Université de Strasbourg

Institut d'Etudes Politiques de Strasbourg

The impact of the overconfidence bias on financial markets

LINTZ Zoé

Mémoire de 4ème année

Direction du mémoire : MERLI Maxime, Professeur des Universités

Mai 2016

Avertissement

L'Université de Strasbourg n'entend donner aucune approbation ou improbation aux opinions émises dans ce mémoire. Ces opinions doivent être considérées comme propres à leur auteur.

Remerciements

Plusieurs personnes m'ont été d'une grande aide dans la réalisation de ce mémoire, et je souhaiterais leur témoigner toute ma reconnaissance.

En premier lieu, je tiens à remercier chaleureusement M. Maxime Merli, Professeur des Universités, qui a accepté de prendre la charge de directeur de mémoire. Je lui suis reconnaissante de m'avoir aidé et dirigé tout au long de mon mémoire. Ses conseils m'ont été d'une aide précieuse, pour structurer et organiser ma réflexion.

Je tiens également à remercier toute l'équipe pédagogique de l'Institut d'Etudes Politiques de Strasbourg, qui m'a permis d'acquérir les connaissances nécessaires pour travailler sur ce sujet. Je tiens plus particulièrement à remercier M. Joël Petey, Professeur des Universités, pour avoir pris le temps de lire mon mémoire.

Enfin, je désire adresser des remerciements à un camarade de promotion, William, pour m'avoir soutenu et encouragé tout au long de l'élaboration de ce mémoire.

Table of contents

General introduction

During his speech on the 5th of December 1996, Alan Greenspan, former Chairman of the Federal Reserve System (i.e. Fed) of the United States, spoke about « *the irrational exuberance of the markets* ». With this expression, he underlined the difference between the price on the financial markets (i.e. the Dow Jones index was at 6437 index points) and his personal evaluation of the stocks' level. The decorrelation between real economy and expectation of agents can create what we commonly call a « bubble ».

With this emblematic speech of Greenspan (1996), but also with all events that stroke on financial markets, like the burst of the new technologies' bubble in 2000 and the financial crisis in 2007, financial researchers wondered the consistence of classical financial models. Economic situations (i.e. the crisis of 2007) called into question hypothesis of financial models, such as market efficiency or rationality of economic agents (for instance, hypothesis of the CAPM model).

Most classical models stand on strong hypothesis, such as perfect information or the absence of transaction costs. One of these axioms is the fact that individuals are rational : this is the « homo economicus » theory. This theory postulates that each individual makes two sets of rational decisions. When an investor gets a new information, he offsets his believes « correctly » (i.e., Bayes rule, Bayes, 1763). Once the balancing is completed, he achieves a computation costs/advantages in making economic choices (i.e., maximization of expected utility). Consequently, markets, and thus financial markets, should lead to the most efficient equilibrium, as its obey to purely rational rules.

This paradigm of individual rationality allowed significant progresses in financial theories, particularly in the field of financial assets valuation. For instance, Sharpe (1964) constructed an equilibrium model for financial assets, and showed that, in market equilibrium, each financial security can be deconstructed in a sum between the riskless rate and some risk premium, dependent of the correlation of the stock with the market (i.e. the beta of the stock). Sharpe (1964) was one contributor of the CAPM (i.e. Capital Asset Pricing Model), which, still today, is a base for pricing individual securities or portfolios. He builded his theory on previous studies of Markowitz (1952), on diversification and portfolio valuation.

Moreover, Modigliani and Miller (1958) studied the relationship between a firm's market value and the capital structure of this same firm. They find that, in an efficient market, the value of the firm remains unaffected by its funding structure. This result have still a strong impact on corporate finance. Black and Scholes (1973) demonstrated a relation for the options' evaluation, standing on five factors : the price and the volatility of the underlying, the exercice price, the riskless rate, and the maturity of the option. Subsequently, Ross (1976) developed an alternative model to the CAPM, called the APT (i.e. Arbitrage Pricing Theory). It supposes the impossibility of making riskless arbitrages in financial markets. Ross (1976) introduced new variables in the evaluation of financial assets, such as interest rates, growth rates, and inflation rates.

Globally, in the classical financial theory, strong assumptions are made. Indeed, models assume that economic agents maximise their expected utility (Bernoulli, 1738). Each individual is making consistant anticipations with their available information and each individual has a perfect knowledge of the probability theory (i.e. Bayes rule). Moreover, the hypothesis of rational expectations is used in a quasi-systematic way in financial researches. It states that economic agents are right in their predictions of future values of economic variables.

Some experiments underlined the capacity of financial markets to reflect the fundamental value of financial assets. Indeed, Forsythe, Palfrey and Plott (1982) have constructed an experiment in a simple environment, with several types of agents, but with no incertitude. They find that models of financial valuation and market efficiency are consistent. Moreover, Plott and Sunder (1982) confirm this result, in a risky environment but with perfectly informed agents.

Nevertheless, the classical models have shown some limits. Empirical studies started to highlight that financial markets, in a real world, do not work in an efficient way. Indeed, classical models stand on strong assomptions (i.e. rationality of economic agents), that may not be observable in real financial markets. De Bonds and Thaler criticized the lack of consideration for individual behavior : « *People optimize but otherwise their behavior is like a black box.* » (De Bondt and Thaler, 1995, pp.385)

The existence of anomalies in financial markets, that are not suitable with the efficient market theory, leads to the rise of a new research branch : the behavioral finance. Behavioral finance is one aspect of the « new behavioral economics », that were born during the 1970's. It consists to apply the axioms of psychology in the field of finance. The behavioral finance was officially recognized in 2002 with the attribution of the Economy Nobel Price to Daniel Kahneman and Vernon Smith, two founding fathers of the behavioral finance. Kahneman (1982) and Smith (1988) studied the behavior of investors during their decision-making and repeatedly observed that the usual axioms of financial theory are false.

The behavioral finance, in opposition to the basic assumption of market efficiency, tries to highlight situations, in which investors are not rational, and to construct explanations, lying on individual psychology. This field relies strongly on the use of empirical studies and experimental researches. Indeed, the use of these kind of studies helps to measure the psychologic features of financial agents and allows to observe both the behavior of agents and the aggregated data of financial markets. Thus, the behavioral finance enables to study the transition from the individual behavior to the market performance and to look for the origin of the « irrationalities » (i.e. not totally rational behavior). Some observed phenomenons can be better explained with models working with not totally rational agents. Consequently, even if classical financial theory leads to great advances, various aspects of finance can be questioned, by applying psychology on financial markets.

During their exchanges in financial markets, individual participants must perform complexe tasks, such as the comprehension of the rules and the functioning of the financial market. Investors also need to value the financial assets, reflecting informations that they are in possession or that they grab from the observation of the competitors. Moreover, investors need to make decision in a short period of time. Considering the limited cognitive capacity of humains, this complexity of financial markets can lead them to express irrational behaviors (i.e., no maximisation of expected utility or a choice without following the probability theory). For example, Edward (1968) questioned the spontaneous and correct utilisation of the Bayes rule (i.e., rational expectations) by individuals. The work of the behavioral finance relies on analyzing the relation between investor's rationality and market's rationality (i.e. price and allocations).

Generally, two schools of behavioral finance are observed. First, the « classical » school, that postulates that even if some investors are not perfectly rational, actions of arbitrageurs ensure the prices to go back to their fundamental value. Second, a school with models standing on errors or biases to the perfect rationality, inspired by the cognitive psychology work.

In this dissertation, we will focus specifically on the major advances of the second school. Behavioral finance studies demonstrated the existence of numerous biases (i.e. pointed out by psychologists) among investors, which can be cognitive, emotional, and social. Individuals are not rational : their sentiments are submitted to systematic judgment errors and are influenced by different biases in their decision-making, on stock markets. For instance, Kahneman and Tversky (1974) achieved to underline the presence of a representative bias among investors (i.e., the tendency to extrapolate from a limited sized sample). Cho, Who and Stultz (1999) stressed out the existence of a momentum bias among institutional investors on the Korean market. Agents tend to grant a probability too high for what would happen in the close future, according to what had happen in the recent past. For De Bondt and Thaler (1986), individuals seem to attribute too much weigh to recent informations with respect to long term tendencies. Individual investors are also inclined to sell their wining positions faster than their losing positions. This is what is commonly named the disposition bias (Shefrin, Statman, 1985).

One of the biases studied by financial researches is the overconfidence bias. Indeed, overconfidence can have important effects. Overconfidence may have strong repercussions in different fields (i.e. wars, strikes, entrepreneurial failures for instance.) because it impacts the basis of judgment and decision-making. Plous (1993) stated : « *No problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence* » (Plous, 1993, pp. 217).

As a consequence of its importance, overconfidence was widely studied, even outside of psychology. The behavioral finance, for example, have applied results, demonstrated by psychologists, to financial markets and investors. Indeed, financial researchers tried to explain the limits of classical models, using this overconfidence bias. The idea that the excessive volatility of transactions cannot totally be explained with arguments of rationality (Shiller, 1981) was studied, by looking at the psychological effect of overconfidence on the decision-making of investors (Odean, 1999, Glaser and Weber, 2007, Malmendier and Tate, 2005, Daniel, Hirshleifer, & Subrahmanyam, 1998). As stated by Stracca (2004 pp.396) : « *More fundamentally, the excess volatility of equity prices as stressed by Shiller (1981) and the large amount of trading in financial markets world-wide are difficult to justify on purely « rational » grounds in the standard expected utility sense* ».

Consequently to the limits of traditional models, and more precisely to the excess of volatility detected on markets, financial researchers studied more deeply the presence and the consequences of overconfidence among investors on financial markets.

Therefore, we can ask ourselves to what extent the overconfidence bias impacts the behavior of individual investors, but also professional investors on financial markets ?

In a first part, we will focus on defining the term of overconfidence, describing its components and characterizing the different ways of measuring it. Then, in a second section, we will concentrate on analyzing the evidences of an overconfidence bias among investors (i.e. individual and professional), and its consequences on financial markets.

Part I : Definition and measure of overconfidence

Introduction

« The economist may attempt to ignore psychology, but it is sheer impossibility for him to ignore human nature . . . . If the economist borrows his conception of man from the psychologist, his constructive work may have some chance of remaining purely economic in character. But if he does not, he will not thereby avoid psychology. Rather, he will force himself to make his own, and it will be bad psychology. »[1] (Clark, 1918, pp.96)

Overconfidence is a fondamental bias in behavioral finance. It assumes that individuals are not as rational as theories postulate. Indeed, individuals, in decision-making, are drawing a certain level of confidence. Confidence can be defined as the degree of certainty that one holds in the accuracy of his/her mental states : beliefs, knowledge, perceptions, predictions, judgements, or decisions.

The degree of certainty of individuals is usually characterized as a subjective probability. For Kahneman and Tversky (1982), the term confidence refers to « *the subjective probability or degree of belief associated with what we 'think' will happen* » (pp. 515)[2].

---

[1] J.M., Clark, Economics and Modern Psychology, Journal of Political Economy, 1918, Vol. 26, pp. 4.

[2] Kahneman, D., & Tversky, A. (1982). Variants of uncertainty. In D. Kahneman, P. Slovic, & A.Tversky (Eds.), Judgment under uncertainty: Heuristics and biases (pp. 509–520). Cambridge, UK: Cambridge Univ. Press.

Since the 1980's, psychologists worked in order to measure this « subjective probability » and tried to observe if individuals' confidence is in line with the objective accuracy of their judgments. If subjective confidence of an individual is superior to the objective accuracy of her or his judgements, she or he is stated as overconfident.

Psychology researchers mostly observed evidences of overconfidence. Psychologists and psychoanalysts have found a tendency of individuals to have a higher confidence level in their judgments than the objective accuracy of these judgments. Two prominent behavioral economists, Werner DeBondt and Richard Thaler (1995) have stated: « *Perhaps the most robust finding in the psychology of judgement is that people are overconfident.* » (DeBondt and Thaler, 1995, pp.389)[3].

Several interpretations were advanced in order to explain overconfidence. First, researchers explained overconfidence by the information-search strategy which leads to final judgment. Individuals tend to perceive their initial guess to be more consistent than what would be normally assessed (Hoch, 1985; Klayman, 1995; Koriat, Lichtenstein, and Fischhoff, 1980). Besides, overconfidence sources can include imperfection in learning the validity of the information (Gigerenzer et al., 1991; Soll, 1996) or in evaluating the information (Erev, Wallsten, and Budescu, 1994).

In the literature, psychologists tried to test the evidence of overconfidence and its correlation with individuals characteristics and judgment's aspects. Researches on overconfidence have, for example, found stable individual differences in the tendency to be overconfident (Klayman et al, 1999; Soll, 1996). For instance, high self-esteem (Rosenberg, 1965), need for uniqueness (Snyder and Fromkin, 1977) and narcissism (Hendin and Cheek, 1997) lead usually to expression of overconfidence. Other studies reached to the conclusion that men are generally more confident than women in « masculine » tasks, and thus tend express a higher level of overconfidence (Lundeberg, Fox and Puncochar, 1994). Moreover, the nature of the judgment can affect the level of

---

[3] DeBondt, W.F.M. and R.H. Thaler (1995): « Financial Decision-Making in Markets and Firms: A Behavioral Perspective. » in R. Jarrow et al., eds., Handbooks in Operations Research and Management, Vol. 9. Amsterdam: Elsevier Science

overconfidence. More difficult tasks usually drive to stronger overconfidence levels (Lichtenstein et al., 1982, Kruger, 1999).

There are four principal definitions, and thus, ways of measuring overconfidence. First, overprecision, that is the excessive certainty (i.e. the miscalibration) regarding the accuracy of one's beliefs. Second, the better-than-average effect, that is when people believe themselves to be better than others, or than the median average. Third, the illusion of control, or the tendency of individuals to overestimate their control over their future. Fourth, unrealistic optimism, that is when individuals are too sure that positive events will happen to them.

We will start this dissertation by discussing successively each definition of the overconfidence bias and we will focus on describing the four different ways of measuring this bias.

A) The overprecision (miscalibration)

The overconfidence bias can be defined as the tendency of individuals to be excessively certain about the accuracy of their beliefs or of their information. This definition is one component of the overconfidence's definition. It is usually called overprecision.

In order to measure the degree of overprecision among individuals, a technique widely used is the « miscalibration » of probability judgements. Indeed, miscalibration helps to underline the correlation or the imperfect correlation between accuracy and confidence. By asking questions to subjects, psychologists are measuring both their degree of confidence (i.e. by demanding their estimated probabilities of success) and their degree of accuracy (i.e. by looking at the actual rate of success in answering the questions). The overconfidence effect occurs « *when the confidence judgements are larger than the relative frequencies of the correct answers* » (Gigerenzer, Hoffrage, & Kleinbölting, 1991, pp. 506)[4].

In general, individuals tend to be not so well calibrated. Accuracy is, on average, associated with a higher level of subjective confidence. This produces the pattern of « miscalibration » as stated by Lichtenstein, Fischoff and Phillips (1982). They said that « *an individual is well calibrated if, over the long run, for all answers assigned a given probability, the proportion correct equals the probability assigned »* (Lichtenstein, Fischoff and Phillips, 1982, pp. 108).

The calibration of individuals is differently labeled among the literature : it is referred as realism (Brown and Shuford, 1973), external validity (Brown and Shuford, 1973), realism of confidence (Adams & Adams, 1961), appropriateness of confidence (Oskamp, 1962), secondary

[4] Gigerenzer, G., Hoffrage, U., & Kleinbolting, H. (1991). Probabilistic mental models: A Brunswikian theory of confidence. Psychological Review, 98, 506–528.

validity (Murphy and Winkler, 1984), or reliability (Murphy, 1973). These numerous appellations focus on the same idea : the comparison of the rate of correct answers and the estimated probability.

We will first focus on the miscalibration with discrete answer alternatives (i.e. a choice between different answer alternatives). Subsequently, we will define the miscalibration with continuous answers (i.e. with an interval of confidence that is ask).

A) 1) Miscalibration using discrete answer alternatives

A first way of measuring overconfidence, is through the miscalibration with discrete answers. This way of measuring overconfidence is constructed the following way. Individuals are asked to answer a set of multiple-choice questions with two (or more) answer alternatives. After that, subjects are asked their estimated probabilities of success in answering these questions. Then, if this probability is superior to the accurate rate of success, the subject is stated as overconfident.

This overconfidence's approach is also called « calibration of probability judgments ». Psychologists are measuring the degree to which individuals are calibrated, with their estimated probabilities.

A variety of scientists, psychologists, but also meteorologists, statisticians, and financial experts, conducted surveys over miscalibration with discrete propositions, in order to measure if individuals are overconfident or not, in decision-making. We can quote researches ran by Pitz (1974), Tversky and Kahneman, (1974), Langer (1975) and Weinstein (1980) (i.e. see Lichtenstein, Fischhoff, and Phillips, 1982, for a review). They mostly found evidences of overconfidence about accuracy of judgments or knowledge among individuals.

For instance, Pitz (1974) tries to explain the process of individuals elaborating probability estimates. Tversky and Kahneman (1974) question the critical capacity of individuals to construct their judgment.

In order to measure miscalibration, one must have a judgment where the correctness of the answer is verifiable and a measure of the confidence level in that judgment. The subjective probability of the correctness of the answer is generally used as a proxy for the degree of confidence of an individual.

Indeed, general-knowledge questions are typically asked to the participants of the studies. Moreover, participants are demanded to estimate the number of questions they answered correctly or the probability that they had answered the question correctly. This is a proxy for the confidence level. For example, if a participant who took a 20-item quiz believes that he answered 10 of the questions correctly, his degree of confidence is 50%. Or, another case is an individual, who is asked a question, and then needs to provide his subjective probability of success, that is : « *I am between 0 and 100% sure that X is the correct answer* ». The probability given is the confidence level of the individual.

Consequently, in order to highlight overconfidence, two variables are compared :

- we define C as the average confidence level in the population. C is computed by using the mean of subjective probabilities given by individuals in a population.
- we define P as the actual proportion of correct answers among the population studied. P is computed by using the mean of correct answers among the same population as C.

The over/under confidence level of the population is computed by making the difference between C and P :

$$O = C - P$$

A positive O suggests overconfidence (i.e. a confidence level superior to actual correct level) whereas a negative O suggests underconfidence (i.e. a confidence level inferior to actual correct level).

We can note that C and P are not necessarily mean levels. It also can be the confidence level and the actual rate of correct answers for a single individual.

This approach of miscalibration, by comparing the average level of confidence (i.e. C) and the accurate rate of correct answers (i.e. P), can be reviewed using the research of Klayman et al. (1999). In this research, Klayman et al. (1999) try to highlight the fact that individuals tend to express overconfidence, when comparisons between subjective probabilities and accurate probabilities are drawn.

They conduct their study over 32 paid participants of the University of Chicago. A total of 480 two-choice questions are presented on a computed monitor. These questions are 40 paired-comparisons on 12 different domains. Subjects are asked to make an ordinal comparison between two items. The two choices are labelled as (A) and (B). When the question appeared on the monitor, subjects need to type (A) or (B). Then, a prompt « Chance correct 50-100 » comes up, asking the candidates to type a number in their range (i.e. to estimate their subjective probabilities of success). Each participant is asked to answer a set of 120 questions from each different domain and to give their subjective probability of correct answer for each question.

