mandate of maximizing returns makes the action of arbitraging the mispricing unattractive. The implication is that a solid investment strategy in low volatility portfolio subsists. Moreover, exploiting the low volatility anomaly for investment managers involves holding stocks with more or less returns, which does not help the manager's performances, and with different risk profiles, which only increases the manager’s tracking error. The lack of incentive then is another consequence for the persistence of the anomaly. Therefore, as a long as fixed benchmark contracts remain the dominant form of implicit or explicit mandate between investors and investment management firms, the anomaly will probably persist.

b. The search for lower volatility strategies

Given the outperformance of low volatility stocks, we can wonder if one could achieve better returns than the lowest volatility group by taking more efficient strategies by using the benefices of diversification. Bradley, Baker and Wurgler (2009) argue that an investor could achieve a better performance if he has a good estimate of not only the firm’s volatility but also of the correlation among the stocks constituting the portfolio. Indeed, a portfolio with two low volatility correlated stocks can be more volatile that another one with two stocks slightly more volatile but uncorrelated.

Clarke, Da Silva and Thorley (2006) conducted a study using the top 1,000 stocks in the CRSP universe. They compared the returns of a low volatility portfolio to the returns of the lowest quintile of the selection, so the bottom stocks of the 200 stocks with the lowest volatility. They found out that the minimum variance of the portfolio had a lower volatility that the bottom selection, 11.5 against 12.8. Also, the compounded annual return was correspondingly higher, 10.7% against 10.1%. This experience shows thus the importance of diversification and of stocks’ correlation.

Conclusion

Behavioral finance explains that irrational investors tend to have a preference for risky and volatile stocks while at the same time institutional investors are incentivized to manage risk against their benchmark. This implies also that investors who want to maximize returns must incentivize their managers to take advantage of the mispricing events created by the extra demand for volatile securities.

The good news would be that, as long as most institutional investors will stick with their benchmarks, low volatility portfolios will be likely to keep performing leaving opportunities for individual investors to exploit.

Chapter 6

Practical Application:

The differences between the Black-Litterman and the Markowitz models of assets' allocation

The aim of this example is to illustrate the use of the two models with a portfolio containing five real life securities. It mainly shows the differences in weights and returns that can be obtained when using the two models, and the influences of the additional inputs of the Black-Litterman model that are connected with behavioral finance: the views and the confidence levels.

I. The Black-Litterman model application

For the example, we are going to work with five real life stocks that will constitute a portfolio. The stocks chosen are all from different important industries: **Jonhson & Jonhson** (Health care), **Wal-Mart Stores** (Consumer Discretionary), **Goldman Sachs** (Financials), **Google Inc.** (Information Technology) and **Exxon Mobil** (Energy). To calculate the returns, we are using the historical prices of the stocks based on the 10 last months (price on the first day of the month). The returns are calculated as percentage through the formula **(P1-P0)/P0**, where **P1** is the price of the period and **P0** the price of the preceding month.
With the historical returns data, we are then able to elaborate a **variance/covariance matrix** between the five assets.

From there, we need to make some assumptions. First of all, we are going to use a market portfolio similar in returns and volatility to the **S&P 500 index**. Between the period 1992 and 2007, the **average return of the index per annum** was approximately **11%** and its **average standard deviation per annum** was **17%.** Second, we are going to use a **risk-free rate** evaluated at **5%**. Therefore, we will have a **global risk market premium** equal to 11% - 5% so **6%**.

With these data, we are thus able to calculate the "*Risk aversion parameter*". It represents the rate at which more returns is required as a compensation for more risk. It is calculated through the division of the global market risk premium by the market portfolio variance, or its squared standard deviation.

Then, for each of the securities, we are going to calculate their "*implied excess return*". It is represented by the multiplication of the risk aversion parameter, the sum of the asset covariance with the other securities and the weight of the asset market capitalization relatively to the total market capitalization of the five stocks. These returns will be used and combined with the views to form newly combined returns.

As we have seen before, the Black-Litterman model introduces some behavioral elements through the use of market views and levels of confidence in the model. We are thus going to elaborate two views, one absolute and one relative, and then attribute them levels of confidence which represent to which degree the investor is convinced of the accuracy of the view.

The absolute view used states that Google will outperform the return of all the other securities by 10%. The relative view used states that Exxon Mobile will outperform in returns Goldman Sachs by 5%. For the first trial, we chose to attribute a 30% rate of confidence to the absolute view, and a 50% rate of confidence to the relative view. From the view, we need to compute the view distribution for each asset. For one stock, the view is computed by the multiplication of the weight of the view on the asset, the percentage affected to this particular view and the rate of confidence level. The view distribution of each asset is then added to its own implied excess of return to give a "*new blended expected return*". For the asset to which no view has been attributed by the investor, the expected return will be the same as the previously computed implied excess of return.

Finally, we can use these data to compute the portfolio returns, variance and weight for each asset. We use the new blended return as expected returns for each asset. We calculate the variance of each of them. The variance of the portfolio is the sum of the variance of each stock and the expected return of the portfolio is the sum of each expected return times their respective variance. By using an Excel spreadsheet and the "Solver option", we are able to compute optimal weights according to a target portfolio return.

II. The Markowitz model application

The procedure of the Markowitz model application is similar to the Black-Litterman one as the latter is mainly constructed from the Markowitz framework. We need to start the same way by a calculation of the historical returns and elaborate a variance/covariance matrix.

However, this model does not take into consideration the market capitalization of the stocks or a parameter representing the market risk and return tradeoff. Views and levels of confidence are also attributes exclusively used by the Black-Litterman model. Therefore, the expected return for each asset is represented by the mean of the stock's historical returns. The same calculations than for the first model are then made to obtain the portfolio variance, standard deviation, expected returns and assets' weights.

III. Results of the trial

a. Weights obtained according to a target return of 2%

When computing through the "Solver" the optimal weights to obtain a portfolio providing a 2% return, the two models propose pretty different allocation.

The Black-Litterman model proposes the following allocation: Jonhson & Johnson (10%); Wal-Mart stores (9%); Google Inc. (53%); Goldman Sachs (13%) and Exxon Mobile (15%).

The Markowitz framework gives significantly divergent results: Jonhson & Jonhson (46%); Wal-Mart stores (3%); Google Inc. (7%); Goldman Sachs (8%) and Exxon Mobile (36%).

Stock	Allocation using Markowitz	Allocation using Black-Litterman	Difference in weight
Johnson & Johnson	46%	10%	**-36%**
Wal-Mart stores	3%	9%	6%
Google Inc.	7%	53%	**46%**
Goldman Sachs	8%	13%	5%
Exxon Mobile	36%	15%	-21%

As we can see there are pretty large differences. For instance, a 36% difference for Jonhson & Jonhson and a 57% difference for Google!

Considering that the same historical prices and returns had been used, the differences can be mostly attributed to the behavioral features of the model and to the taking of consideration of the stocks market capitalization.

b. Weights obtained according to a target return of 3%

When trying to obtain a portfolio providing a 3% return, the models can give different results.
Indeed the Markowitz model gives the following weights for a 3% return: Jonhson & Jonhson (71%); Wal-Mart stores (-1%); Google Inc. (-1%); Goldman Sachs (-3%) and Exxon Mobile (36%).

For the Black-Litterman, the weights proposed are: Jonhson & Jonhson (-4%); Wal-Mart stores (9%); Google Inc. (66%); Goldman Sachs (3%) and Exxon Mobile (26%).

Stock	Allocation using Markowitz	Allocation using Black-Litterman	Difference in weight
Johnson & Johnson	71%%	-4%	**-75%**
Wal-Mart stores	-1%	9%	10%
Google Inc.	-3%	66%	**67%**
Goldman Sachs	-3%	3%	6%
Exxon Mobile	36%	26%	-10%

We can notice still large differences in weighting with a difference of 75% for Jonhson & Jonhson and 67% for Google Inc.

c. The importance of the views and levels of confidence

The evaluation of the accuracy of the views attributed appears to be fundamental in the Black-Litterman model. Indeed, a change of the levels of confidence in each of the view can generate completely different portfolio allocations.