On Table 1 (p.17), we can see examples of questions asked across the 12 different domains of the study. We can also see the proportion of correct answers P and the confidence level C. On the last column, we can observe the difference between the confidence level and the proportion of correct answers, as the measure of miscalibration of individuals. If we take the first line, « *Which of these American museums or galleries had more visitors in 1991 ?* », we can see that the proportion of correct answers is 54.1%, whereas the subjective proportion of correct answers (i.e. the level of confidence) is 67%. The level of overconfidence is the difference between the two proportion, so 13%.

Table 1 : Mean overconfidence level across 12 different domains (Klayman et. al., 1999)

Domain of questions	Proportion correct	Confidence	Over-confidence[a]
Which of these American museums or galleries had more visitors in 1991?	.541	.670	.130
Which of these 1992-model cars gets more miles-per-gallon in real driving (mix of highway and city)?	.613	.662	.050
Which of these "tourist cities" has a warmer daily high temperature in July, on average?	.637	.762	.124
Which of these U.S. colleges or universities charged higher tuition in 1991? (For state colleges, use the in-state-resident tuition.)	.656	.689	.033
Which of these food items has more calories?	.672	.795	.123
Which brand of shampoo costs more per ounce (national average)?	.684	.715	.031
Of these two "principal mountains of the world," which is taller?	.688	.615	−.073
Which of these states had a higher percentage of its population with incomes below the federal poverty line in 1990?	.697	.712	.015
Which of these cities is farther from Los Angeles, in air miles?	.728	.801	.073
Which of these states had a higher population in 1990?	.750	.799	.049
Which of these nations has higher life expectancy, averaged across men and women?	.791	.774	−.017
Which of these U.S. presidents held office first?	.856	.869	.012
Total	.693	.739	.046

Note. Facts used are from 1990–1992 because the earliest experiment was begun in 1993.
[a] Overconfidence = confidence − proportion correct. Negative numbers indicate underconfidence.

As stated above, a positive number O, when making the difference C - P, suggests overconfidence, whereas a negative number suggests underconfidence. Here, we can point out that, for most of the domains, the mean degree of confidence is superior to the proportion of correct answers. Thus, individuals tend to be overconfident (i.e. only not for questions about mountains and level of life expectancy). In total, the confidence level is higher than the proportion of correct answers (4.6% of difference). These results mean that individuals, in this study, are stated as overconfident, because of their miscalibration level.

Another way of measuring overprecision can be, more specifically, studied in the survey conducted by Fischoff, Slovic, and Lichtenstein (1977). 361 subjects are asked a general knowledge question (on a wide variety of topics, included history, music, geography…), but are also asked their degree of certainty (i.e. their estimated probability) that their answer to the question is correct. The survey of Fischoff, Slovic and Lichtenstein (1977) is conducted over paid volunteers in the University of Oregon.

In their experiment, four question formats are used :

- open ended questions : subjects are asked to write down the answer to the question. For example, « Absinthe is a ____ ». Then, subjects need to provide an estimate between 0.00 and 1.00 that their answer is correct.
- one alternative questions : subjects are asked the probability that some statements are correct. For example, « *What is the probability that absinthe is a precious stone ?* ».
- two-alternative questions : individuals are asked to choose the correct answer between two alternatives. For example, « *Absinthe is a precious stone (a) or a liqueur (b)* ». Then, they need to provide a probability of success estimate between 0.00 and 1.00.
- two-alternative questions : the same procedure than the latter, but with a range of estimates that goes only from 0,5 to 1. The range is restricted because it is assumed that individuals are more

likely to choose a correct answer between the two, so they estimated probability of success is certainly over 0.5.

Subjects are distributed in four groups according to their time and date experiment preferences. Each group receives only one question's format.

Table 2 : Results for each question format (Fischoff, Slovic and Lichtenstein, 1977)

Question format	No. items	No. subjects	Total no. responses	Certainty responses (p)	% certainty responses	% correct certainty responses
1. Open ended	43	30	1,290	1.00	19.7	83.1
2. One alternative	75	86	6,450	1.00	14.2	71.7
				.00	13.8	29.5
3. Two alternative (half range)	75	120	9,000	1.00	21.8	81.8
4. Two alternative (full range)	50	131	6,500	1.00	17.3	80.7
				.00	19.1	20.5

Table 2 provides the results of this study of Fischoff, Slovic and Lichtenstein (1977). On Table 2, we can see the results for the four types of question formats. On the first column, we can observe the number of items (i.e. the number of questions asked) for each format. Then, on the second column, the number of subjects is reported. The total number of responses is also disclosed. We can clearly notice that Fischoff, Slovic and Lichtenstein (1977) try to focus on the two alternative answers, but with half range estimates asked.

The fourth column gives one kind of probability expressed by individuals : the emphasis is put on extreme cases (i.e. estimate probabilities of success stated that are 1.00 or 0.00). Then, the percentage of individuals who gave theses extremes probabilities is given, as well as the percentage of actual correct responses among these individuals.

On Table 2, we can see that a non-negligible part of subjects questioned gives an extreme estimate. There are 19.7% of the individuals, in the group which were asked an open-ended question, who answers that they are 100% confident of their answer. This result even reaches 21.8% in the group with two alternative questions (i.e. with half range of probability allowed). A part of individuals also is absolutely not sure about their answer. In the one alternative question group, 13.8% of individuals give a probability of success of 0%, and 19.1% in the two alternative question group (i.e. with a full range of probabilities allowed).

For both cases (i.e., when people are 100% sure that their answer is correct, or when they are 0% sure of their response), the estimate and the accurate correct answer rate are different. In fact, for the 19.7% subjects who are thinking that their probability of correct answer is 100 % (i.e. open ended questions), only 83.1% of their answers are correct. It is the same for the other types of question : the accurate number of correct answers is never 100%, and even fall at 71.7% for the 14.2% subjects who express an extreme certainty (i.e. 100% estimate), in the one alternative question group. Here, it is clear that the level of confidence C is superior to the accurate rate of correct answer P. When C is equal to 100%, P is inferior to 100%. Thus C-P is superior to 0, which means that individuals express overconfidence.
When subjects are absolutely not sure about their estimate (i.e. 0% probability estimate), the results are the opposite. The percentage of actual correct answer is more than 0%. For the 13.8% of people who give an estimate of 0 for the one alternative question, the actual correct rate is 29.5%, far more than 0. It is the same for the extremely not sure individuals in the two alternative question group. Their actual rate of correct answer reaches 20.5%.

Two conclusions can be drawn from this experiment of Fischoff, Slovic and Lichtenstein (1977) :

- around 20% of sampled individuals tend to express extreme estimates about their probabilities of success. A large part of the subjects of the experiment gives a absolute certain probability (1) or absolute no certain probability (0), regardless of the question type.

- a major part of these individuals tend to give estimates that differ from their accurate correct answer. Indeed, when they provide a 100% estimate, they would have need a 100% of correct answer rate. As the actual answer rate is under 100% in the four groups, subjects are wrong too often when they are certain about their responses. Consequently, they are stated as overconfident. Inversely, when subject are absolutely not sure about their answer, the actual response rate is over 0%. These subjects are stated as underconfident.

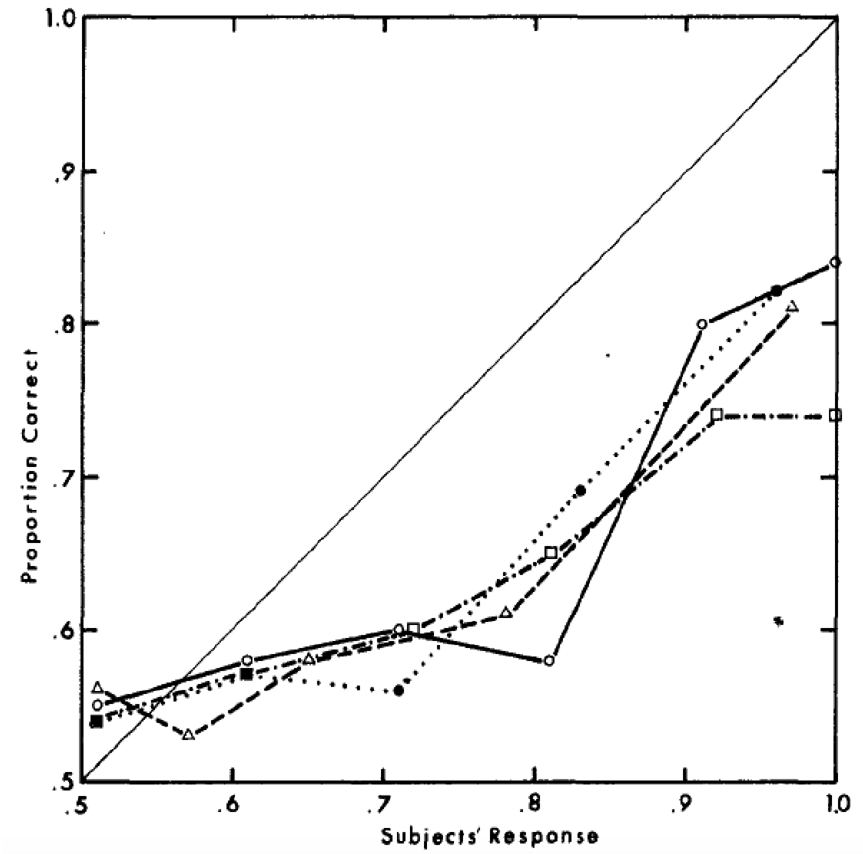
So, when subjects express absolute certainty, they tend to be overconfident. But, when they express absolute uncertainty, they tend to be underconfident.

Fischoff, Slovic, and Lichtenstein (1977) attempt to construct a calibration curve in order to highlight the overconfidence level of individuals, in this same experiment. A calibration curve is a common way to represent miscalibration among individuals.

To construct this calibration curve, the first step is to divide the subjective estimates, asked to individual, into discrete ranges. Usually, responses are grouped together in the ranges of .50–.59, .60–.69, .70–.79, .80–.89, .90–.99, and 1.0.
After grouping the subjects' answers into categories, the second step is to plot the calibration curve on a graph. For that, the objective proportion of correct answer is plotted against the mean subjective confidence, for each category stated above. Indeed, a calibration curve exhibits on the horizontal axis the mean estimated probability of success of the range and on the vertical axis their objective proportion of correct answer. This method helps to compare the level of confidence, for each category, with the accurateness of the answers.

An identity line is also set up. The identity line is the 45° curve, for which each probability stated by subjects would have been equal to their proportion of correct answers. This means that perfectly calibrated individuals should lay on the identity line. Perfect calibration would be shown by all points falling on the identity line. Furthermore, when the accurate proportion of correct answer is less than the subjective probability stated (i.e. when the calibration curve is under the identity line), the range is stated as overconfident (as C-P > 0). On the opposite case, when the accurate proportion of correct answer is more than the subjective probability (i.e. when the calibration curve is above the identity line), this is an expression of underconfidence (C-P < 0). The further the calibration curve from the identity line, the stronger the over/under confidence effect.

Figure 1 : Calibration curve using results for each question format (Fischoff, Slovic and Lichtenstein, 1977)



An exemple of calibration curve is depicted on Figure 1. This calibration curve is constructed using the results of the experiment described above (i.e. four question formats). Fischoff, Slovic and Lichtenstein (1977) group their results in ranges, and then plot the proportion of correct answer, with respect to the mean subjective probability, for each range. Indeed, here we can see four calibration curve for each four types of answer. The white circle line is the calibration curve for the open ended questions group, the triangle one is for the two alternative question with half range probability allowed group, the black square is for the two alternative question with the whole range allowed group and the white square is for the one alternative question group. A range between 0.5 and 1 is deliberately chosen in order to show that overconfidence is stronger with higher probability estimates.

The identity line, as stated before, is the 45° line, in which perfectly calibrated individuals should lay. But here, we can see that all of the four calibration curves fall below the identity line. This implies that, for exemple, subjects, who think to be right 70% of the time, are only right 60% of the time. It is the same for subjects thinking that their probability of success is 90%. They are actually right only around 75% of the time. We can see that, the higher the subjective confidence level, the larger the difference between the calibration curve and the identity line. The overconfidence effect seems to be stronger for higher subjective probabilities. Moreover, we can see that, for ranges of subjective probability below 0.9, the results between each group are comparable. Calibration curves for each type of questions are mostly the same. Nevertheless, for more extreme subjective probabilities (i.e. superior to 0.9), there are more differences between the groups. The confidence level for the one alternative question group is stronger than the one of other groups, as its calibration curve lies far below the others.

As a consequence, we clearly see, here, that the different calibration curves for each type of questions are under the identity line. This is a typical feature of overconfidence. Moreover, it seems that the type of question impacts the level of overconfidence in extreme expressions of confidence.

To conclude, we can highlight that one way of measuring overconfidence is the measure of calibration of individuals. Nevertheless, otherwise than with discrete propositions, overconfidence is generally computed using continuous propositions (i.e. intervals).

A) 2) Miscalibration using intervals

As we have seen previously, psychologists commonly ask individuals discrete answers in order to measure overconfidence. Another method is widely spread among the overconfidence literature : measuring miscalibration with intervals.

With this approach, individuals are asked the value of an uncertain continuous quantity. Individuals are customarily quizzed using a questionnaire of continuous propositions (i.e. open-ended questions). For example :

- Since when Roma is the capital of Italy ?
- How long is the Seine River ?
- What is the distance between the Earth and the Sun ?

We can note that questions are the same as the measure of miscalibration with discrete answers. The shift is concerning answers to these questions. In these case, individuals are not given a choice, among which they need to make a choice. Here, individuals need to provide an interval.

As continuous variables, answers, to the questions written above, can be expressed as a probability density function across the possible values of quantity. Nevertheless, it is not possible to ask individuals to draw their entire function. Consequently, the procedure most commonly used is the fractile method.

With the fractile method, individuals are asked to state the uncertain quantity that are associated with a small number of predetermined fractiles of the distribution. For example, for the 0.5 fractile, individuals assert the value of the quantity such that the true answer is equally likely to be above or below the asserted value.

Usually, studies are using what is called the « interquartile index ». Individuals need to provide two values, in order to construct a range that contains the right answer. For example, if individuals are asked to provide the 90% confidence interval for a specific question, they need to state two values. First, the lower bound (i.e. only 5% of odds that the true value will fall below this bound) and the upper bound (i.e. only 5% of odds that the true value will fall above this bound). A perfectly calibrated person will have an interquartile index of 0.90 in this case.

The « surprise index » is the percentage of true values that fall outside the fractiles assessed. The « hit rate » is the opposite. It is the percentage of true values that fall inside the fractiles assessed. For example, with an interquartile range that lies between 0.01 and 0.99, the perfectly calibrated person will have a surprise index (hit rate) of 2% (98%). In the higher example, the surprise index (hit rate) would have been 10% (90%).

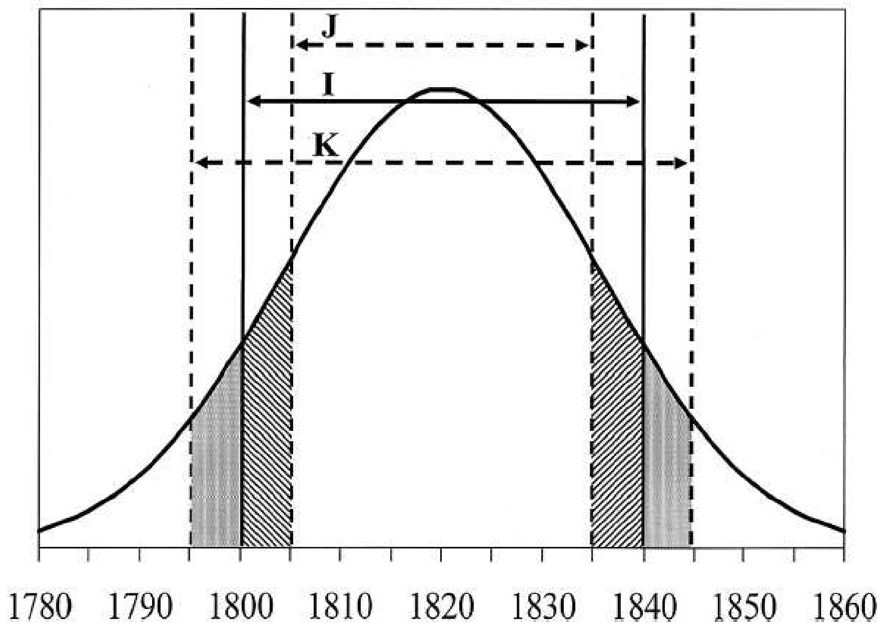
A large surprise index means that the individual's confidence interval is too narrow to enclose enough of the true values. This is an indication of overconfidence, or hyper-precision (Pitz, 1974). For example, in the latter example, if the surprise index is higher than 2%, that is if more than 2% of the answers are outside the interval, the individual is stipulated as overconfident.

On Figure 2 (p.26, drawn from Soll and Klayman, 2004[5]), we can observe an hypothetical subjective probability density function. The interval I is the interval which contains 80% of the

[5] Soll, J. B., J. Klayman. 2004. Overconfidence in interval estimates. Journal of Experimental Psychology: Learning, Memory, and Cognition 30(2) 299 – 314.

continuous probability (i.e. for the question among the year in which Charles Darwin was born). The interval K is 10 years too large, whereas the interval J is 10 years too small.

Figure 2 : A hypothetical subjective probability density function for an estimate of the year in which Charles Darwin was born. Intervals J and K represent opposite 10-year errors in estimating the interval, I, that contains 80% of the probability (Soll and Klayman, 2004)



With this figure, we can point out the fact that the width of the interval is the most important measure in the computation of continuous calibration. Indeed, subjects would have interest to deliver the largest allowed interval. Nevertheless, psychologists found evidence of narrow intervals, given by individuals. This is an indicator of overconfidence.

We can underline the existence of an arbitrage between knowledge and precision. A subject can feel that he is an « expert » on a question, and thus he gives a small interval. Nevertheless, even if the subject is not 100% sure about the question, he will not provide the largest allowed interval (i.e. although they are allowed). Consequently, a narrow interval is generally stated as a sign of overconfidence : individuals overestimate the precision of their knowledge, and so give narrower intervals than the hypothetical interval, given by the density function.

Soll and Klayman (2004) work to prove that a large surprise index (i.e., a low hit rate) is caused mostly by the width of the interval, and not by the variability of the interval. They conduct an experiment over 32 undergraduate and graduate students from the University of Chicago. Students are asked to answer some small « cases » in various subjects. Then, they need to provide their 80% estimates, that is the two numbers such as they are 80% sure that the correct answer lies between the two.