For this example, we kept a target portfolio return of 2%. We then made a trial by replacing the level of confidence of the absolute view from 30% to 60%. We are first keeping the same level of 50% for the relative view. The weights proposed for the portfolio are then: Jonhson & Jonhson (32%); Wal-Mart stores (9%); Google Inc. (31%); Goldman Sachs (17%) and Exxon Mobile (11%).

Stock	Allocation using 30% confidence	Allocation using 60% confidence	Difference in weight
Johnson & Johnson	10%	32%	**22%**
Wal-Mart stores	9%	9%	0%
Google Inc.	53%	31%	**-22%**
Goldman Sachs	13%	17%	4%
Exxon Mobile	15%	11%	-4%

Therefore, we can see that a change in just one of the view of 10% can provoke a difference of 22% weighting for Jonhson & Jonhson and of 22% for Google Inc as well. The only stock not affected by this change is Wal-Mart stores that stayed at 9%.

When the investor gets vey confident on his/her views, it appears that the portfolio can start to act in a different manner For instance, when attributing levels of confidence of 80% and 60% respectively to the absolute and the relative views, we obtain a different allocation: Jonhson & Jonhson (37%); Wal-Mart stores (9%); Google Inc. (26%); Goldman Sachs (19%) and Exxon Mobile (9%). However, the differences of weights between two same stocks are still a lot less important than when using the two different models with a same target return.

Stock	Allocation using 30% & 50% confidence	Allocation using 60% & 80% confidence	Difference in weight
Johnson & Johnson	10%	37%	**27%**
Wal-Mart stores	9%	9%	0%
Google Inc.	53%	26%	**-27%**
Goldman Sachs	13%	19%	6%
Exxon Mobile	15%	9%	-6%

The importance of the view can also be seen when adjusting the levels of confidence of the example of a target 3% return. When using confidence levels of 50% and 70%, we can obtain a portfolio allocation more intuitive with no negative weight: Jonhson & Jonhson (19%); Wal-Mart stores (9%); Google Inc. (43%); Goldman Sachs (8%) and Exxon Mobile (21%).

Stock	Allocation using 30% & 50% confidence levels	Allocation using 50% & 70% confidence levels	Difference in weight

Johnson & Johnson	-4%	19%	**23%**
Wal-Mart stores	9%	9%	0%
Google Inc.	66%	43%	**-23%**
Goldman Sachs	3%	8%	5%
Exxon Mobile	26%	21%	-5%

Conclusion

These applications and examples can illustrate the impact of the additional features of the Black-Litterman model compared to the Markowitz framework.

First of all, we can see that the two models can provide very different allocations for same target returns. The main inputs taken into consideration are the market capitalization of the assets, the market portfolio risk and return tradeoff and the views and their own levels of confidence attributed by the investor. The importance of the views and levels of confidence is significantly consequent when we see that changes in these parameters can affect greatly the assets' allocation. The behavior of investors is thus fundamental as the levels of confidence are affected by numerous behavioral characteristics such as overconfidence and loss aversion biases.

Behavioral finance theories can thus be useful and applied in the context of portfolio management. As the Black-Litterman model starts from the Markowitz framework, its results are not totally different in the same situation as we have seen in one the example. However, the fact that it takes into consideration the investors' sentiment can provide a different assets' allocation by taking into account capitalization, risk and return tradeoffs and sentiments on expected returns. Nevertheless, this simplified illustration cannot represent a demonstration that the Black-Litterman model is more efficient and can replace the Markowitz model used by portfolio managers presently. The model remains flawed, especially within its additional features as we have seen that investors are prone to biases. A need more testing would be compulsory in order to assert the usefulness and the potential of this model.

CONCLUSION

Behavioral finance, or behavioral economics, uses cognitive and emotional factors in order to understand financial and economic decisions of individuals and institutions. The field is primarily concerned with the issue of the agents' rationality assumed by the traditional neoclassic finance theories.

As we have seen through this survey, behavioral finance encompasses numerous contradictions with traditional finance. This field of study has knows increasing progresses over the last years and can propose more an more interesting assumptions and solutions to financially puzzles, unsolved by the traditional field.

However, despite the interest of this field and its undeniable logic, one cannot deny that it is still in need of clear mathematical models that could be used in order to mitigate errors of traditional finance models such as the CAPM.

This lack of empirical findings remains one of the main shortcomings of the field. In addition, taking into account organizational and sociological aspects could also allow more accuracy to the theories.

To conclude, this field is still in need of further validation but still remains an interesting theoretical basis which researchers can start working from.

BIBLIOGRAPHY

- Baker, Brendan and Bradley, 2011, Benchmarks as limits to arbitrage: understanding the low volatility anomaly, *Financial analyst journal*, vol. 67, number 1

- Baker, Bradley and Wurgler, 2009, A behavioral explanation for success of low volatility portfolios.
-
- Barber and Odean, 2001, Boys will be boys: gender, overconfidence and common stock sentiment, *The quarterly journal of Economics*, 116(1), p.261-292.

- Barberis and Thaler, 2003, A survey of behavioral finance, Barberis and Thaler.

- Benartzi and Thaler,1995, Myopic loss aversion and the equity premium puzzle, *The quarterly journal of economics*, 110(1), p.72-92

- Black and Litterman, 1992, Global portfolio optimization, *Financial Analysts Journal*, p.28-43

- Camerer and Loewenstein, 2002, Behavioral economics: Past, present and future.

- De Bondt and Thaler, 1985, Does the stock market overreact?, *The Journal of Finance*, 40(3), p.793-805.

- Fama, 1970, Efficient capital market: a Review of theorical and empirical work, *The Journal of finance*, p. 338-417.

- He and Litterman, 1999, Intuition behind the Black-Litterman model, *Investment Management Research*, Goldman Sachs Quantitative Research Group

- Kanheman and Tversky, 1979, Prospect theory: an Analysis of decision under risk, *Econometrica*, 47(2), p.263-292.

- Kanheman and Tversky, 1982, Judgment under uncertainty: Heuristics and biases, Cambridge University Press.

- Kanheman, Knetsch and Thaler, 1991, Anomalies: the endowment effect, loss aversion and status quo bias, *The Journal of economic perspectives*, 5(1), p. 193-206.

- Mahmood, Ahmad, Zahid Kan and Anjum, 2011, Behavioral implications of investors for investments in the stock market, *European Journal of Social Sciences*, Volume 20, number 2.

- Mankert, 2006, The Black-Litterman model – Mathematical and behavioral finance approaches toward its use in practice, Royal institute of technology of Sweden.

- Markowitz, 1952, Portfolio selection, Blackwell, Oxford

- Michaud, 1989, The Markowitz optimization enigma: Is "optimized" optimal?", *Financial analyst Journal*, vol. 45, number 1, January/February p.3742.

- Odean, 1998, Are investors reluctant to realize their losses?, *The journal of finance*, 53(5), p.1775-1798.

- Scheilfer, 2000, Inefficient markets: an introduction to behavioral finance", Oxford University Press.

- Sewell, 2007 (revised 2010), Behavioural finance.