Soll and Klayman (2004) also attempt to construct a ratio, in order to compare the width of intervals given by individuals and the « accurate » width. For that, they compute M, which represents the ratio of the observed average interval width to the well-calibrated interval width. If M is less than one, it shows that the observed interval width is lower than the well-calibrated interval width (i.e. that the observed interval is narrower). Thus, with the ratio M, Soll and Klayman (2004) can measure the bias that cannot be associated with variability, but only with the width of the interval.

Soll and Klayman (2004) find that when people are asked to give their 80% confidence intervals, only 39% of the ranges hits the right answer. Thus, 41% of individuals are overconfident. Moreover, as the ratio M is under than 1 for the assessed sample, overconfidence can be stated as a consequence of the narrowness of intervals and not of their volatility.

Researchers, that are looking for overconfidence by measuring the miscalibration with continuous propositions, are generally asking 90% confidence intervals to subjects. Thereafter, the surprise index is assessed by quantifying the number of true values that fall outside the confidence intervals stated by individuals. The width of confidence intervals is also measured : the narrower they are, the more individuals are stated as overconfident (Soll and Klayman, 2004).

Interval questions can be a more accurate measure of the miscalibration of individuals. Indeed, constructing a probability range is widely used in the development of many real-wold judgments (Kruger et al., 1999). For example, when individuals need to plan when they need to leave their residence in order to be on time, or more related to this dissertation, when people need to decide how much they invest in financial securities : they often implicitly construct a confidence interval for the time the ride will take, for the first case, or for the return of the stock over the next 20 years for the second case.

B) The better-than-average effect

The term of better-than-average effect (Taylor and Brown, 1988; Goethals et al., 1991) is widely used in the literature in order to name an overplacement bias. It can be summarized as the fact that people tend to believe that they have greater capacities or competences (i.e. intellectual or physical, for example) than the average (Alicke et al., 1995; Heine and Lehman, 1997). Moreover, it can label people who tend to have excessively positive judgments of themselves. This kind of overconfidence measure needs to be used into perpective with individual's judgment, of their position relative to the others.

In order the measure the better-than-average effect, individuals need to provide their judgment of their rank in a group. For example, an investor guesses that her/his portfolio's return will be the best of a group of investors, and, in fact, half of the investors in the group has a best portfolio's return than him/her. This investor over-places his/her return relative to the return of others. He/she is stated as overconfident. Moreover, subjects generally judge positive traits to be more descriptive of self than negative traits (Alicke, 1985, Brown, 1986).

Numerous psychologists underlined the importance of this overplacement bias. For Taylor and Brown (1988), the better-than-average effect is even a characteristic of the « *normal human thought* ». They say that positive self-evaluation can help to develop the ability of individuals to care about others, to be happy and to engage in productive and creative work. Overplacement is widely spread, according to them, because the social world and cognitive-processing mechanisms create filters on the information available to individuals.

Studies, over the better-than-average effect, have been conducted in various fields and are not limited to psychology. Baumhart (1968) extends the measure to the domain of ethics, Larwood and Whittaker (1977) find evidence of a better-than-average effect in sales management. Indeed, Larwood and Whittaker (1977) conduct a survey over management students and corporate presidents. They observe an overplacement bias of the subjects regarding their own competence, bias that may lead to overly optimistic and risky planning for the future. Larwood and Whittaker (1977) find evidence of a positive link between better-than-average bias and risk taking behavior.

Furthermore, some psychological studies even described the better-than-average effect as a more consistant measure of overconfidence than both the miscalibration and the illusion of control. Indeed, Festiger (1954) states that people have a « *fundamental desire* » to assess their own abilities, but often face a lack of objective standards. Consequently, they use the social comparison and the abilities of others as the subjective reality and as a proxy for objective standards. Individuals tend to assess themselves as better than the median individual because of their self-enhancement tendency (Greenwald, 1980).

One of the former study conducted on the overplacement effect was directed by Svenson (1981). He operates an experiment over 161 subjects from an US sample and from a Sweden sample. 81 are students at the University of Oregon (i.e. Group 1, US sample), with a median age of 22 years old, and 80 are psychology students at the University of Stockholm (i.e. Group 2, Swedish sample), with a median age of 33 years old. The subjects are asked, in a written form, about their competence as drivers, in relation to a group of drivers.

The following question is asked : « *We want you to compare your own skill to the skills of the other people in this experiment. By definition, there is a least safe and a most safe driver in this room. We want you to indicate your own estimated position in this experimental group* ». The question about the driving skill is nearly the same, with only small changes of words. Then, individuals are asked to assess both their safety and their skills in comparison to the others, by checking a box on a percentile scale, with 10 percent intervals.

Table 3 : Distribution of percent estimates over degree of safe and skillful driving in relation to other drivers (Svenson, 1981)

	Estimated position in sample (percentiles)									
	0–10	11–20	21–30	31–40	41–50	51–60	61–70	71–80	81–90	91–100
Safety										
US sample	2.5	0.0	5.0	0.0	5.0	2.5	2.5	22.5	37.5	22.5
Swedish sample	0.0	5.7	0.0	14.3	2.9	11.4	14.3	28.6	17.1	5.7
Skill										
US sample	0.0	2.4	2.4	2.4	0.0	12.2	22.0	12.2	26.8	19.5
Swedish sample	2.2	6.7	2.2	4.4	15.5	17.7	11.1	24.4	13.3	2.2

Table 3 depicts the distribution of the results of the study. On this table, we can observe the distribution of the sample, according to individual estimated position in the sample. Moreover, results are divided in distribution of estimates for the two groups (i.e. Swedish and US) and for the two questions asked (i.e. safety and skill).

We can see that most of the subjects, in both groups, view themselves as safer and more skillful drivers than the median driver of the group, as most part of the sample is falling above the 50% percentile. By adding up the percentages of the samples that are over the 50 percentile, we find that 88% of the sample in the US group and 77% in the Swedish group, estimate their position as above median, for the safety measure.

Results are even stronger for the skill measure in the US group. 93% of the US group believe that they are more skilled than the median driver. For the Swedish group, 69% of the drivers estimate their position over the median individual (i.e. the skill measure). Both of these measures have the same characteristic : they are statistically impossible. Indeed, statistically speaking, it is impossible to have more than 50 percent of the population above median. In order to be consistent, results should have shown 50 percent of the population, no more or less, in the top 50 percent of the drivers. As the results are statistically impossible, this phenomenon can be labelled as a bias.

Moreover, the median for the distribution of safety judgment is between 81-90% for the US group and between 71-80% for the Swedish group. This means that 50% of the US group consider themselves to be among the safest 20% (US group) or 30% (Swedish group) of the drivers. For the skill judgment, the median of the distribution is between 61-70% for the US-group and between 51-60% for the Swedish group.

To summarize, we can see that this study of Svenson (1981) exhibits that individuals tend to regard themselves as more skillful and safer than the median driver, in each group. Moreover, 50% of the sample, in each group, believe to be in the top 20% or 30% of, respectively, the US and the Swedish group. Both of these results are statistically impossible : Svenson (1981) underlines the existence of a bias (i.e. better-than-average effect).

Svenson (1981) aims to show that a majority of individual tends to express better-than-average effect or, in other words, overplacement bias. These individuals are stated as overconfident, as they believe that their capabilities are superior to the median individual's capabilities.

In order to measure the better-than-average effect among individuals, Svenson (1981) compares the perceived percentile (i.e. the assessed subjective place in the sample) to the median percentile and identifies a population level bias (i.e. more than 50% of the individuals think that they are above 50%).

Nevertheless, there is another way to measure the better-than-average (BTA) effect . The perceived percentile of the subject can also be compared with the actual percentile of the subject. The actual percentile can be determined objectively or assessed by an external examiner (i.e., the actual rank of a subject in a population). The perceived percentile is the subjective rank given by the same subject. If the perceived percentile is higher than the accurate percentile, this is a manifestation of overconfidence. It is relatively close to the calibration measure (i.e. calibration curves), in the exception that it is not the perceived probability of success that is measured, but the perceived position in a group of individuals.

Goethals et al. (1991) expend the results of Svenson (1981), by comparing the perceived percentile and the actual percentile of individuals. They reach to the conclusion that many social comparisons and evaluations are susceptible to lead to systematic bias and to better-than-average-effect.

Larrick et al. (2007) conduct further studies on the better-than-average effect, using the measure at the individual level. They conduct a survey over 40 University of Chicago students, who are asked 100 questions during a 45 minutes period. These 100 questions consist of 20 questions over 5 different domains (i.e. college acceptance rates, dates of Nobel Prizes, length of time recent pop songs had been on the charts, financial worth of richest people, and games won in the previous season by National Hockey League teams).

After completing the questionnaire in each domain, participants are asked to give their estimate percentile (i.e. their rank) of performance for that domain, among all the surveyed students. Larrick et al. (2007) compare the estimated percentile provided by students, to their actual percentile in the population (i.e. the actual percentile was computed by making a rank, using the rate of success of each participant). They find that, for the majority of participants, their perceived percentile was higher than their accurate percentile. This shows evidence of a better-than-average effect among participants of this study, at an individual level.

To sum up, we can say that psychologists reached to the conclusion that the better-than-average effect is widely spread among individuals. Most people tend to see themselves as better than the average individual. Moreover, the subjective position of individuals, in a sample, is generally above their accurate position. These two manifestations can be seen as an expression of overconfidence.

C) The illusion of control

Overconfidence does not only encompass the overprecision (i.e. miscalibration) and overplacement (i.e. better-than-average effect) of individuals. Overconfidence can also be defined as the tendency of individuals to overestimate probabilities of their success or their own performance. Indeed, individuals tend to overstate their own ability, capacity and control over their chances of success : Langer (1975) speaks of « *illusion of control* ».

The illusion of control, as a component of overconfidence, can be characterized, as the tendency of individuals to have a wrong perception of their own control over their life's events. In fact, individuals perceive that they have more control over their life than they actually have. They perceive that they have high level of ability and they notice covariance effects, between their comportement and their success, when it does not exist. Langer (1975) defines illusion of control as « *an expectancy of a personal success probability inappropriately higher than the objective probability would warrant* »[6].

The overestimation of control, or the illusion of control, is negatively correlated with the notion of control. On the one hand, when control is high, there is less probability of illusion of control expression. On the other hand, when control is low, there is more probability of the occurrence of this bias (Presson and Benassi, 1996).

Presson and Benassi (1996) study more deeply this illusion of control. They conduct a meta-analytic analysis on the expression of the illusion of control, in the behavior of individuals. A large part of psychology researches, over the confidence of individuals, focus on the illusion of control effect. Psychologist as Langer (1975) and Langer and Roth (1975) try to point out the expression of

[6] Langer, E.J. (1975). The illusion of control. Journal of Personality and Social, Psychology, 32, 311-328

control among individuals (i.e. even in events that are actually driven by chance and randomness). They try to determine which effects can influence the illusion of control. Moreover, Langer and Roth (1975), as well as Miller and Ross (1975), underline the correlation between illusion of control and positive events.

Among the literature on illusion of control, several causes of illusion of control are pointed out by psychologists.

Langer (1975) underlines the link between choice and illusion of control. Even if events are random, individuals tend to think that they have control over it. He conducts a survey over 27 individuals, who are in a choice condition, and 26 individuals, who are in a no-choice condition. The two groups (i.e. choice and no-choice groups) are approached by a ticket agent in order to purchase lottery tickets. The lottery tickets are football cards, costing $1. The choice group is given the choice of the ticket, whereas the second group is handed a card, randomly chosen. After they have purchased a lottery tickets, subjects are approached by the experimenter and ask to sell their lottery tickets to another individual. Each individual is instructed to tell the amount of money, for which they would sell their lottery tickets.

The amont of money constitutes the dependent measure. Langer (1975) finds a difference between the choice and the no-choice group. People who choose their own numbers require more money than individuals who get random lottery tickets. The mean amount of money required for the subject to sell his lottery ticket is $8,67 for the choice group and only $1.96 for the no-choice group. Moreover, 15 subjects decide not to sell. 10 of these subjects are in the choice group.

Consequently, participants, who are allowed to choose their own tickets, want less to trade their ticket, or at a higher price, than subjects who are not given the choice.

Thus, a lottery gives an illustration of the illusion of control effect. The outcome of the lottery is entirely driven by chance (apart from the decision of entering the lottery, i.e. buying or not the initial ticket). Moreover, the feeling of control over the lottery outcome increases the value of the ticket. The more an individual feels a control over the lottery, the higher value he gives to this lottery ticket. As individuals, who are given a choice, require a higher price than the no-choice individuals, Langer (1975) concludes to an evidence of illusion of control. Indeed, with the choice, individuals attribute more value to the lottery ticket. As the ticket value is the proxy for the feeling of control, the choice creates an illusion of control over the probabilities of success (i.e. the ticket is sold at a higher price), even in a perfectly random outcome (i.e. a lottery).

If individuals face a sequence of correct predictions at the beginning of a task, they will perceive events as being controllable. Indeed, a sequence of correct predictions creates an illusion of control. This fact is checked even when the task outcome is uncontrollable (i.e. for example, a lottery).

This evidence is tested by Langer and Roth (1975). They conduct a survey on college students. 62 participants need to participate in 30 trials of a coin-toss game. Three groups are builded with rigged coins. One faces large number of wons during initial trials and large number of loss toward the end (descending sequence) and the other faces the opposite configuration (ascending sequence) and the last one faces a random configuration (random sequence). Moreover, subjects need to report their feelings of control and their predictions for upcoming trials during the experience. Langer and Roth (1975) find that individuals in the descending sequence group express a stronger illusion of control than students in the ascending sequence group.

Table 4 : Mean questionnaire responses as a function of outcome sequence (Langer and Roth, 1975)

	Question				
Sequence	Predicting ability	These 30 trials	Next 100 trials	Practice	Distraction
Descending	5.70	16.7	54.2	2.13	4.72
Random	5.10	14.4	51.1	2.00	4.53
Ascending	4.93	13.3	49.1	1.37	4.78

Note. Values under "Predicting ability," "Practice," and "Distraction" represent answers to questions along an 11-point (0–10) scale; values under "These 30 trials" and "Next 100 trials" are the numbers of successful trials expected out of those groups.

On Table 4, we can observe a set of values for the three groups : descending, random and ascending. The predicting ability, practice and distraction column represents the results of a questionnaire answered by the individuals, in order to underline the fact that the three groups present the same characteristics. As these values are relatively similar for the three groups, Langer and Roth (1975) reach to the conclusion that the three groups present the same abilities. Nevertheless, we can observe that the number of successful trials expected by the three groups are not the same. People in the descending sequence group are expected 54.2% chances of success in the next 100 trials, whereas subject in the random group are expected 51.1% chances of success and individuals in the ascending group are expected only 49.1% chances of success.

Langer and Roth (1975) explain these results by the fact that people who won at the beginning, think that they can handle the game (i.e. and thus are expecting more successes in the next trials), and then attribute their further failures to temporary chance fluctuations. On the opposite, people who loss at the beginning can measure their lack of control over the game, and face the fact that it is a chance-determined event.

Burger (1986) conducts the same kind of experience than Langer and Roth (1975), but with an additional variable : the desirability of control, which is an individual characteristic measured with a scale. He shows that individual differences have a strong impact in the expression of illusion of control. The more the expressed desirability of control, the stronger the illusion of control.

In another experiment, Langer (1975) makes 15 subjects to complete a circuit in order to ring a buzzer. One group needs to manipulate directly the circuit (high involvement), whereas the other just needs to give instruction to some intermediary (low involvement). Moreover, each group is divided into two sub-groups. One is made familiar with the circuit (high familiarity), whereas the other does not know the circuit before the experiment (low familiarity). Then, subjects are asked to provide their degree of control, on a 1 (very unsure) to 10 (pretty certain) scale.

Table 5 : Mean pretrial confidence ratings of success on illusion of control (Langer, 1975)

	Involvement	
Familiarity	High	Low
High	6.07	5.67
Low	5.67	3.80

Note. n = 15 per cell.

On Table 5, we can observe the mean level of confidence assessed by the subjects in the experiment, in the four conditions described above : high and low involvement, and high and low familiarity. We can underline that people with high involvement tend to feel a higher degree of confidence (i.e. respectively 6.07 and 5.67 with high and low familiarity and high involvement, whereas 5.67 and 3.80 with low involvement). Thus, we can see a positive correlation between degree of involvement and overestimation of control. Moreover, we can see that with a high familiarity, the level of confidence of individuals tends to be higher. The level of confidence with high familiarity is respectively 6.07 and 5.67 with high and low involvement, whereas this level decrease to respectively 5.67 and 3.80, with low familiarity (i.e. with high and low involvement).

Consequently, Langer (1975) shows that both the familiarity and the involvement have a positive effect on the confidence and the sensation of control of individuals. Inversely, a low involvement and a low familiarity tends to generate a low level of confidence.

To conclude, we can say that the illusion of control bias is confirmed by the academic researches in psychology. It is correlated with the notion of choice, the previous outcome sequence and the degree of involvement and familiarity of the subject.

Moreover, further implications of the illusion of control were found. For example, Langer (1975) points out also the effect of the « elegance » of the adversary and the competition, on the illusion of control. Indeed, in a bet, when individuals are confronted to a dapper (i.e. classy individual), they are likely to bet a lower amount of money than when they are confronted to a « schnook ». Their confidence on their success, and thus on their control, tend to be higher when they face individuals with less « charism ». Miller and Ross (1975) reach to the conclusion that individuals overestimate their role in the accomplissement of positive events (i.e. when the positive event actually occurs). This overestimation of one's role in an event is generally named as « self-attribution » bias.

D) The unrealistic optimism

Finally, overconfidence can refer to expectations that individuals draw for their future. Indeed, most individuals underestimate their driving, health and financial risks, but overestimate their probabilities and chances of experiencing favorable events, relative to the median individual and to the objective probability of occurence. This expression of overconfidence is called « *unrealistic optimism* » (Weinstein, 1980).

Psychologists widely try to point out this « unrealistic optimism » effect, by measuring the subjective estimation, of events' occurence, given by individuals. For example, Weinstein (1980) conducts a survey in order to compute subjective probabilities expressed by individuals, concerning both positive and negative events. He finds evidence of unrealistic positive views for the future among the subjects. Wenglert and Svenson (1982) and Wenglert and Rosen (2000) extend these results to a Swedish population. Furthermore, Hoch (1985) reaches to the conclusion that MBA students overestimate their future salary and the number of job offer they will receive. Baker and Emery (1983) find that, even with high divorce rates, individuals tend to think that they are not concerned (i.e. that their marriage will succeed).

Furthermore, individuals tend to underestimate their probabilities of experiencing negative events. Renner et al. (2000) observe an underestimation of the individual risk of cardiovascular disease, in a large sample of men and women, between 14 and 87 years old. Robertson (1977) finds that individuals believe that they are less likely than the others to experience automobile accident. Perloff and Fetzer (1986) extend this result to the event of being a crime victime or becoming ill.

The unrealistic optimism bias was pointed out the first time by Weinstein, (1980). By conducting two studies, he finds evidences that people tend to be unrealistically optimistic about their future life events.

First, Weinstein (1980) tests the hypothesis that « *People believe that negative events are less likely to happen to them than to others, and they believe that positive events are more likely to happen to them than to others* ».