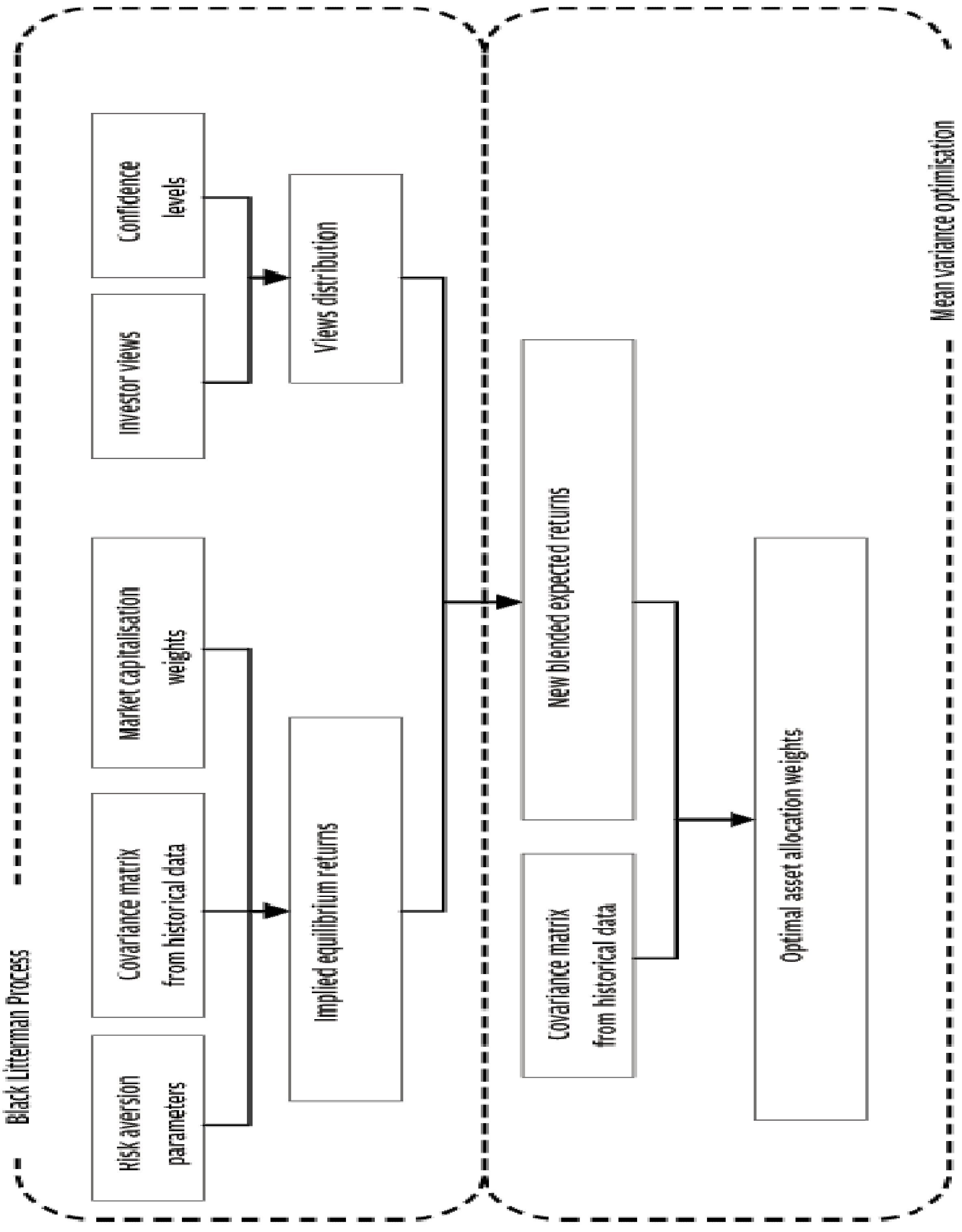
- Shefrin, 2000, Beyond greed and fear: understanding behavioral finance and the psychology of investing, Havard Business School Press.

- Shiller, 2000, Irrational exuberance, Princeton University Press.

- Shiller, 2002, From efficient market theory to behavioral finance, Cowles Foundation discussion paper, number 1385.

ANNEXES

The Black-Litterman Process Scheme (Idzorek, 2005)


Black Litterman Process
Risk aversion parameters
Covariance matrix from historical data
Market capitalisation weights
Investor views
Confidence levels
Implied equilibrium returns
Views distribution
New blended expected returns
Covariance matrix from historical data
Optimal asset allocation weights
Mean variance optimisation

Historical Stock Prices

	Johnson & Johnson	Wal-Mart Stores	Google Inc.	Goldman Sachs	Exxon Mobil
05.02.2011	86,97	55,04	538,56	151,63	86,97
04.01.2011	84,68	52,13	591,8	159,66	84,68
03.01.2011	84,8	52,07	600,76	161,31	84,8
02.01.2011	83,91	56,53	611,04	165,33	83,91
01.03.2011	74,55	54,15	604,35	173,05	74,55
12.01.2010	71,33	54,39	564,35	158,45	71,33
11.01.2010	66,95	54,02	615	161,57	66,95
10.01.2010	62,54	53,36	525,62	147,7	62,54
09.01.2010	60,91	51,2	460,33	139,74	60,91
08.02.2010	61,94	51,41	490,41	152,74	61,94
Market Capitalization (B$)	182,22	194,53	170,24	73,24	398,37

Historical Stock returns (%)

	Johnson & Johnson	Wal-Mart Stores	Google Inc.	Goldman Sachs	Exxon Mobil
05.02.2011	2,70%	5,58%	-9,00%	-5,03%	2,70%
04.01.2011	-0,14%	0,12%	-1,49%	-1,02%	-0,14%
03.01.2011	1,06%	-7,89%	-1,68%	-2,43%	1,06%
02.01.2011	12,56%	4,40%	1,11%	-4,46%	12,56%
01.03.2011	4,51%	-0,44%	7,09%	9,21%	4,51%
12.01.2010	6,54%	0,68%	-8,24%	-1,93%	6,54%
11.01.2010	7,05%	1,24%	17,00%	9,39%	7,05%
10.01.2010	2,68%	4,22%	14,18%	5,70%	2,68%
09.01.2010	-1,66%	-0,41%	-6,13%	-8,51%	-1,66%
08.02.2010	-	-	-	-	-

Variance/Covariance Matrix

	Johnson & Johnson	Wal-Mart Stores	Google Inc.	Goldman Sachs	Exxon Mobil
Johnson & Johnson	0,167%	0,062%	0,093%	0,054%	0,167%
Wal-Mart Stores	0,062%	0,141%	0,035%	0,005%	0,062%
Google Inc.	0,093%	0,035%	0,794%	0,465%	0,093%
Goldman Sachs	0,054%	0,005%	0,465%	0,371%	0,054%
Exxon Mobil	0,167%	0,062%	0,093%	0,054%	0,167%

Additional Data	
Market Portfolio	S&P 500
Market Portfolio standard deviation	17%
Risk free rate	5%
Market Return	11%
Market Risk Premium	6%
Risk aversion parameter	2,21799308
Total Market Capitalization	1018,6

IER (Implied Excess Returns for the asset)	
Johnson & Johnson	0,001494105
Wal-Mart Stores	0,001289761
Google Inc.	0,005489085
Goldman Sachs	0,001514221
Exxon Mobil	0,003266418

Historical Stock Prices					
	Johnson & Johnson	*Wal-Mart Stores*	*Google Inc.*	*Goldman Sachs*	*Exxon Mobil*
05.02.2011	86,97	55,04	538,56	151,63	86,97
04.01.2011	84,68	52,13	591,8	159,66	84,68
03.01.2011	84,8	52,07	600,76	161,31	84,8
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01.03.2011	74,55	54,15	604,35	173,05	74,55
12.01.2010	71,33	54,39	564,35	158,45	71,33
11.01.2010	66,95	54,02	615	161,57	66,95
10.01.2010	62,54	53,36	525,62	147,7	62,54
09.01.2010	60,91	51,2	460,33	139,74	60,91
08.02.2010	61,94	51,41	490,41	152,74	61,94

Historical Stock returns (%)					
	Johnson & Johnson	*Wal-Mart Stores*	*Google Inc.*	*Goldman Sachs*	*Exxon Mobil*
05.02.2011	2,70%	5,58%	-9,00%	-5,03%	2,70%
04.01.2011	-0,14%	0,12%	-1,49%	-1,02%	-0,14%
03.01.2011	1,06%	-7,89%	-1,68%	-2,43%	1,06%
02.01.2011	12,56%	4,40%	1,11%	-4,46%	12,56%
01.03.2011	4,51%	-0,44%	7,09%	9,21%	4,51%
12.01.2010	6,54%	0,68%	-8,24%	-1,93%	6,54%
11.01.2010	7,05%	1,24%	17,00%	9,39%	7,05%
10.01.2010	2,68%	4,22%	14,18%	5,70%	2,68%
09.01.2010	-1,66%	-0,41%	-6,13%	-8,51%	-1,66%
08.02.2010	-	-	-	-	-