In order to demonstrate that, he asks 258 college students to estimate the difference between their own chance of experiencing 42 events and the average chance of their classmates. They are asked to choose between values, in order to reflect their deviation from a response of the « average » (-100%, -80%, -60%, -40%, -20%, -10%, 0%, 10%, 20%, 40%, 60%, 80%, 100%, 200%, and 400%.).

This comparative judgment asked to students, can be summarized mathematically by the expression :

$$Pi - P,$$

where Pi is the estimated probability that an event will happen to a particular individual and P is the population (i.e. sample) mean of Pi. We can note that here the estimated difference asked is in percentage (i.e. 100% x (Pi - P) / P), because it is easier and more nature for students. It does not change the interpretation of the results.

If judgments given by students are not biased, the mean value of their comparative judgments (i.e. Pi - P) should be zero. If the mean value of their comparative judgments is significantly different from zero, we are in presence of a systematic bias. Indeed, when the mean comparative judgment of one's own chances is above zero (i.e. Pi > P), this implies that individuals think that this event will more probably happen to them than to the others. The inverse is also true. When the mean comparative judgment is under zero (i.e. Pi < P), individuals tend to think that this particular event will less probably happen to them than to the others.

On a group basis, it is relatively easy to test for an optimistic bias. If all people claim that their chances of experiencing a negative event are less than average or their chances of experiencing a positive event are more than average, they are clearly making a systematic error. Thus , they are demonstrating unrealistic optimism. Recall that this method is relatively close to better-average-effect measure. A summary of the results of the experience is given in Table 6.

Table 6 : Unrealistic optimism for future life events (Weinstein, 1980)

	Measures of optimism	
Abbreviated event description	Mean comparative judgment of own chances vs. others' chances (%)[a,b]	No. of optimistic responses divided by no. of pessimistic responses[b,c]
Positive events		
1. Like postgraduation job	50.2***	5.93***
2. Owning your own home	44.3***	6.22***
3. Starting salary > $10,000	41.5***	4.17***
4. Traveling to Europe	35.3***	2.25***
5. Starting salary > $15,000	21.2**	1.56*
6. Good job offer before graduation	15.3**	1.42
7. Graduating in top third of class	14.2	1.02
8. Home doubles in value in 5 years	13.3*	1.78*
9. Your work recognized with award	12.6*	1.72*
10. Living past 80	12.5**	2.00**
11. Your achievements in newspaper	11.3	1.66*
12. No night in hospital for 5 years	8.5	1.23
13. Having a mentally gifted child	6.2*	2.26**
14. Statewide recognition in your profession	2.1	1.00
15. Weight constant for 10 years	2.0	.82
16. In 10 years, earning > $40,000 a year	− .7	.64*
17. Not ill all winter	− .7	.89
18. Marrying someone wealthy	− 9.1	.36*

[a] In making a comparative judgment, students estimated the difference in percent between the chances that an event would happen to them and the average chances for other same-sex students at their college. $N = 123$ to 130, depending on rating form and missing data. Student's t was used to test whether the mean is significantly different from zero.
[b] For positive events, the response that one's own chances are greater than average is considered optimistic, and the response that one's own chances are less than average is considered pessimistic. For negative events, the definitions of optimistic and pessimistic responses are reversed.
[c] Significance levels refer to a chi-square test of the hypothesis that frequencies of optimistic and pessimistic responses are equal.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Overall, values of Table 6 (i.e. the 24 positive events can be observed in Weinstein, 1980) strongly suggest that individuals tend to be unrealistically optimistic about their future life events, calling the hypothesis stated above. For positive events, students report a positive comparative judgment (i.e. the mean of Pi - P is superior to 0, for 15 of the 18 events), whereas for negative events, they communicate a negative comparative judgment (i.e. the mean of Pi - P is inferior to 0, for 22 of the 24 events). They feel that positive events are more likely to happen to them than to the others, whereas negative events are less likely to happen to them than to the others.

We can underline the fact that, with some events, the expression of unrealistic optimism tend to be really strong. For example, for the event « like post graduation job », subjects think that they have 50,2% more chances than the others to experience this particular event. The same is true for negative events : for « having drinking problems » or « attempting a suicide », the unrealistic optimism is sharp. Students feel that their probabilities of experiencing such events are respectively 58,3% and 55,9% lower than the other’s probabilities.

Globally, Weinstein (1980) finds that the mean of comparative judgments of individuals, for all positive events, is significantly greater than zero (+15.4%). The mean for all negative events is significantly less than zero (-20.4%).

Furthermore, in Column 2, we can see the ratio of the number of optimistic responses (i.e. for positive events, number of responses in which the subject thinks his/her chances are above average and the opposite for negative events) over the number of pessimistic responses (i.e. for positive events, number of responses in which the subject thinks his/her chances are under average and the opposite for negative events) and thus have an expression the optimistic direction of the judgment bias. If this ratio is superior to 1, it implies that the number of optimistic responses is greater than the number of pessimistic responses.
For example, if we take the first line, « like post-graduation job », the ratio of the number of optimistic responses over the number of pessimistic responses is 5.93. As this is largely superior to 1, it indicates a strong optimistic tendency. Data shows same results for almost each question. The

existence of strong optimistic tendencies for both positive and negative life events is clear. Almost all values are superior to 1, suggesting a higher number of optimistic answers than pessimistic answers.

Thanks to this survey, Weinstein (1980) highlights the evidence of « *unrealistic optimism* » among a group of individuals. Globally, subjects rate their own chances of experiencing an event to be above average, for positive situations, and below average for negative situations.

Weinstein (1980) tries to explain the reasons for the existence of unrealistic optimism among individuals. He reaches to the conclusion that, the degree of desirability, the perceived probability, the perceived controllability (i.e. illusion of control) and the stereotype salience (i.e. the effect of social stereotypes on individuals) can influence judgments that individuals make about their future life events.

Weinstein (1980) tests the correlations between the unrealistic optimism bias and these four hypothetical explanatory factors, previously listed (i.e. degree of desirability, perceived probability, perceived controllability and stereotype salience). He constructs five groups in order to test the influence of each factor.

Globally, Weinstein (1980) reaches to the conclusion that all tested factors are significant in order to explain unrealistic optimism (in exception of stereotype salience). When the degree of desirability, the perceived probability and the illusion of control are high, unrealistic optimism tend to be stronger.

To conclude, we can state that the unrealistic optimism bias is measured by using comparative judgment questions (Weinstein, 1980). As the mean of comparative judgments differs from zero, we can assume that individuals tend to express a judgment bias. They consider that they have more chances to face a positive event than other people, and less chances to face a negative event than other people. Some explanations can be the degree of desirability expressed by individuals, the probability perceived of an event, their personal experience or their perceived controllability over the event (i.e. illusion of control).

Conclusion

Overconfidence is a bias widely measured by psychology studies. It can be expressed by both overprecision (i.e. miscalibration), overplacement (i.e. better-than-average effect), overestimation of control (i.e. illusion of control), and overestimation of positive outcomes (i.e. unrealistic optimism).

These four manifestions of overconfidence can be measured in different ways. Overprecision (i.e. miscalibration) can be assessed using the calibration method and by constructing calibration curves. The better-than-average effect is measured by comparing the subjective rank in a group to its accurate rank. The illusion of control is pointed out by measuring the degree of control perceived by individuals over an event, and the unrealistic optimism by asking the perceived probability of experiencing an event in comparison to the average probability.

These different ways of measuring overconfidence are commonly used in finance in order to compute the level of confidence of investors. Indeed, financial researchers try to explain abnormalities (i.e. the high level of volume), observed on financial markets. As a consequence, researchers, such as Odean (1999) or Glaser and Weber (2007) proceed in two steps. First, they used measures constructed by psychologists, in order to find evidences, or not, that investors are overconfident. In a second step, they attempt to measure the main consequences on financial markets, of the overconfidence bias measured in a first step.

Thus, we will now focus on the overconfidence bias on financial markets.

Part 2 : Overconfidence on financial markets

Introduction

« *There is a simple and powerful explanation for the high levels of counterproductive trading in financial markets: overconfidence* »[7]
(Barber and Odean, pp.261)

Market efficiency was defined by Fama (1972) as the idea that when investors are in competition with one another, in frictionless financial markets, assets will be priced to fully reflect all available information. Thus, market efficiency relies strongly on the assumption that investors are rational.

But, as stated in the introduction of this dissertation, market efficiency, constructed by traditional models, is not always observed empirically. Studies, conducted by psychologists, showed evidences that the behavior of economic actors is influenced by psychological biases. Moreover, some imperfections are observed on financial markets. Financial markets tend to deviate from the classical axioms of financial theories and from the paradigm of rationality.

---

[7] Barber, B., Odean, T., 2001. Boys will be boys: gender, overconfidence, and common stock investment. Quart. J. Econ. 116, 261–292.

The volume of trades actually observed cannot be explained only by rational motives. Rational arguments, that can lead investors to trade, can be liquidity reasons (i.e., a need for cash, in order, for exemple, to face an accident) and the need to rebalance, in order to get a more diversified portfolio (i.e. under-diversified portfolio are more influenced by asymmetric shocks).

Nevertheless, these motives seem not sufficient to explain the volume of transactions, and furthermore, the large transaction costs associated. Glaser and Weber (2007) underlined the vast size of the trade volume. Over the period 1980-2014, the annualized average turnover, for the 500 largest US stocks, was, on average, 223 percent, thus just a little more than $100 billion per day. Over the year 2014, the total dollars traded, for these 400 largest US stocks, was $29.5 trillion (i.e. Collin-Dufresne and Daniel, 2014), which is almost the double of the US GDP for this year. The data are even larger in foreign exchange markets. In 1989, the average volume of trade on the foreign exchange was around $430 billion per day, in comparison to a $22 billion of US GDP per day and $11 billion of goods and services trades per day (i.e. Froot and Thaler, 1990).
The average annual turnover rate on the New York Stock Exchange (NYSE) is greater than 75 percent (i.e. this means that 3 over 4 securities were exchanged) and the daily trading volume of foreign exchange transactions in all currencies (i.e. including forwards, swaps, and spot transactions) is roughly one-quarter of the total annual world trade and investment flow, in 1995 (i.e. Dow and Gorton, 1997). Shiller (1999) and Leroy and Porter (1981) found also evidences of excess volatility and volume in equity markets.

Traditional paradigms do not seem sufficient in order to explain this level of trading volume. Financial researchers focused their studies on the overconfidence bias and its consequences on the volumes of trades.

Odean (1998a) writes that, as the stock selection (i.e. the selection of assets, in the buying and selling process, that are more likely to generate high returns than similar assets) is a difficult task, with low predictability, it leads to great expression of overconfidence. Indeed, as stated in Part

I, studies showed that overconfidence level is higher in difficult tasks (i.e. Lichtenstein et al., 1982 ; Kruger, 1999). Moreover, this effect of overconfidence is not limited to newcomer investors. Griffin and Tversky (1992) reached to the conclusion that experts can even be more subject to the overconfidence effect. Indeed, for Griffin and Tversky (1992), when predictability is low (i.e. as in the financial market environment), professionals have approaches and methods, that they tend to overbalance and overestimate its accuracy.

Financial markets is a field where the calibration and the adjustment of judgment can be difficult. Indeed, Odean (1998b) spoke of securities markets as « *difficult and slow places in which to calibrate one's confidence* » (Odean, 1998b). In stock markets, the feedback is often very noisy and thus conduct to slow learning process. The endogeneity of the evaluation exacerbates this phenomenon.[8]

In the financial literacy, the overconfidence bias is mostly depicted as the systematic overweighting of the precision of one's believes, which leads the investor to underestimate the risk of random variables. In other terms, in overconfidence models, investors overestimate not only the relevance of their knowledge regarding the valuation of the security, but also the relevance of their personal evaluation with respect to the others.

As stated in Part I, individuals tend to overestimate the degree to which they are responsible for their own success or for a positive event (i.e. the phenomenon of illusion of control, demonstrated by Langer, 1975, Miller and Ross, 1975, and Langer and Roth, 1975). Therefore, successful investors may, by the effect of illusion of control, overweight the effect of their own competence in their past success, and thus become even more overconfident. « *Don't confuse brains with a bull market* » : this old Wall Street motto underlines the danger of attributing positive returns to self-competence.

[8] For Shefrin and Statman (1985), because investors judge their decisions on the basis of returns realized (i.e. and not on the basis of returns accrued), they prefer to sell winners and hold losers and hence appreciate their performance as better as it actuality is (i.e. disposition bias).

In this dissertation, we will first focus on demonstrating the way the overconfidence bias is measured among investors, using the different components of the overconfidence bias described in Part I (i.e. miscalibration, better-than-average effect, illusion of control and unrealistic optimism). After that, we will sum up the main consequences of this bias on financial markets, among both individual investors but also professional investors.

A) Measure of overconfidence in financial markets[9]

Researches show empirically that individuals do not behave rationally. One expression of the deviation from the rational behavior is the overconfidence bias (Odean, 1999 and Glaser and Weber, 2007) .

As an excessively high number of trades is observed on financial markets, researchers tried to look for explanations. Consequently to the results and the demonstrations of numerous bias among individuals in psychology, financial researchers tried to check if these biases were expressed by individuals on financial markets.

One of these bias is the overconfidence bias. The first step of behavioral studies is to assess the presence or the absence of the overconfidence bias, among individuals or groups that are acting on financial markets.

The overconfidence was tested empirically among investors. A lot of behavioral financial researches tried to underline the existence of the different components of the overconfidence effect (i.e. the miscalibration, the better-than-average effect, the unrealistic optimism and the illusion of control) among investors (i.e. both individual and professional investors, in this part).

[9] i.e. here, among both individual investors (database and experimental studies) and professional investors (researches on traders and funds managers)

A) 1) The miscalibration among investors

Recall that miscalibration is the tendency of individuals to be certain about the accuracy of their beliefs or of their information. As stated in Part I, it is generally computed using general knowledge questions, asked to individuals. After that, individuals are asked their subjective level of confidence. In order to define an individual as overconfident or not, the subjective rate of success is compared to the actual rate, using a calibration curve. If the subjective rate of success is above the actual rate, the individual is stated as overconfident. Moreover, continuous proposition are usually used. Individuals are asked to provide their 90% confidence interval that contains the true answer. Individuals are declared as overconfident when their interval is too narrow compared to the « actual» interval : they overestimate their precision.

Glaser and Weber (2007), but Broihanne et al. (2014) use miscalibration measures in order to assess if investors are overconfident. The miscalibration measure is the same as described in the first part. In addition, researchers (i.e. the same as above, Glaser and Weber, 2007, and Broihanne et al., 2014) also measure the overconfidence level using « volatility estimates », a measure that seems more adapted to the context of financial markets.

A) 1) a) Miscalibration measure

Glaser and Weber (2007) try to measure the miscalibration among individual investors. They run a study over 3 079 individual investors from a German online broker in the period from January 1997 to April 2001, by using different datasets. All of the individual investors get an e-mail from the online broker, with a link to an online questionnaire, designed to collect several measures of overconfidence. The response rate was of 6.98%, which seems low, but is similar to responses rates in analogous questionnaires.

In this questionnaire, individual investors are asked to provide their 90% confidence intervals, by giving their upper and lower bounds to five questions concerning general economics and finance knowledge. Glaser and Weber (2007) process by computing the percentage of surprises for the questions answered by individual investors. As we have stated before, for a perfectly calibrated person, the percentage of surprises should be 10%.

The mean, minimum, maximum and the most important fractiles of the percentage of surprises in the general knowledge questions are depicted in Table 7.

Table 7 : Overconfidence in knowledge questions (miscalibration) results (Glaser and Weber, 2007)

Number of observations	137
Mean	0.75
Standard deviation	0.24
Minimum	0
5th percentile	0.4
10th percentile	0.4
25th percentile	0.6
Median	0.8
75th percentile	1
90th percentile	1
95th percentile	1
Maximum	1

This table presents the mean, minimum, maximum, and several percentiles of the percentage of surprises in knowledge questions (i.e., the number of correct answers that fall outside the 90% confidence interval for knowledge questions stated by investors in % of the number of questions answered by these investors). For example, the median of 0.8 shows that, for the median investor, four out of five correct answers fall outside the 90% confidence interval given by this investor

On Table 7, we can see that the mean percentage of surprise is 75%. The median is even greater, at 80%. This means that four over five of the answers fall outside the 90% confidence interval given by the individual investors. This is obviously much higher than the percentage of surprises for a perfectly calibrated individual (i.e. 10%).

This can be a proof that these individual investors are miscalibrated. Their confidence intervals are too narrow and does not contain the correct answer in a rate equal to the interquartile index rate (i.e. 90%). In the study of Glaser and Weber (2007), individuals can be designated as overconfident, according to their miscalibration.

Broihanne et al. (2014) also measure the miscalibration of investors. They conduct a study over financial experts. They sample 64 high-level professionals. These 64 high-level professionals are interviewed in May 2011, and 61 questionnaires were completed. These professionals are customers of CCR Asset Management, and agree to participate, without any monetary incentive, in a survey on decision under risk (i.e. jointly conducted by Morningstar and the University of Strasbourg). They are informed that the general results of the study would be made public.

Among the 61 professionals who complete the questionnaire, 39 are fund managers, 12 CFOs, 3 CEOs, 5 wealth managers, 2 analysts and 3 treasurers. The 61 professionals are questioned through a face-to-face interview, with the insurance that participants do not have Internet access (i.e. with Internet, they can check their answers).

The interviews last, on average, 28 minutes. The participants are mostly men (i.e. 17% of women among the sample), single, with a university degree. The average age is 44 years old and the average experience level is of 12 years of experience. These figures are comparable to other studies.

Then, Broihanne et al. (2014) work in order to measure the different components of the overconfidence effect among these professionals. Indeed, Broihanne et al. (2014) try to measure the miscalibration of probabilities, the better-than-average effect and the unrealistic optimism among these professionals.

In order to achieve that, Broihanne et al. (2014) conduct two questionnaires across the sample. The first is a questionnaire with general questions, and the second is a questionnaire with finance questions.

Broihanne et al. (2014) first ask 10 questions to the professionals, in order to assess their risk attitude, their risk perception, their risk taking tendency, their overconfidence level and their expectations.
They structure the questionnaire with questions among risk perception in first place, then questions among risk taking behavior and then risk attitude outside a market related context. The questions among risk perception are conducted using a Likert scale, ranging from 0 to 10. Professional investors need to assess their attitude in a portfolio choice, by investing in a risky lottery or by investing in a 3% risk-free investment. A second lottery is presented, in order to assess their risk taking propension and their risk perception.

Then, Broihanne et al. (2014) ask several questions to subjects in order to measure their overconfidence level and their self-evaluation of competences. They ask 10 questions to individuals, which were general finance questions. The individuals need to provide their 90% confidence interval. There is no constraint on the length of interval. The miscalibration level is measured by the number of wrong answers. Recall from Part I that the degree of miscalibration is measured by the number of answers provided that falls outside the 90% confidence intervals. Broihanne et al. (2014) find that on average, 5 answers out of 10 are wrong, and thus fall outside intervals.

Broihanne et al. (2014) find evidence of an overconfidence bias among professional investors. Indeed, the number of wrong answers is of 5.07 for general knowledge questions and 5.26 for financial knowledge, which exceeds the surprise index for a well-calibrated respondent (i.e. one wrong answer). The respondents are thus overconfident to their own knowledge. Moreover, their expected number of correct answer is largely nine, which is higher than the observed number.

Broihanne et al. (2014) explain this high level of wrong answer as a consequence of the narrowness of the interval. The width of interval is measured by the range. Broihanne et al. (2014) find that range is correlated with the number of correct answers (i.e. a coefficient of correlation of 0.787). It means that individuals with large calibration errors tend to propose narrow intervals, which is the definition of overconfidence in general knowledge.

A) 1) b) Volatility estimate measure

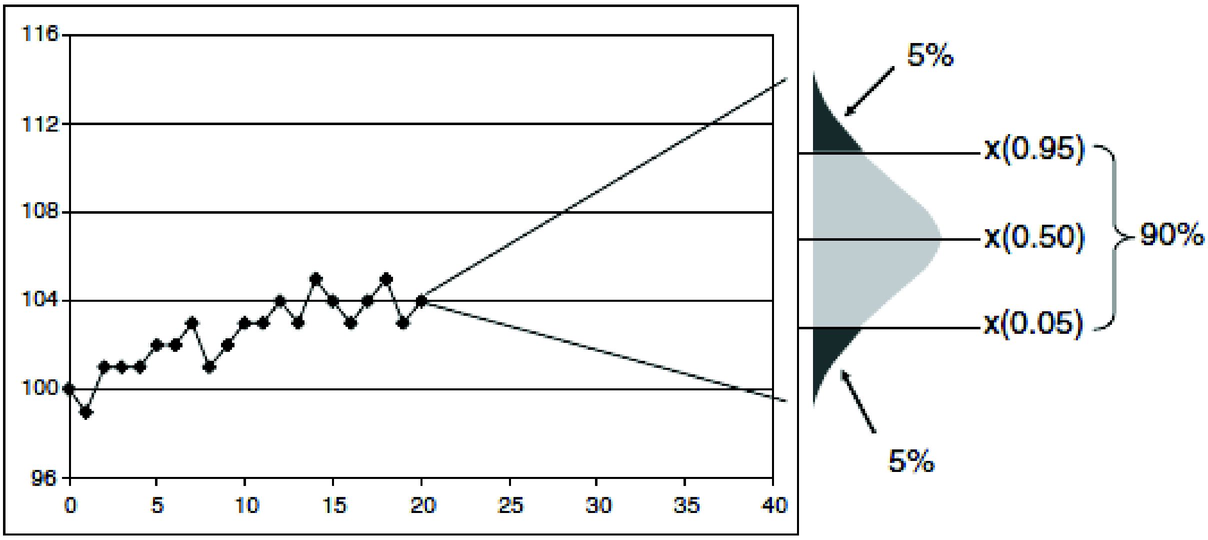
Studies of Kyle and Wang (1997), Benos (1998), Wang (1998), but also Hirschleifer and Luo (2001), Gervais and Odean (2001) and Chuang and Lee (2006) focus on the fact that the overconfidence effect leads to an underestimation of the risk level of investissement. Indeed, financial researches tend to point out the link between overconfidence and an underestimation of the volatility of the return. Financial studies try to underline the link between overconfidence and the underestimation of risk, through the miscalibration of expected returns.

Glaser and Weber (2007) use this kind of measure, in addition to the miscalibration computation, in order to highlight the overconfidence of investors. As said before, Glaser and Weber (2007) conduct a survey over 3 079 individuals and provide an online questionnaire to these individual investors.
This questionnaire contains, in addition to the general knowledge questions, questions on stock market forecasts. Individuals are asked to provide their 90% confidence intervals (i.e. this is the lower and upper bonds) to five questions concerning stock market forecasts (i.e. Deutscher Aktienindex DAX, Nemax50 Performance Index, and three German Stocks) for the end of year 2001.

Figure 3 (p.56) can help to summarize this process of asking investors their stock market forecasts. (i.e. the horizontal axis represents the time and the vertical axis represents the value of the stock).

After asking the stock market forecasts with confidence intervals, Glaser and Weber (2007) compute the return volatility estimate of each individual, by using the approximation of the standard deviation of a continuous random variable formula, given Keefer and Bodily (1983). The volatility estimate is the standard deviation of stock returns, given by individuals.

Figure 3 : Stock market forecasts with confidence intervals (Glaser and Weber, 2007)



They find that individual standard deviations lie below the standard deviation of historical returns. Individual investors underestimate the volatility of stock returns. They can be stated as overconfident, as they overestimate the precision of their believes and the precision of their information. Their standard deviations are too tight compared to the market actual standard deviations.

We can see on Table 8 (p.57) that the median standard deviation of stock returns for the first group is much lower than the historical standard deviation. Individuals in this group tend to underestimate the volatility of the stock returns. In the DAX, individuals estimated a volatility of 6.53% for the first group (i.e. median of estimation for 21-week returns at the August 2nd 2001), whereas the actual volatility was of 14.65% (i.e. the historical volatility of non-overlapping 21-week returns). It was the same for the BASF stock.

Table 8 : Volatility forecasts : results (Glaser and Weber, 2007)

		First group, August 2nd, 2001	Second group, September 20, 2001	p-value (Mann–Whitney)
DAX	Median across subjects	6.53%	12.39%	<0.0001
	Number of observations	115	75	
	Historical standard deviation (January 1988-time of response)	14.65%	12.31%	
	Implied volatility	12.73%	22.90%	
BASF	Median across subjects	6.97%	14.43%	<0.0001
	Number of observations	99	65	
	Historical standard deviation (January 1988-time of response)	15.65%	11.80%	

This table presents median volatility forecasts of the two groups of respondents for the German stock market index DAX and the BASF stock as examples. Investors were asked to state median as well as upper and lower bound of a 90% confidence interval (see also Fig. 1). In addition, the table shows historical volatilities over the respective forecast horizon, i.e. historical volatilities of (non-overlapping) 21-week returns (column 3) and 14-week returns (column 4), respectively. For the DAX, the table reports the implied volatility of the respective response date as well. These implied volatilities were calculated using the VDAX. The VDAX expresses the fluctuation range or implied volatility of the DAX index, as expected by the forward market. Column 5 contains p-values of a two-sided Mann–Whitney test (Wilcoxon ranksum test). Null hypothesis is that the two populations are from the same distribution (volatility forecasts are equal in both groups). For an in depth analysis of the effects of September 11 on stock return expectations, see Glaser and Weber [2005a]

We can point out the fact that the estimated volatility is higher than the historical volatility in the second group. Glaser and Weber (2007) explain this by the fact that the September 11 attacks increased the historical standard deviation (i.e. historical volatilities using non-overlapping 14-week returns) and made it impossible to have a clear picture of the degree of the underestimation of the variance of stock returns. Nevertheless, the estimated volatility is still below the implied volatility (i.e. the implied volatility is the future market volatility, using forward index, the VDAX, whereas the historical standard deviation is the actual market volatility using past and present index). In the

DAX, the second group estimates in median a volatility of 12.23%, whereas the implied volatility is of 22.90%, because of the panic of the terrors attack of the 11th of September.

Consequently, by asking investors to provide their estimated range of stock market forecasts, researchers find again evidences of overconfidence among the sampled investors. Indeed, confidence intervals (i.e. of the value of an index, the return, or the price of a stock) provided by investors are too tight.

Broihanne et al. (2014) also use this stock forecast measure. Recall that they sample 64 high-level professionals. They ask financial questions to this professional subjects. They also provide graphs of 3 years time series of prices for five French stocks (i.e. Alcatel, BNP, Peugeot, Thalès, Sanofi, from March 2008 to March 2011).

Then, the participants need to provide their one year 90% confidence interval of these stock prices, and also their median price forecast. Professional investors are also asked to scale their perception of risks of the 5 stocks (i.e. from 0 to 10, 10 for the riskier grade) and then to propose a portfolio allocation (i.e. between one stock and a 3% risk-free asset). They are finally asked to provide the number of stock prices that will fall in the intervals provided. Respondents also needed to estimate the subjective expected returns and the volatility of the stocks (i.e. ESR, as expected subjective return and ESV, as expected subjective volatility).

In order to measure the overconfidence level of professionals, Broihanne et al. (2014) compare 90% confidence intervals (i.e. 0.90) with a theoretical probability mass associated with the two extreme prices, provided by subjects[10]. This constitutes a second miscalibration measure (i.e. GLW measure). They also compute the ESV (i.e. expected subjective volatility for each stock). Moreover, Broihanne et al. (2014) compare the estimated expected returns to the historical returns, in order to measure the optimism level.

[10] The GLW measure is constructed by making the difference between 0.90 (i.e. 90% confidence interval) and the probability distribution of the returns, computed using the two extreme price estimations. See Broihanne et al. (2014) for more precisions.

On Table 9, we can see the results of Broihanne et al. (2014) for each stock. On Panel A, B, and C, we can see the distribution of past moments of the stocks, with a measure of realized returns and realized volatilities. The Panel A is a period of three years, Panel B two years and Panel C one year. The Panel D summarized the average forecasts of returns and volatilities of each stock.

Table 9 : Realized and subjective expected moments of 5 stocks (Broihanne et al., 2014)

Realized and subjective expected moments of 5 stocks. Panel A presents the first two moments over the full period of 3 years. Panels B and C present the same statistics over shorter periods of 2 years and 1 year, respectively. Panel D presents average forecasts of ESR and ESV. In panels A–C, calculations are done with daily returns over the period under consideration, and annualized on a basis of 260 trading days per year.

	ALCATEL (%)	BNP (%)	PEUGEOT (%)	THALES (%)	SANOFI (%)
Panel A: 2008–2011					
Realized returns	2.25	−5.53	−17.35	−12.79	0.66
Realized volatilities	58.99	55.64	50.61	26.82	31.65
Panel B: 2009–2011					
Realized returns	87.21	37.71	35.74	−4.93	8.82
Realized volatilities	49.94	42.63	42.88	24.27	24.26
Panel C: 2010–2011					
Realized returns	45.56	−9.91	24.07	−9.59	−16.28
Realized volatilities	43.48	41.28	36.54	21.60	22.38
Panel D: Forecasts					
ESR (average)	10.13	8.76	10.09	9.04	5.56
ESV (average)	32.28	23.24	27.07	19.50	13.64

On Table 9, we can see that the ESV (i.e. expected subjective volatility) is lower than the historical ones, for each period. For exemple, for the stock PEUGEOT : the expected subjective volatility among the 64 professional sampled is 27.07%. The expected subjective return is 10.09%. Both indicator are average. The historical data, for the period of 2008-2011, but also 2009-2011 and 2010-2011 (i.e. Panel A, B and C in the Table), are quite different. Indeed, the realized volatilities (i.e. daily data, annualized on a basis of 260 trading days per year) are much higher than the expected ones : 50.61% for the 2008-2011 period, 42.88% for 2009-2011 and 36.54% for 2010-2011.

For Broihanne et al. (2014), it is an indicator of miscalibration in expectations (i.e. the risk is underestimated). They are overconfident in the risk, as their ESV is too small in comparison to historical volatilities. For the other stocks, results are the same : on average, expected volatility is lower than the historical one.

Thus, miscalibration is assessed in two ways, in financial studies. Researchers use the same miscalibration intervals as in the psychology studies (i.e. 90% confidence intervals). But researches also use volatility estimates, as the expected subjective volatility of investors, in order to assess their level of overconfidence. Both Glaser and Weber (2007) and Broihanne et al. (2014) find evidence of miscalibration among investors (i.e. individuals and professionals).

A) 2) The better-than-average effect among investors

Recall, from Part 1, that the better-than-average effect is the tendency of individual to consider their skills, performances, aptitudes, to be better than the median individual. This measure have been extended to finance, and several studies tried to test the evidence of a better-than-average effect among investors.

The better-than-average effect has been widely measured in finance, because some theories explained the existence of transactions by the difference in subjective capabilities across individuals. For example, Harris and Raviv (1993) explained that each investor is convinced of the correctness of his/her model, and thus each group of investors believes that the other group is making decisions based on an incorrect model.
Moreover, Shiller (1999) considers the overconfidence effect (i.e. better-than-average effect) as an explanation for the differences in opinion existing among investors, and thus for the high volume of

trade that occurs among investors. As investors believe they are better than the others, they are encouraged to trade more often (i.e. investors think that they make « good » decisions, that others do not have seen, and thus believe they make a better choice than the counterpart).

In a first time, we will see the measure of the better-than-average effect, achieved by Glaser and Weber (2007). In a second time, we will see the one of Broihanne et al. (2014).

Recall that Glaser and Weber (2007) conduct a survey over 3 079 individuals and provide an online questionnaire to these individual investors.

In order to measure the BTA effect among investors, Glaser and Weber (2007) ask to the sampled investors two questions :

- Question 1 : What percentage of customers of your discount brokerage house have better skills (e.g. in the way they interpret information; general knowledge) than you at identifying stocks with above average performance in the future? (Please give a number between 0% and 100%).
- Question 2 : What percentage of customers of your discount brokerage house had higher returns than you in the four-year period from January 1997 to December 2000? (Please give a number between 0% and 100%).

One question is about the comparison of skills (i.e. Question 1) and the other is about comparison of returns (i.e. Question 2).

Table 10 : Better-than-average effect : results (Glaser and Weber, 2007)

	Observations	Mean	Median	Standard deviation
Question 1	212	43.821%	50%	18.42
Question 2	212	46.986%	50%	19.33
bta1 (based on Question 1)	212	0.124	0	0.37
bta2 (based on Question 2)	212	0.060	0	0.39

Table 10 provides several results. The variables Question 1 (i.e. skills) and Question 2 (i.e. returns) are described above (i.e. the two questions asked to subjects of the study). The variables bta1 and bta2 are the better-than-average score, computed by making the difference between the rational answer (i.e. 50) and the provided answer. The difference is then divided by 50 (i.e. (50-answer)/50). Consequently, if bta1 is superior to 0, it means that individuals tend to think that a percentage of investors, inferior to 50, has better skills than them. They think that they are better-than-average (i.e. Part I). Note that bta1 is the better-than-average score for skill perception and bta2 is the better than average score for return perception.

Here, both for Question 1 and for Question 2, the mean is inferior to 50%, that is respectively 43.821% and 46.986%. The variables bta1 and bta2 are both superior to 0 (i.e. 0.124 and 0.060), which means that individuals tend to think that the others have less skills and less returns than them. Consequently, Glaser and Weber (2007) find evidence of better-than-average effect among individual investors.

Broihanne et al. (2014) also achieve to measure the better-than-average effect. Recall that they sample 64 high-level professionals. They ask 10 questions to individuals, which were general finance questions. In order to measure the better-than-average effect, they ask the participants to guess the number of their answers that were right (i.e. contained in the intervals they provided, Nmyself) and the average number of answers of others that were right (i.e. contained in the intervals provided by the others, Nothers). The better-than-average effect is thus the difference between Nmyself and Nothers (i.e. Part I).

Nevertheless, Broihanne et al. (2014) find no significant BTA effect among professional investors. The coefficient is negative and not significant.

To conclude, we can say that studies generally compute the better-than-average effect in the same way that psychologists. Researchers ask the sampled individuals their subjective rank of skills or returns, in comparison with the ones of the population (i.e. Glaser and Weber 2007, or Broihanne et al, 2014), that is relatively closed to what was done by psychologists.

When Glaser and Weber (2007) find evidence of a better-than-average bias among investors (i.e. individual investors), Broihanne et al. (2014) do not measure a significant better-than-average bias among professional investors.

A) 3) The illusion of control among investors

Recall from Part I that the illusion of control is the tendency of individuals to have a wrong perception of their own control over their life's events (i.e. Langer, 1975). Financial studies are not numerous to measure this link, because of the difficulty to construct a measure method. Indeed, measuring the miscalibration or the better-than-average effect is relatively simple, using questionnaires. But, measuring the illusion of control is trickier.

Fenton O'Creevy et al. (2003) try to measure the illusion of control, using a computer-based task. They also compute the individual performance by using traders' self-rating, total annual earnings and the performance assessments of a senior trader-manager.

Fenton O'Creevy et al. (2003) investigate among 107 traders in four City of London investment banks (i.e. 32 from the firm A, 30 from the firm B, 22 from the firm C and 23 from the firm D). The panel is thus composed of professional traders.

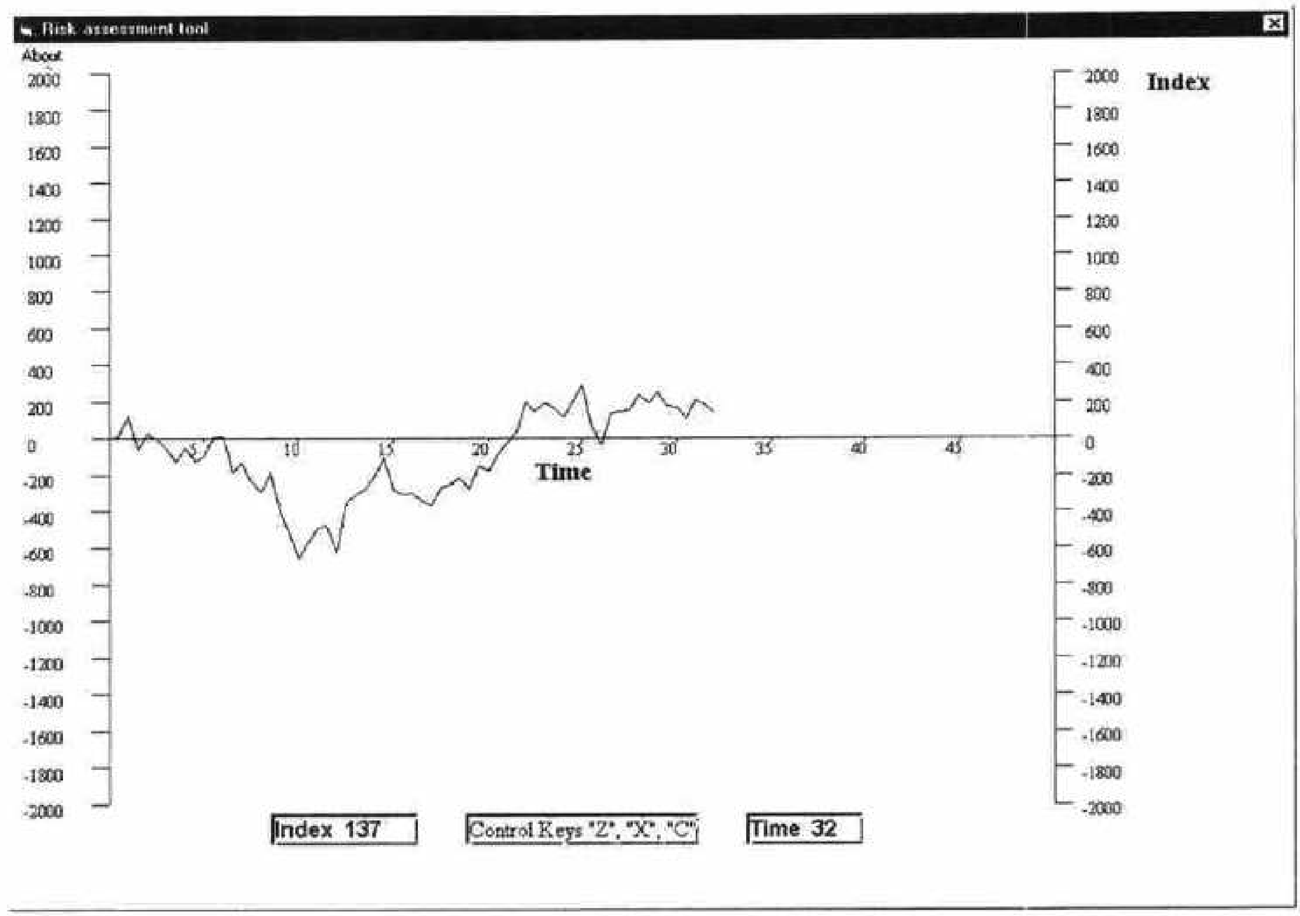
The traders are chosen after a discussion with the senior managers. They are traders operating in markets based on equities, bonds or derivatives, and with a degree of risk (i.e. not executing traders, who only execute an order for customers). 97% of the traders accepted to be part of the study. 105 are male and 2 female. 52 are traders, 40 are traders managers and 15 are senior manager. The experience varies between 6 months and 30 years.