Variance/Covariance Matrix					
	Johnson & Johnson	*Wal-Mart Stores*	*Google Inc.*	*Goldman Sachs*	*Exxon Mobil*
Johnson & Johnson	0,167%	0,062%	0,093%	0,054%	0,167%
Wal-Mart Stores	0,062%	0,141%	0,035%	0,005%	0,062%
Google Inc.	0,093%	0,035%	0,794%	0,465%	0,093%
Goldman Sachs	0,054%	0,005%	0,465%	0,371%	0,054%
Exxon Mobil	0,167%	0,062%	0,093%	0,054%	0,167%

Annex 2: Weights obtained according to a target return of 2%

Market Views and Confidence Levels		
Absolute view	*"Google will outperform all other assets by"*	**10%**
Relative view	*"Exxon Mobile will outperform Goldman Sachs by"*	**5%**
Confidence level absolute view	**30%**	
Confidence level relative view	**50%**	

Views distribution		New blended expected returns
Johnson & Johnson	0	0,00149411
Wal-Mart Stores	0	0,00128976
Google Inc.	0,03	0,03548909
Goldman Sachs	-0,025	-0,02348578
Exxon Mobil	0,025	0,02826642

Portfolio repartition

	Johnson & Johnson	Wal-Mart Stores	Google Inc.	Goldman Sachs	Exxon Mobil	
% Portfolio	**10%**	**9%**	**53%**	**13%**	**15%**	**100%**
Expected Return	0,15%	0,13%	3,55%	-2,35%	2,83%	
Variance	0,010%	0,004%	0,267%	0,042%	0,015%	
Return	0,015%	0,012%	1,869%	-0,316%	0,420%	

Variance	0,339%
Standard deviation	0,058200407
Return	**2,000%**

The Markowitz Model Application

Annex 2: Weights According to a target return of 2%

Portfolio repartition						
	Johnson & Johnson	Wal-Mart Stores	Google Inc.	Goldman Sachs	Exxon Mobil	Total
% Portfolio	46%	3%	7%	8%	36%	100%
Expected Return	2,70%	0,68%	-1,49%	-1,93%	2,70%	
Variance	0,069%	0,002%	0,011%	0,008%	0,055%	
Return	1,240%	0,023%	-0,102%	-0,146%	0,985%	

Variance	0,145%
Standard Deviation	3,81%
Returns	**2,000%**

Annex 3: Weights obtained according to a target return of 3%

Market Views and Confidence Levels		
Absolute view	*"Google will outperform all other assets by"*	**10%**
Relative view	*"Exxon Mobile will outperform Goldman Sachs by"*	**5%**
Confidence level absolute view	**30%**	
Confidence level relative view	**50%**	

Views distribution		***New blended expected returns***
Johnson & Johnson	0	0,00149411
Wal-Mart Stores	0	0,00128976
Google Inc.	0,03	0,03548909
Goldman Sachs	-0,025	-0,02348578
Exxon Mobil	0,025	0,02826642

Portfolio repartition

	Johnson & Johnson	**Wal-Mart Stores**	**Google Inc.**	**Goldman Sachs**	**Exxon Mobil**	
% Portfolio	**-4%**	**9%**	**66%**	**3%**	**26%**	**10**
Expected Return	0,15%	0,13%	3,55%	-2,35%	2,83%	
Variance	-0,004%	0,004%	0,375%	0,011%	0,027%	
Return	-0,006%	0,011%	2,353%	-0,081%	0,723%	

Variance	0,413%
Standard deviation	0,064277806
Return	**3,000%**

The Markowitz Model Application

Annex 3: Weights according to a target return of 3%

Portfolio repartition						
	Johnson & Johnson	***Wal-Mart Stores***	***Google Inc.***	***Goldman Sachs***	***Exxon Mobil***	***Total***
% Portfolio	**71%**	**-1%**	**-3%**	**-3%**	**36%**	**100%**
Expected Return	2,70%	0,68%	-1,49%	-1,93%	2,70%	
Variance	0,124%	-0,001%	-0,002%	-0,001%	0,064%	
Return	1,920%	-0,009%	0,043%	0,061%	0,985%	

Variance	0,184%
Standard Deviation	4,28%
Returns	**3,000%**

Annex 4: Target portfolio return of 2% - Level of confidence of 60% (absolute) and 50% (relative).