Participants are first given a questionnaire with educational qualifications, job level and trading experience questions. Then, in order to gather information about performance, Fenton O'Creevy et al. (2003) ask data to the supervisors of each trader.
As a consequence, supervisors are asked the contribution to trading desk profits, the skill in managing risk, the analytical ability and the individual skills of each trader. They need to provide answers on a scale from 0 to 100, in percentile of the rank of the traders (i.e. 60 means that the trader in question is better than 60% of the similar traders). Fenton O'Creevy et al. (2003) use annual remuneration as a second performance measure (i.e. by asking the participant and not the supervisors this time).

In order to measure the illusion of control, Fenton O'Creevy et al. (2003) submit each trader to a computer-based task. They chose a computer-based task because it is a short task (i.e. traders are unlikely to pay serious attention during a long questionnaire) and because it simulates trading (i.e. noisy feedback and decision-making under limited information).

Consequently, Fenton O'Creevy et al. (2003) process to a computer-task after having initially interviewed the traders. The display of the computer-task is shown on Figure 4 (p.65). The computer-task allows to measure the judgment of the control of traders over changes in the value of an index.

Figure 4 : Computer task : screenshot of the main screen (Fenton O'Creevy et al., 2003)



The index values fluctuates between -2000 and 2000 (i.e. vertical axis). The horizontal axis represents the time. It starts at zero. Every half second, during 50 seconds, the value of the index increases or decreases randomly. The traders are informed that the three keys on their keyboard may have an effect on the value of the index. The task is to raise the index as high as possible.[11]

[11] The traders sampled were told : « When the game starts you will see a chart, similar to the picture shown below (i.e. Figure 1). The vertical axis represents an index with values between - 2000 and 2000. The horizontal axis shows time. The index starts at zero and every half second for 50 seconds the index is increased or decreased by some amount. Changes in the index are partly random, but three keys on the keyboard may have some effect on the index. The possible effects are to raise or lower the index by some amount, to increase the size of the random movements, or no effect. There is some time lag to the effects. The keys are 'Z', 'X' and 'C'. There is no advantage to pressing keys more than once in any half second. Your task is to raise the index as high as possible by the end of 50 seconds. At the end of the game the final value of the index will be added to your pool of points. »

Nevertheless, the keys pressed by the traders have no effect on the index (i.e. but this was not told to the participants). The game is repeated 4 times, with different configurations. The first and second lead to an increase in points, whereas the third in a decrease in points and the fourth in a constance in points.

At the end of the experiment, traders are told their score (i.e. the level of the index). They are asked to tell their score and to rate their success in increasing the index using the keys (i.e. in a scale from 1 to 100, in which 1 represents ’not at all successful’ and 100 represents ‘very successful’). The rate of the success, given by individuals, constitutes the measure of the illusion of control (i.e. the measure is aggregated in one single factor for each of the four experiments).

The mean level of illusion of control in the sample was of 41.96. This variable will be used in a second step by Fenton O’Creevy et al. (2003), in order to test for the influence of the illusion of control on the behavior of traders. The regression will be explained in the second subpart.

Fenton O’Creevy et al. (2003) however underline the fact that the study is realized after a long period of consistant and sustained growth of the market. This fact can be an element that accentuates the propension of traders to express illusion of control.

To sum up, the illusion of control can be more difficult to measure, as it is not directly quantifiable through a questionnaire. As a consequence, finance researchers use experiments (i.e. Fenton O’Creevy et al., 2003) in order to test for the illusion of control among investors.

A) 4) The unrealistic optimism among investors

Recall from Part I, that the unrealistic optimism is the overestimation of one's probability and chance of experiencing favorable events (i.e. Weinstein, 1980). This unrealistic optimism can be extended to finance, because people tend to be over-optimistic about their future income and their returns.

Individuals tend to overestimate their portfolio's returns. There is generally a positive difference between individual investor's forecast and the actual return on the stock market. The forecast return tend to be higher than the actual return (i.e. Mangot, 2005).

Puri and Robinson (2007), but also Broihanne et al. (2014) conduct studies in order to measure the unrealistic optimism among investors.

Puri and Robinson (2007) try to measure the impact of optimism on individual economic choices. They use dataset from the Survey of Consumer Finances (SCF), a dataset which is updated every three years. Since 1989, this survey samples individuals (i.e. randomly sampled individual subjects) in order to collect figures about the economic conditions in the United States. In this survey, participants are asked about a large number of variables : employment status, whether they own their own business, retirement plans, portfolio holdings but also their beliefs regarding the outlook of the economy, their life expectancy, and attitudes toward risk.

In order to measure the optimism among sampled individuals, Puri and Robinson (2007) process to a comparison between the self-reported life expectancy of subject and the implied life expectancy (i.e. implied by statistical tables). The goal of Puri and Robinson (2007) is to check if this measure of optimism is correlated with positive beliefs about future economic conditions. They reach to the conclusion that optimism people tend to work harder, expect to retire later, tend more to remarry, invest more in individual stocks and save more.

Puri and Robinson (2007) process in two parts. They first test the significance of their new measure of optimism, and then test its correlation with economic variables.

As said above, Puri and Robinson (2007) use life expectancy miscalibration as a measure of optimism. They compare the self-reported life expectancy of participants to their implied life expectancy (i.e. using actuarial tables).

Puri and Robinson (2007) consider the self-reported life expectancy, for a participant with personal characteristics, x (i.e. defined as E_x). In parallel, they compute the conditional life expectancy, as observed in actuarial table (i.e. E_j). Thus, the optimism is measured by computing the difference between the two values : E_x. - E_j.

In order to measure E_x (i.e. self-reported life expectancy), Puri and Robinson (2007) ask sampled participants the following question : « *About how long do you think you will live ?* ». Then, Puri and Robinson (2007) process to the calculation of the expected life-expectancy using « life tables ». Life tables are a demographic and economic tool, constructed using a large sample of individuals, who are supposed to represent the whole population (i.e. from very young to very old). The life tables are adapted to individual conditions. In the study, the data for the years 1995, 1998 and 2001 are used.

Puri and Robinson (2007) also observe the influence of different variables, such as a male dummy, a white dummy and the impact of having attended college. They observe that male tend to be more over-optimistic. Finally, Puri and Robinson (2007) check the consistency of using life expectancy miscalibration in measuring optimism, by using a standard psychometric test (i.e. Puri and Robinson, 2006a).

Table 11 : Main results concerning optimism (Puri and Robinson, 2007)

Panel B: Calculating life expectancy miscalibration

		Life expectancy, based on age, gender, race:			Smoking/educ. corrected:	
	Age	Self-reported	Life table	Optimism	(%) who smoke	Optimism
Female	51.24	82.76	82.17	0.59	26	−0.33
Male	49.61	81.66	78.54	3.12	21	2.00

Panel C: $Self\text{-}reported = \alpha_0 + \alpha_1 statistical + \alpha_2 male + \alpha_3 white + \alpha_4 attended\ college$

	Constant	Statistical	Male dummy	White dummy	Attended college
Estimate	23.76	0.73			
(se)	(0.02)	(1.75)			
Estimate	5.12	0.99	3.14	−6.66	1.67
(se)	(2.04)	(0.03)	(0.25)	(0.32)	(0.11)

We can see the results in Table 11. In Panel B, both the self-reported and the rational life expectancy (i.e. using mortality tables) are depicted. For female, the average self-reported age is of 82.76, whereas the life table age is of 82.17, so a difference of 0.59 (i.e. level of optimism). Males tend to be more optimistic than women : the self-reported age is of 81.66, whereas the life table age is of 78.54, so a difference of 3.12. Even when data are corrected by the variables smocking and education, the difference is still there for male (i.e. a difference of 2).

Moreover, Puri and Robinson (2007) regress the self-reported life expectancy on statistical life expectancy (i.e. Statistical), plus some controls. The « Constant » variable is the difference between the self-reported age and the statistical age, and is usually of 5.12 years. Both males (i.e. 3.14 more years of difference) and people who have attended college (i.e. 1.67 more years of difference tend to express higher level of life expectancy. On the other side, white people (i.e. 6.66 less years of difference) tend to express lower level of life expectancy.

Puri and Robinson (2007) check the consistency of their measure of optimism. They tested the correlation of optimism over economic conditions and income and life expectancy miscalibration of sampled individuals. They found that each correlation is positive and significant, Puri and Robinson (2007) consider that their measure of optimism is checked.

Puri and Robinson (2007) attempt to compare the behavior of moderate optimists and extreme optimists. According to them, extreme optimists are what we called in the first part the « unrealistic optimists », and thus are overconfident investors. In order to stress the difference, Puri and Robinson (2007) pick out the 5% of participants who have expressed the greater level of optimism, and label them as extreme optimists.

Broihanne et al. (2014) also attempt to measure optimism among investors. Broihanne et al. (2014) compare the estimated subjective returns, expressed by investors, to the historical returns, in order to measure the optimism level. The results are presented, above, in Table 9 (p.59).

For five French stocks (i.e. Alcatel, BNP, Peugeot, Thalès, Sanofi, from March 2008 to March 2011), professional investors tend to express subjective returns that are relatively high. Historical returns tend to be below the estimated subjective returns provided by the professionals. If we take the results for the stock PEUGEOT, on Table 9, we can see a difference between the historical returns and the estimated returns. The returns of PEUGEOT are overestimated for the period 2008-2011, as the realized returns is of -17.35% for the period 2008-2011, whereas an expected return of 10.09%. Results are mostly the same for the other stocks : the average expected return is higher than the historical one, in average. Thus, Broihanne et al. (2014) find evidence of optimism among professionals.

To conclude, the unrealistic optimism is generally computed using basic measures of optimism, as the subjective life expectancy. Puri and Robinson (2007) find evidence of optimism among individuals. Broihanne et al. (2014) also reach to the conclusion that investors tend to express over-optimism, using the difference between expected subjective returns and historical returns.

Conclusion

To conclude, we can say that overconfidence, in financial researches, is measured in different ways. Financial researchers use approaches, constructed by psychologists, but also methods that are adapted to finance. Glaser and Weber (2007), Broihanne et al. (2014), Puri and Robinson (2007) and Fenton O'Creevy et al. (2003) demonstrate the existence of each component of the overconfidence bias (i.e. miscalibration, better-than-average effect, illusion of control and unrealistic optimism), among both individual investors and professional investors. Broihanne et al. (2014) find however no evidence of a better-than-average effect among professionals.

Consequently, using miscalibration, better-than-average, illusion control and unrealistic optimism measures, financial researches reach to the conclusion that investors tend to express overconfidence. The second step is to find the consequences of this overconfidence bias, expressed individuals and professionals, on financial markets. Financial researches, after having demonstrated evidences of overconfidence among investors, try to point out the effects of this overconfidence bias on the financial behavior of individual and professional investors.

B) The effect of overconfidence on financial markets

B) 1) The effect of overconfidence among individual investors

> « *The excessive trading of individual investors can be called the active investing puzzle* »[12]

As stated before, some axioms of financial theories are not checked empirically. One major characteristic of financial markets is the dramatically high volume of trades that occur in a given period of time. Indeed, recall what Glaser and Weber (2007) underlined, the turnover is extremely high on the US market. Over the period 1980-2014, the annualized average turnover for the 500 largest US stocks, was, on average, 223 percent, thus just a little more than $100 billion per day.

Arguments given by rational theories cannot explain this extent of trades. As evidences were found of an overconfidence bias among investors, both individual (Glaser and Weber, 2007) and professional (Broihanne et al. 2014), researchers tested the link between the overconfidence bias of investors and their volume of trades. Empirical studies analyzed the consequences of both miscalibration, tightness of volatility estimates, better-than-average effect, illusion of control and unrealistic optimism, on the behavior of the investors.

Conclusions of researches conducted by Odean (1999), Barber and Odean (2001, 2002), but also Glaser and Weber (2007) and Puri and Robinson (2007) will be summed up in this part. These studies focus on the effect of overconfidence bias on the behavior of individual investors (i.e. sampled investors and household studies).

[12] Odean, « Do Investors Trades Too Much, 1998 », pp.1279.

Odean (1998) states : « *Trading volume is the most robust effect of overconfidence* » (Odean, 1998[13], pp.1888). Indeed, he checks empirically the positive link, supposed by behavioral models (i.e. Gervais and Odean, 2001 or Odean, 1998a), between overconfidence of investors and trading volume. He also observes the relationship between overconfidence and return.

Odean (1999) uses data from a discount brokerage house. 10,000 customer accounts are selected, in a random way, across all active accounts (i.e. with at least one transaction) in 1987. He gathers trade information, in the time period elapsing from January 1987 through December 1993. We can note that multiple buys or sells of the same security, occurring in the same account on the same day and at the same price, are aggregated. Odean (1999) uses also data providing information on the monthly position for the 10,000 customer accounts studied (i.e. daily data from the Center for Research in Security Prices, CRSP).

According to traditional theories, if informed rational traders (i.e. who trades in order to increase their returns) are trading more, they will increase their returns, at least enough to cover their additional transaction costs. It means that, assets, bought by these investors, will outperform the ones they sell, making a positive difference which at least covers their transaction costs. According to Odean (1999), if overconfidence is only about the precision of unbiased information (i.e. overconfident investors believe they have information that is not actually existing), expected trading losses can not be higher than transaction costs. Indeed, even if the overconfident investor invests in a security because of an information he have, and if this information is not checked, this security will still perform around the same return than securities this investor has sold. The loss is confined to the transaction costs.

Nevertheless, for Odean (1999), if investors are overconfident about their ability to interpret information, they may experience average trading losses beyond transactions costs. Indeed, if an investor is buying or selling a security because of an information he has interpreted, but this

[13] Odean, T., 1998a. « Volume, Volatility, Price, and Profit When All Traders Are Above Average ». *Journal of Finance*, 53(6). 1887-934.

information is misinterpreted, he maybe did not have any interest to buy or sell this stock, and thus he can occur a loss beyond the transaction costs (i.e. if he buys a security with a value that will decrease or if he sells a security with a value that will increase).

In order to measure these two types of overconfidence (i.e. overconfidence in precision of unbiased information and overconfidence of abilities to interpret information), Odean (1999) focuses on the buying and selling operations of individual investors. By looking at return horizons of four months, one year and two years, following a transaction, Odean (1999) checks if, ex-post, bought securities outperform sold securities by enough to cover transaction costs (i.e. if not, it is a case of overconfidence of precision). He also checks if bought securities underperform sold securities, when trading costs are not taken into account (i.e. if yes, it is a case of overconfidence of ability).
By adding the commission paid in the purchase and in the selling of the stock, but also the spread experienced by investors, Odean (1999) computes an average round-trip trade (i.e. buying and then selling a security) cost of 5.9 percent. It means that individual investors are expecting to benefit of a security return (i.e. the difference of return between the securities they buy and the securities they sell) that is higher than this cost, and thus almost equal to 6 percent. If the actual difference between the bought and sold stocks is superior or equal to 5.9 percent, investors are rational : they are not too confident on the precision of their information or of their abilities.

Following this hypothesis of rationality, Odean (1999) compares the average return of purchased securities, after the purchase, and the average return of sold securities, after the selling (i.e. the difference needs to be equal or higher than 5.9 percent in order to check rationality), across the studied investors.

Odean (1999) reaches to the conclusion that average return of bought securities is less than the average return of sold securities. Indeed, he find an average difference of -3.3 percent (i.e. in an interval of 504 trading days, in Table 12, p.75), which means that bought securities have a return actually 3.32 percent lower than than sold securities. If we take the column « 504 trading days later » (i.e. which means that 504 days have elapsed since the day on which the sales or purchases were observed), the average return of bought securities is 24.00%, and the average return of sold security is 27.32%. The bought securities underperform the sold ones by 3.32%, and the difference is statistically significant (i.e. p- value is of 0.001 for N1 and 0.002 for N2[14]).

Table 12 : Average returns following purchases and sales (Odean, 1999)

Panel A: All Transactions

	n	84 trading days later	252 trading days later	504 trading days later
Purchases	49,948	1.83	5.69	24.00
Sales	47,535	3.19	9.00	27.32
Difference		−1.36	−3.31	−3.32
N1		(0.001)	(0.001)	(0.001)
N2		(0.001)	(0.001)	(0.002)

The results show the same conclusions for periods of 84 trading days and 252 trading days. Not only individuals make transactions with returns that do not cover transaction costs, but they buy securities that perform less than securities they sell. Consequently, according to Odean (1999), investors are not only overconfident of the precision of their information but they are overconfident of their abilities to interpret information.

[14] N1 : Null hypothesis that the expected returns to securities purchased are 5.9 percent (the average cost of a round-trip trade).
N2 : Null hypothesis that the expected returns to securities purchased are higher than the expected returns to securities sold.

Odean (1999) reaches to the conclusion that overconfidence can lead to excessive trading volume, as the average return does not cover the transaction costs (i.e. costs that are a positive function of the number of trades). Moreover, he finds that individuals are overconfident of their abilities, as the average return is even negative : the bought securities underperform the sold securities.

Thus, Odean (1999) shows that, more than the trading volume, overconfidence can lead to return that does not cover transaction costs (i.e. because of the number of trades), and even negative return, that can result from a poor security selection or a poor selling/buying timing.

In a second part of his study, Odean (1999) focuses on the calculation of the average returns. He wants to compare the performance of an average portfolio to a « benchmark », which represents the American market. In order to compute that, he calculates, for each month, the average return of the « buy » portfolio (i.e. bought securities during a given period of time) minus the average return of the « sell » portfolio. Using both the CAPM and the Fama-French (1993) models, Odean (1999) reaches to the conclusion that excess returns (i.e. the difference of returns between bought and sold stocks) are negative, as computed in these models.

Then, Odean (1999) tries to exhibit if these poor returns are linked to bad choices in stock picking (i.e. security selection) or bad choices in timing. By adjusting these returns to the market, Odean (1999) removes the effect of market timing on performance. He finds that even these market-adjusted returns are negative. It means that investors are making bad choices in picking the securities they sell or buy (i.e. stock picking).

To sum up, we can say that Odean (1999) reaches to the conclusion that, not only individuals make trades that do not cover their transaction costs, but tend to buy securities that underperform the sold ones. For Odean (1999), this is a clear indicator of an overconfidence bias (i.e. overconfidence of precision and of ability). The consequence is a dramatic high volume of trades (i.e. individuals trade so much, that returns do not cover the transactions costs), but also poor individual returns (i.e. individuals tend to overestimate their capacities and thus make bad choices in stock picking).

Odean (1999) explains that the process of buying a security is very complex. As individuals face an extremely large amount of information, they are more likely to choose the security to which their attention has been drawn (i.e. stocks with greater media attention, usually stock that have performed unusually well or poorly). On the opposite, the decision to sell is less complex. The choice is confined to securities that the individual owns. Nevertheless, in making a such decision, the investor needs to consider both the past and the future performance of the stock.

Odean (1998b) exhibits that investors are more likely to sell their winning positions, but to hold their losing positions (i.e. even if their winning sold positions usually outperform their losing hold positions). This is the disposition effect (i.e. Shefrin and Statman, 1985).[15]

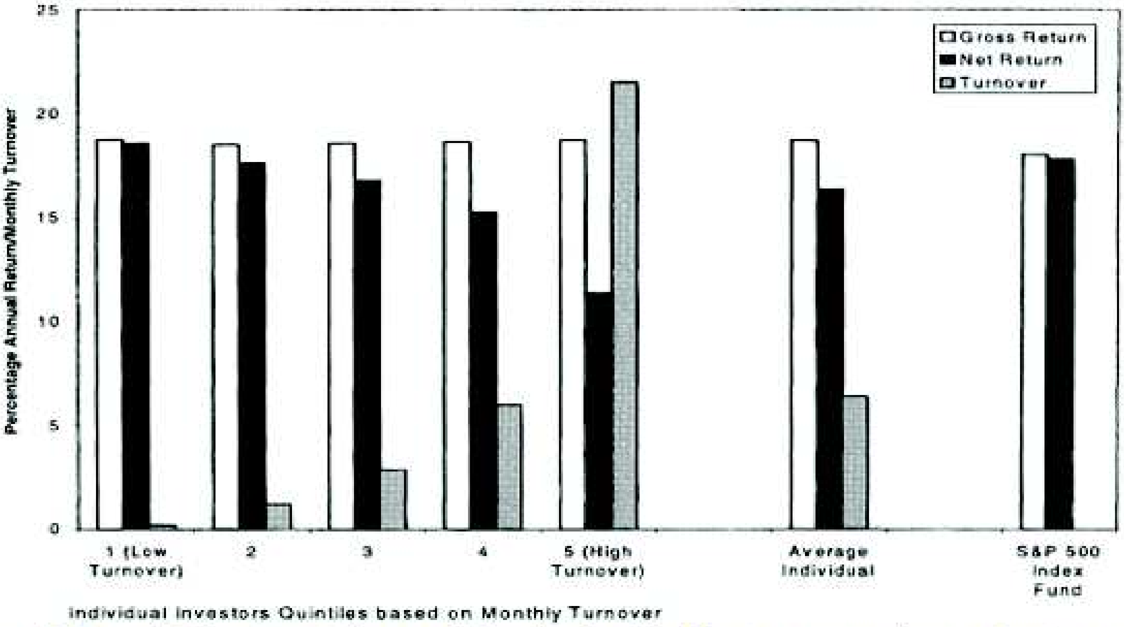
Figure 5 (p.78), taken from Barber and Odean (2000)[16], helps to see the impact of the trading volume on the net return of individual investors. We can see that Barber and Odean (2000) have depicted the gross return, the net return (i.e. the gross return minus transaction costs) and the turnover of individual investors. These indicators are represented on average (i.e. average individual) and divided into quintiles according to the individual turnover (i.e. 1 to 5 quintiles). The gross return of the market is represented using the S&P 500, and the net return of the market is represented using the Vanguard Index 500.

---

[15] Similar behavior were observed by Heisler (1994) in the negotiation of future contracts and by Heath et al. (1999) in the exercise of employees stock options.

[16] Barber and Odean (2001) conducted their study using a data set, that consists of position statements and trading activity for 78,000 households at a large brokerage discount firm over a six-year period ending in January 1997.

Figure 5 : Monthly turnover and annual return of individual investors (Barber and Odean, 2000)



Source: Barber and Odean (2000), Figure 1. The white bar (black bar) represents the gross (net) annualized geometric mean return for February 1991 through January 1997 for individual investor quintiles based on monthly turnover (grey bar). The net return on the S&P 500 Fund is that earned by the Vanguard Index 500.

We can see a net difference between the first quintile (i.e. low turnover) and the last quintile (i.e. high turnover). The percentage of monthly turnover is nearly null in the first quintile, when it is higher than 20% in the last quintile. The net return is mostly the same than the gross return in the first quintile (i.e. nearly 20%), but falls dramatically in the last quintile (i.e. 11.4% of net return vs nearly 20% of gross return).

Consequently, trading volume leads to lower returns, as a consequence of higher transaction costs. Overconfident investors tend to trade more, and so, tend to have lower net returns.

Barber and Odean (2002) use the same data than Odean (1999). They focus on the consequences of going online, on the trading behavior of individuals.

Barber and Odean (2002) study the trading volume and the performance of a group of investors who changed from a phone-based to a online based trading. They use data from 1607 investors and gather their trades and monthly positions from January 1991 to December 1996. The data comes from a large discount brokerage firm.

Barber and Odean (2002) focus on four effects that can lead online investors to be overconfident, according to them :

- **the self-attribution bias** : the fact that people tend to think that their past successes are a consequence of their personal abilities and that their past failures are a result of bad luck.
- **the illusion of knowledge** : when traders face additional information, this procures an illusion of knowledge and thus leads to an increase of the overconfidence level. As online investors have access to important amounts of information and data, they may be more subjected to this effect.
- **the illusion of control** : online investors tend to be more actively involved. They do not place an order through the intermediary of a telephone broker, but place an order directly online. Moreover, online brokers tend to emphasize the importance of the control (i.e. Discover Brokerage advertised « *Online Investing is about control* »).
- **the selection bias** : overconfident investors tend to trade more and thus are more likely to go online.

In order to compare the online traders' groups, Barber and Odean (2002) attempt to construct a « size-matched » sample[17]. This size-matched group is a group composed of traders, whose market

[17] « As is the case for the online sample, the matched investor must have in common stock position in each month of our six-year sample period and at least one common stock trading during the six years. However, the size-matched samples households differ from the online households in that they made no online trades during the six years » p.463, Barber and Odean (2002).

value of common stock positions is close to the market value of positions, hold by the online investors group.

In order to calculate the trading costs and the return performance (i.e. gross and net), Barber and Odean (2002) compute several formulas. They first compute the risk-adjusted return performance with two indicators :

- **the mean monthly market-adjusted abnormal return for online investor**. They construct this computation by subtracting the return of a value-weighted index (i.e. of NYSE/AMEX/Nasdaq) from the return earned by the online investor.
- **the own-benchmark abnormal return**. They construct this computation by subtracting the own-benchmark return (i.e. the return the household would have earned if it have hold its beginning of the year portfolio for the entire year) from the return earned by the online investor.

Barber and Odean (2002) also compute, using the CAPM model, the Jensen's alpha. They regress the monthly excess return earned by online investors on the market excess return. Barber and Odean (2002) finally use the three-factor model of Fama and French (1993).

Barber and Odean (2002) observe a tendency of traders to have a strong performance before going online. Moreover, they observe a change in their trading volume. Individual investors tend to trade more after going online. We can see a significative difference on Table 13 (p.81), between the « Before online trading » column and the « After online trading » column. The total turnover goes from 73.7% before online trading, to 95.5% after going online (i.e. Panel A : Total turnover). The difference between these households is of 21.8% (i.e. the difference is significative). The difference between online households and the size-matched group is also significative (i.e. 95.5% vs 48.2%, so a 47.3% difference). Online households trade more actively than size-matched households. Barber and Odean (2002) thus demonstrate that online trading has a significative positive impact on trading volume through time (i.e. difference between before and after online trading) but also between online and not online investors (i.e. difference between online and size-matched households).

Table 13 : Mean annual turnover of online households and size-matched households (Barber and Odean, 2002)

	Before online trading	After online trading	Change (after online less before online)
Panel A: Total turnover			
Online households	73.7	95.5	21.8***
Size-matched households	53.2	48.2	−5.0**
Online less size-matched	20.5***	47.3***	26.8***
Panel B: Speculative turnover			
Online households	16.4	30.2	13.8***
Size-matched households	11.5	13.9	2.4
Online less size-matched	4.9***	16.3***	11.4***

***, **, * Significant at the 1%, 5%, and 10% levels, respectively (two-tailed).

Online households are 1,607 households with 72 consecutive months of common stock positions, no online trades prior to January 1992, and at least one online trade between January 1992 and December 1995. Each size-matched household is the household with the closest account size to the sample firm in the month preceding its first online trade. The matched household must also have 72 consecutive months of common stock positions, no online trades during the 72 months, and at least one trade between January 1992 and December 1995. Monthly turnover for each household is one-half the sum of all trades for that household divided by the sum of all month-end positions. Monthly turnover times 12 yields annual turnover. Speculative turnover is calculated using only trades classified as speculative. We define speculative trades as all profitable sales of complete positions that are followed by a purchase within three weeks and all purchases made within three weeks of a speculative sale. Test statistics for the difference in means are based on a two-sample t-statistic assuming unequal variance for the two samples.

Barber and Odean (2002) attempt to construct a speculative turnover because rational reasons can exist in order to explain trading volume. For exemple, liquidity needs, desire to rebalance or the impact of tax losses can explain some trades. Consequently, Barber and Odean (2002) construct a Panel B, where all these reasons are eliminated, and only the speculative trading subsists. We can see that even when rational reasons of trades are eliminated, the turnover nearly doubles after going online (i.e. from 16.4% to 30.2%).

The change is not only a change in volume. Barber and Odean (2002) also observe a change in performance after going online. They compared the return earned by online investors : online traders who have not yet gone online and them who have yet gone online (i.e. return expressed in monthly return).

Barber and Odean (2002) show that the net percentage of monthly return of traders who already went online is 0.36% inferior to the net percentage of monthly return of traders who have not yet gone only. Adjusted to their own benchmark, the difference is still significant : the performance of online traders is 15bps lower than the investors who have not yet gone online. The drop of performance is verified for market and own-benchmarked adjusted comparisons, but also using the CAPM and Fama and French (1993) alphas.

Thus, Barber and Odean (2002) show that online trading leads traders to trade more aggressively and less effectively (i.e. lower performance). Barber and Odean (2002) explain theses observations by the presence of lower trading costs in online trading. As a consequence, the lower costs make the fact of trading more, more profitable. Online traders trade more actively, more speculatively but less profitably, after going online.

Barber and Odean (2002) also consider these results as a confirmation of the presence of a relationship between the four effects described above (i.e. self-attribution, illusion of knowledge, illusion of control, and selection-bias) and trading performance.

To conclude, Barber and Odean (2002) demonstrate a positive significative impact of the online trading on trading volume. Barber and Odean (2002) also underline the negative impact of the online trading on the portfolio return, as a consequence of the higher trading volume (i.e. which means higher transaction costs, so lower returns). The study of Barber and Odean (2002) can be seen as an evidence of the effect of the illusion of control on trading volume. People, when trading online, tend to overestimate their control over the future, more than when they trade through phone-call and delegate the trade to the intermediary on the phone.

Barber and Odean (2001) use also the same database than Odean (2001), in order to test the impact of the overconfidence bias, on investors, but this time, according to their gender. Data are also the same as the one used by Barber and Odean (2002).

Barber and Odean (2001) compare the trading volume and performance of men and women, with a data set composed of sampled investors of an US online broker. They reach to the conclusion that men trade more than women.

Barber and Odean (2001) use account data from 37,664 households. The database comes from a large discount brokerage, and data are measured from the period from February 1991 through January 1997. The database provides the end of month position and the trades for each account, but also the estimate monthly return.
Barber and Odean (2001) use a second data set, in order to gather demographic information, on the studied investors. These data are demographic information compiled by Infobase Inc. (on the 8th of June, 1997), and provided to Barber and Odean (2001) by the brokerage. Informations are various and include the gender, the marital statuts, the number of children, the age and household income.

Barber and Odean (2001) also use the self-reported data, provided by investors, the first time they opened an account. These data include informations such as the net worth of investors and their investment experience. Thanks to these informations, Barber and Odean (2001) construct the ratio of the market value of equity among to the self-reported net worth, in order to measure the part of the worth that is invested in equity.

Recall that Lundeberg et al. (1994) demonstrate that men are more overconfident than women (i.e. same conclusions are reached by Deaux and Farris, 1977). Consequently to these findings, Barber and Odean (2001) try to test the difference in their investment behavior. The effect of overconfidence should be stronger among men, as they are stated as more overconfident than women.

Barber and Odean (2001) construct several computations in order to calculate the return for each investor. First, Barber and Odean (2001) estimate the average purchase cost and sale cost, by comparing the reported closing prices to the actual paid prices. Barber and Odean (2001) find that the average purchase cost is 0.31% and that the average sale cost is 0.69%.
Recall that the own-benchmark abnormal return is also used by Barber and Odean (2002). The own-benchmark abnormal return is constructed by subtracting the own-benchmark return (i.e. the return the household would have earned if it have hold its beginning of the year portfolio for the entire year) from the return earned, by the studied investor.

Barber and Odean (2001) find that both men and women reduce their net return through trading. Results are presented in Table 14 (p.85). Nevertheless, Barber and Odean (2001) find that men reduce their own-benchmark monthly abnormal net return by 0.078% more than women. It means that, by doing transactions, men and women reduce the performance of their portfolio, in comparison with keeping the same portfolio. Men reduce their performance in a stronger way, both in own-benchmark monthly net return and gross return. The stocks, sold by the sampled investors, outperform the bought stocks (i.e. Odean, 1999), but the effect is stronger among men investors. The difference is statistically significant.

Barber and Odean (2001) also find a difference in turnover. When women have a mean monthly turnover of 4.40%, men of the sample have a monthly turnover of 6.41%. The difference is also statistically significant.

Table 14 : Mean position value, turnover and performance of common stock investments of female and male households (Barber and Odean, 2001)

	All households		
	Women	Men	Difference (women–men)
Number of households	8,005	29,659	NA
Panel A: Position Value and Turnover			
Mean [median] beginning position value ($)	18,371 [7,387]	21,975 [8,218]	−3,604*** [−831]***
Mean [median] monthly turnover (%)	4.40 [1.74]	6.41 [2.94]	−2.01*** [−1.20]***
Panel B: Performance			
Own-benchmark monthly abnormal gross return (%)	−0.041*** (−2.84)	−0.069*** (−3.66)	0.028*** (2.43)
Own-benchmark monthly abnormal net return (%)	−0.143*** (−9.70)	−0.221*** (−10.83)	0.078*** (6.35)

On Table 14, we can see results of Barber and Odean (2001) described before. When the mean monthly turnover of women is of 4.40%, the one of men is of 6.41%, so a negative significant difference of 2.01%. Moreover, in Panel B, we can see that Barber and Odean (2001) find that men traders reduce their gross return (i.e. own-benchmark monthly abnormal gross return) by 0.028% per month more than women. The difference between the gross monthly own-benchmark abnormal return of women and men is statistically significant. The impact is even greater on net return (i.e. a negative significative difference of 0.078%).

Barber and Odean (2001) conduct the same observations for differentiated households. They compute the turnover and the performance for married households and for single households. Barber and Odean (2001) find that differences in turnover and in return performance are more pronounced between single men and women. On the other side, the difference is less pronounced for married households and even not significant for own-benchmark monthly gross return. Barber and Odean (2001) reach to the conclusion that the difference in trading behavior between men and women is less strong among married couples. Indeed, married couples influence each other's during their investment decisions, and thus the difference of behavior between gender (i.e. the effect of overconfidence) is reduced.

Moreover, Barber and Odean (2001) find that men tend to take riskier positions than women. Men tend to hold portfolios and stocks with greater volatility than the ones hold by women. They also tend to hold smaller firms and stocks with higher betas than women. Thus, men tend to adopt a riskier behavior.

To conclude, Barber and Odean (2001) underline the difference in trading volume, portfolio return but also risk exposure, between men and women, as a consequence of the difference in overconfidence level between gender (i.e. men tend to be more overconfident than women, Lundeberg et al., 1994).

Apart from the studies of Odean (1999), Barber and Odean (2001) and Barber and Odean (2002), that focus on individual investors, further studies were conducted, in another context. Glaser and Weber (2007) and Puri and Robinson (2007) also find results concerning the consequences of the overconfidence bias on financial markets.[18]

Recall from the first subpart, that Glaser and Weber (2007) conduct a survey over 3 079 individuals and provide an online questionnaire to these individual investors. They find evidences of overconfidence, through measures of miscalibration and better-than-average effect among individual investors.

Glaser and Weber (2007) conduct several regressions in order to test the influence of the different measures of overconfidence on trading volume. They construct three regressions, using respectively the logarithm of the number of stock market transactions, the logarithm of the number of stock market purchases and the logarithm of mean monthly turnover, in order to measure the trading volume (i.e. trading volume is a variable that is positively skewed, as stated by Spanos, 1986).

In these three regressions, they include independent variables, that do not change : the gender (i.e. dummy variable, taking value of 1 when the subject is a male), the age, the experience, the past experience of the trader in warrant trading (i.e. warrant trader, which is a dummy variable taking the value 1 when the trader traded warrant in the studied period), the level of risk of the investment strategy (i.e. high risk, a dummy variable, taking value of 1 in case of risky investment strategy), the size of the portfolio (i.e. ln(Portfolio value), the logarithm of the portfolio values, in order to measure the wealth of the investor), the information (i.e. the number of hours per week that the investor spends seeking for information and used as a proxy for the level of involvement of the

[18] Biais et al. (2004) find also results concerning overconfidence effect on financial markets. They measured directly the link between miscalibration and economic behavior in an experimental market. Indeed, in their study, based on the responses to a questionnaire of 245 students subjects, they exhibited the degree of confidence through calibrations tasks. Then, individuals needed to participate in an experimental asset market. Biais et al. (2004) point out the existence of a link between overconfidence (i.e. as measured through miscalibration) and the reduction of trading performance, in this experimental asset market. Inspired by Plott and Sunder (1988), they submitted subjects to a trading game.

investor) and a different overconfidence variable in each regression. These different variables are chosen because that are known to affect financial decision-making.