Market Views and Confidence Levels		
Absolute view	*"Google will outperform all other assets by"*	**10%**
Relative view	*"Exxon Mobile will outperform Goldman Sachs by"*	**5%**
Confidence level absolute view	**60%**	
Confidence level relative view	**50%**	

Views distribution		New blended expected returns
Johnson & Johnson	0	0,00149411
Wal-Mart Stores	0	0,00128976
Google Inc.	0,06	0,06548909
Goldman Sachs	-0,025	-0,02348578
Exxon Mobil	0,025	0,02826642

Portfolio repartition

	Johnson & Johnson	Wal-Mart Stores	Google Inc.	Goldman Sachs	Exxon Mobil	
% Portfolio	**32%**	**9%**	**31%**	**17%**	**11%**	**100%**
Expected Return	0,15%	0,13%	6,55%	-2,35%	2,83%	
Variance	0,037%	0,005%	0,115%	0,040%	0,013%	
Return	0,048%	0,012%	2,037%	-0,403%	0,307%	

Variance	0,209%
Standard deviation	0,045686395
Return	**2,000%**

Annex 5: Target Portfolio Return of 2% - Levels of confidence of 80% (Absolute) and 60% (Relative)

Market Views and Confidence Levels		
Absolute view	*"Google will outperform all other assets by"*	**10%**
Relative view	*"Exxon Mobile will outperform Goldman Sachs by"*	**5%**
Confidence level absolute view	**80%**	
Confidence level relative view	**60%**	

Views distribution		***New blended expected returns***
Johnson & Johnson	0	0,00149411
Wal-Mart Stores	0	0,00128976
Google Inc.	0,08	0,08548909
Goldman Sachs	-0,03	-0,02848578
Exxon Mobil	0,03	0,03326642

Portfolio repartition

	Johnson & Johnson	**Wal-Mart Stores**	**Google Inc.**	**Goldman Sachs**	**Exxon Mobil**	
% Portfolio	**37%**	**9%**	**26%**	**19%**	**9%**	**100%**
Expected Return	0,15%	0,13%	8,55%	-2,85%	3,33%	
Variance	0,044%	0,005%	0,087%	0,041%	0,010%	
Return	0,056%	0,012%	2,186%	-0,546%	0,292%	

Variance	0,187%
Standard deviation	0,043199661
Return	**2,000%**

The Black-Litterman Model Application

Annex 6: Target Return 3% - Confidence Levels of 50% (Absolute) and 70% (Relative)

Market Views and Confidence Levels		
Absolute view	*"Google will outperform all other assets by"*	**10%**
Relative view	*"Exxon Mobile will outperform Goldman Sachs by"*	**5%**
Confidence level absolute view	**50%**	
Confidence level relative view	**70%**	

Views distribution		New blended expected returns
Johnson & Johnson	0	0,00149411
Wal-Mart Stores	0	0,00128976
Google Inc.	0,05	0,05548909
Goldman Sachs	-0,035	-0,03348578
Exxon Mobil	0,035	0,03826642

Portfolio repartition

	Johnson & Johnson	Wal-Mart Stores	Google Inc.	Goldman Sachs	Exxon Mobil	
% Portfolio	**19%**	**9%**	**43%**	**8%**	**21%**	**100%**
Expected Return	0,15%	0,13%	5,55%	-3,35%	3,83%	
Variance	0,022%	0,005%	0,183%	0,019%	0,025%	
Return	0,028%	0,012%	2,411%	-0,253%	0,802%	

Variance	0,254%
Standard deviation	0,050352657
Return	**3,000%**