The overconfidence variable is different in each regression : the miscalibration, the volatility estimate but also the better-than-average effect are respectively and independently regressed with the other variables in order to explain trading volume (measured in three ways in order to compare the results, i.e. the number of stock market transactions, the number of stock market purchases, and the mean monthly turnover). Results are presented in Table 15.

Table 15 : Trading volume and measures of overconfidence : cross-sectional regressions (Glaser and Weber, 2007)

	(1) ln(Stock transactions)	(2) ln(Stock transactions)	(3) ln(Stock transactions)	(4) ln(Stock purchases)	(5) ln(Stock purchases)	(6) ln(Stock purchases)	(7) ln(Turnover)	(8) ln(Turnover)	(9) ln(Turnover)
Overconfidence variable	misc	volest	bta	misc	volest	bta	misc	volest	bta
Gender (dummy)	−0.498	−0.126	−0.096	−0.405	−0.109	−0.078	−0.362	0.489	0.539
	(0.70)	(0.21)	(0.16)	(0.62)	(0.19)	(0.14)	(0.38)	(0.67)	(0.76)
Age	−0.008	−0.006	−0.007	−0.009	−0.005	−0.008	−0.011	−0.011	−0.008
	(0.63)	(0.52)	(0.71)	(0.71)	(0.47)	(0.79)	(0.63)	(0.86)	(0.63)
Experience	0.005	0.002	0.008	0.025	0.013	0.017	−0.019	−0.016	−0.011
	(0.14)	(0.07)	(0.27)	(0.70)	(0.40)	(0.58)	(0.36)	(0.38)	(0.29)
Warrant trader (dummy)	0.509	0.615	0.692	0.467	0.572	0.639	0.335	0.391	0.516
	(2.21)**	(3.01)***	(3.62)***	(2.20)**	(3.05)***	(3.62)***	(1.07)	(1.62)	(2.27)**
High risk (dummy)	−0.144	−0.245	−0.282	0.053	−0.049	−0.134	0.218	0.374	0.374
	(0.45)	(0.84)	(1.08)	(0.17)	(0.18)	(0.55)	(0.48)	(1.03)	(1.15)
ln(Portfolio value)	0.564	0.569	0.540	0.554	0.557	0.522	−0.090	−0.170	−0.238
	(7.05)***	(8.01)***	(8.28)***	(7.40)***	(8.47)***	(8.59)***	(0.81)	(1.99)**	(3.00)***
Information	−0.014	−0.010	−0.018	−0.005	−0.002	−0.010	−0.020	−0.018	−0.033
	(0.93)	(0.69)	(1.15)	(0.33)	(0.17)	(0.67)	(0.94)	(1.04)	(1.80)*
Overconfidence	−0.396	−0.115	0.475	−0.376	−0.114	0.479	0.359	0.093	0.694
	(0.87)	(0.90)	(1.74)*	(0.89)	(0.98)	(1.89)*	(0.58)	(0.62)	(2.10)**
Constant	−0.471	−1.147	−1.043	−1.138	−1.713	−1.481	0.510	0.586	1.007
	(0.42)	(1.27)	(1.26)	(1.11)	(2.06)**	(1.94)*	(0.34)	(0.55)	(1.02)

If we take the three last columns, we can see respectively the regression of the miscalibration (i.e. misc), the volatility estimate (i.e. volest) and the better-than-average effect (i.e. bta) and the different variables described above, over the logarithm of the mean monthly turnover.

The gender is never significant in these three regressions. It has an impact of -0.362 when the overconfidence variable is the miscalibration, an impact of 0.489 when the volatility estimate is used, and an impact of 0.539 when the better-than-average variable is used. But the impact is not significant. It is the same for variables age, experience, high risk and information in each regression : these are not significant. We can also see that the warrant trader dummy has an impact in the regression using bta. The logarithm of the turnover rises of 0.516, when the trader uses warrant. The same is observed for the variable ln(Portfolio value), for the volest and the bta regression. The size of the portfolio has a negative impact on the turnover, of -0.170 for the volest regression and of -0.238 for the bta regression. Finally, we can see, if we look at the range « overconfidence », that, only in the regression using the bta, the overconfidence variable is significant. There is a positive effect of the better-than-average effect of 0.694, and the variable is significant at the 5% level.

The results are mostly the same for regressions over the number of stock market transactions and the number of stock market purchases. Glaser and Weber (2007) find that the only significant overconfidence variable is the better-than-average variable. In the three kinds of regressions (i.e. volume of stock market transactions, but also volume of stock market purchases and stock market turnover), the better-than-average measure is significant at 10% (i.e. one star), and even significant at the 5% level (i.e. two stars) in the regression concerning the stock market turnover. We can see that the effect of the better-than-average bias is positive in the three cases (i.e. between 0.47 and 0.69 increase of the volume). Glaser and Weber (2007) exhibit that, in their sample, the link between miscalibration and trading volume, but also between volatility estimate and trading volume, is not significant. Miscalibrated investors (i.e. in their general knowledge but also in their estimation of risk) are not displaying a higher level of trading volume.

Glaser and Weber (2007) also point out other variables that have a significant effect on the trading volume. The warrant trader variable and the mean portfolio value[19] have a positive effect on

[19] The influence of the portfolio value is positive, in the regression explaining level of stock transactions and purchases but negative in the regression explaining stock turnover. Glaser and Weber (2007) explain this difference given the fixed costs per transaction : investors with high portfolio value trade more and in a higher amount, but have a lower turnover, as the turnover is the trading volume relative to portfolio size (i.e. Dorn and Huberman 2005 reached to the same conclusion : wealthiest investors turnover their portfolio less frequently).

the trading volume. Glaser and Weber (2007) explain the influence of the warrant variable, as a measure of the investor « sophistication » (i.e. warrants are comparable to options, and presumed as difficult to use for novices) : the more sophisticated the investor, the higher the trading volume. Glaser and Weber (2007) find no evidence of influence of the gender, contrary to Barber and Odean (2001), but comparable to findings of Don and Huberman (2002) and Glaser and Weber (2004).

For Glaser and Weber (2007), as the better-than-average effect has shown consistency, and not the miscalibration measure, the result of their study is more congruent with what was shown in the « *difference of opinion literature* »[20]. Investors who think that they are above average trade more, but investors who overestimate the precision of their information (i.e. miscalibrated investors) will not necessary trade more.

To conclude, we can say that a positive effect of overconfidence on the trading volume is demonstrated by Glaser and Weber (2007). Overconfident investors tend to trade more, as their number of stock market transactions, their number of stock market purchases, and their mean monthly turnover is higher when they are overconfident. Nevertheless, Glaser and Weber (2007) find no evidence of a link between miscalibration and trading volume, but a consistant link between the BTA effect and trading volume. They explain the impact of this effect by the difference of opinion between investors.

Puri and Robinson (2007) also achieve to prove the effect of overconfidence on the trading behavior, using the unrealistic optimism expressed by individuals.

Recall that Puri and Robinson (2007) use a dataset from the Survey of Consumer Finances (SCF), which is up-to-date every three years. They want to test the link between optimism and financial behavior.

---

[20] Difference of opinion literature : literature that explains the behavior of individual agents by the fact that traders construct mental models that ignore the perspective of others. According to this literature, trading volume arise from differences in opinion across individual investors (i.e. Harris and Raviv, 1993, Shiller, 1999, and Hales, 2005).

Puri and Robinson (2007) consider the ratio of stock wealth over total equity wealth. Puri and Robinson (2007) find a positive and significant effect of optimism on the ratio of stock wealth over total equity wealth. Puri and Robinson (2007) call optimist investors, « stock-pickers ». Indeed, they tend to have a greater part of their equity wealth invested in individual stocks, and not in mutual funds. Puri and Robinson (2007) explained this effect by the fact that optimist people tend to think that retirement will happen in a more distant horizon.

Puri and Robinson (2007) also observe a difference of behavior between moderate and extreme optimists. They find that when moderate optimists tend to have prudent financial habits (i.e. a large amount of saving and a lower tendency to make day trading), extreme optimists tend to have risky financial behavior. The results are presented in Table 16.

Table 16 : Optimism and extreme optimism and financial prudence (Puri and Robinson, 2007)

"Saving is good" is a dummy for the respondent answering yes to "I save because saving is a good thing to do." "Pays off credit cards" is a dummy that equals one whenever the respondent reports that they pay their credit card balances off in full each month. "Long planning horizon" is a dummy for whether the respondent uses 10-year or longer planning horizons when making their financial decisions. Optimism is as defined elsewhere. Extreme optimism is a dummy equaling one if the respondent's optimism places them in the right 5% tail of optimists. Demographic controls are age, marital status, education, race, and gender. These and other controls are suppressed for brevity.

	Saving is good	Pays off credit cards	Long planning horizons
	(1)	(2)	(3)
Optimism	0.0004	0.0251	0.0785
	[0.3496]	[0.0000]	[0.0000]
Extreme optimism	−0.0051	−0.0403	−0.2778
	[0.0857]	[0.0508]	[0.0000]
Demographics	Yes	Yes	Yes
Net worth	Yes	Yes	Yes
Self-employed	Yes	Yes	Yes
Risk tolerance	Yes	Yes	Yes
Health quality	Yes	Yes	Yes
Constant	Yes	Yes	Yes
R-squared	0.0908	0.2324	0.1095

We can see three regressions : « Saving is good », « Pays off credits cards » and « Long planning horizons ». These variables are dummy variables, taking value of 1 when the respondent answers positively. These variables are regressed over an optimism variable, an extreme optimism variable (i.e. the right 5% tail of optimists), and some control variables (i.e. demographics, net worth, self-employed, risk tolerance and health quality). For each regression, we can see that the optimism has a positive impact on the answer (i.e. coefficients respectively of 0.0004, 0.0251 and 0.0785). The extreme optimism has a negative impact (i.e. coefficients of -0.0051, -0.0403 and -0.2778). When optimist investors think that saving is good, pay off credit cards and have long planning horizons, over-optimist investors tend to think in an opposite way.

Puri and Robinson (2007) underline that the behavior of extreme optimists is consistent with the theory of the overconfident investor. Puri and Robinson (2007) consider this « extreme optimism » as close to the concept of overconfidence. Extreme optimists are less likely to think that saving is good, to pay their credit cards debts and to consider a long planning horizon when making financial decisions. Their behavior tend to be riskier and they are more likely to be day-traders. Consequently, they trade more aggressively and underestimate the risk of their investments.

The degree of optimism have a strong impact on the individual behavior of investors, according to Puri and Robinson (2007). Despite of the fact the extreme optimism can be negative, with the conclusions stated above (i.e. a more aggressive and risky behavior), a moderate optimism has a positive effect on financial decisions.

Conclusion

According to Odean (1999), Barber and Odean (2001), Barber and Odean (2002), Glaser and Weber (2007) and Puri and Robinson (2007), the overconfidence bias of individual investors (i.e. sampled individuals or household data), is linked to their trading volume. There is a positive relationship : the higher the level of overconfidence, the higher the trading volume. Another consequence is that overconfident investors tend to earn lower returns, by the effect of transaction costs. Finally, overconfident investors tend to have a greater exposure to risk.

Also, Barber and Odean (2001) underline the difference in behavior between men and women. Women tend to be less subjected to the effects of the overconfidence bias. Glaser and Weber (2007) point out the absence of a link between miscalibration and trading volume, but focus on the impact of better-than-average effect on trading volume

B) 2) The effect of overconfidence among professional investors

Generally, financial studies focused on the behavior of individual investors on stock markets and the effect of overconfidence on their behavior. Researchers find evidences of a positive effect of the overconfidence bias on trading volume, but a negative effect on trading returns.

However, researches that focus on the effect of overconfidence on the behavior of professional investors are less numerous. Indeed, professional investors can be a population that is difficult to access (i.e. difficulty to sample traders, to find agreements with financial companies, data security etc…). Despite these obstacles, Broihanne et al. (2014) and Fenton O'Creevy et al. (2003) conduct their studies among professional investors (i.e. respectively funds managers and traders). They try to test the effect of the overconfidence bias on trading behavior (i.e. the risk taking behavior) of professional investors.

Broihanne et al. (2014) sample 64 high-level professionals. They find evidence of miscalibration and optimism among professionals, but not of better-than-average effect.

In order to measure the influence of individual characteristics on risk taking, Broihanne et al. (2014) conduct several regressions. The regressions are presented in Table 17 (p.95). The dependent variable is the proportion of wealth invested in the risky assets[21] (i.e. the tendency to express a risk taking behavior). Broihanne et al. (2014) use four independant variables that stay the same in each model : the BTA effect, the optimism, the risk aversion (i.e. measured with the Lickert scale) and the experience (i.e. measured in years).

---

[21] Broihanne et al. (2014) ask to investors how much they will allocate their wealth, between a risky asset and a 3% risk-free investment (i.e. measure in percentage of wealth). This is the measure of the risk taking behavior.

Then, Broihanne et al. (2014) construct 6 different models, with different measures in order to assess the risk perception : the Lottery A (i.e. investing in a risky lottery or investing in a 3% risk-free investment), the PCA (i.e. risk perceptions for the five stocks, recall the first subpart), the overconfidence measure (i.e. GLW, miscalibration in the forecast of future stock prices)[22] and the ESV (i.e. expected subjective volatility, measure of subjective risk).

Table 17 : Regression estimates for end-of-March prices (Broihanne et al., 2014)

Regression estimates for end-of-March prices. Models 1–6 differ by the measure chosen for risk perception (risk perception of lottery A and PCA loadings of risk perceptions for the five stocks). Risk aversion (alpha) is measured with lottery B. BTA is the better-than-average value measured on the 20 knowledge questions. Miscalibration (global) is the total number of wrong answers to the 20 knowledge questions. Overconfidence (GLW) is the probability mass induced by price forecasts. ESV is the subjective expected volatility, that is the second moment of the distribution of stock returns based on the individual price forecasts. Experience is the number of years respondents have been working in the finance domain. All standard deviations (in parentheses) are clustered for individuals. As usual, "***", "**" and "*" mean significance at the 1%, 5% and 10% levels respectively.

Independent variables (proportion invested)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Risk perception (lottery A)	−0.010		−0.010		−0.011	
	(0.008)		(0.008)		(0.009)	
Risk perception (PCA)		−0.035**		−0.032**		−0.032**
		(0.013)		(0.014)		(0.014)
Overconfidence (GLW)	0.188**	0.169**				
	(0.072)	(0.079)				
Miscalibration (global)			−0.008*	−0.004	−0.007	−0.003
			(0.004)	(0.005)	(0.004)	(0.005)
ESV					−0.150*	−0.134
					(0.084)	(0.096)
BTA (global)	0.006	0.007	0.009	0.008	0.009	0.008
	(0.007)	(0.006)	(0.008)	(0.007)	(0.008)	(0.007)
Optimism	0.242***	0.209***	0.203***	0.176**	0.229***	0.199***
	(0.073)	(0.072)	(0.075)	(0.070)	(0.072)	(0.069)
Experience	−0.005*	−0.003	−0.004*	−0.003	−0.005*	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Risk aversion (alpha)	0.007	0.018***	0.004	0.015***	0.006	0.016***
	(0.004)	(0.006)	(0.004)	(0.005)	(0.004)	(0.006)
Intercept	0.277***	0.205***	0.425***	0.304***	0.450***	0.323***
	(0.078)	(0.048)	(0.088)	(0.064)	(0.092)	(0.066)
Adjusted R^2	0.078	0.121	0.075	0.107	0.082	0.111
N	305	305	305	305	305	305

If we take the Model 1 (Table 17), we can see that the risk perception, measured with Lottery A, the BTA and the risk aversion, has no significant impact on the risk taking behavior of professional investors. The overconfidence (i.e. measured through forecast of future stock prices,

[22] The GLW measure is constructed by making the difference between 0.90 (i.e. the 90% confidence interval asked to the subjects) and the probability distribution of returns (i.e. computed using the two extreme price estimations given by investors).

GLW) variable has a positive significative impact of 0.188. The optimism (i.e. the expected subjective return) has also a positive significative impact of 0.242, on risk trading behavior.

Broihanne et al. (2014) find a negative relationship between risk taking and the two measures of risk perception (i.e. Lottery A and PCA), the risk aversion and the experience. The effects of risk perception (i.e. PCA) on the risk taking behavior is significant in each configuration. This observation underlines the strong impact (i.e. negative) of the risk perception in risk-taking behavior.

Moreover, the overconfidence measure (i.e. miscalibration in the forecast of future stock prices) has a strong positive and significant effect on the risk-taking behavior, in each configuration. Nevertheless, Broihanne et al. (2014) find no evidence of a significant effect of the BTA bias and the miscalibration in general knowledge questions, on the risk-taking behavior. Thus, the miscalibration in risk (i.e. the difference between 90% and the implicit probability mass provided by respondents) plays a stronger role in explaining risk taking decisions.

Broihanne et al. (2014) find also that optimism has a positive relationship with risk-taking, whereas ESV has a negative relationship with risk-taking. The optimism variable is significant in each model. The ESV variable is not significant in each model. Broihanne et al. (2014) explain that the ESV has a low quality as a measure of risk. Indeed, respondents closely follow the evolution of stocks under consideration. They may have in mind the current prices and not the end of March prices, appearing on the graph (i.e. and thus the ESV variable may be affected).

Broihanne et al. (2014) underline the fact that optimism is much more significant than the overconfidence in future stock prices.

To conclude, we can say that the overconfidence effect on trading behavior is not confined to individual investors. Professional investors are also affected by their overconfidence level in making financial decisions. Broihanne et al. (2014) achieve to demonstrate the positive effect of overconfidence (i.e. in the forecast of future stock prices) and over-optimism on the risk-taking behavior of professional. They do not observe a BTA effect and also a significant link between BTA effect and risk-taking behavior, contrary to Glaser and Weber (2007).

Fenton O'Creevy et al. (2003) also achieve to find evidences of the consequences of overconfidence bias (i.e. illusion of control) among professional investors. Fenton O'Creevy et al. (2003) sample 107 traders in four City of London investment banks.

Fenton O'Creevy et al. (2003) underline the fact that financial markets are a place where the tendency to express illusion of control is strong. Traders are more likely to express the illusion of control bias. Indeed, the decision of trading involves judgment and risk at each stage (i.e. selling, buying or keeping an asset). The process of risk judgement is sensitive to the effect of control (i.e. March and Shapira, 1987, find that the level of risk is frequently underestimated by executives, because of their assumption about the control of the situation).

Moreover, the trader's task is also subject to the illusion of control effect. In fact, traders can earn excess returns by exploiting asymmetric informations (i.e. privileged information, for example) and this kind of informations is usually short-lived. Markets are noisy and unpredictable. As a consequence, the returns are usually treated as results of traders' informations and skills. Traders tend to establish a link between their private information and the market movements, and thus construct an illusion of control.

Fenton O'Creevy et al. (2003) underline several characteristics of trader's environment, that can accentuate the illusion of control effect :

- **the stress** : trading is stressful with a low visibility and a high uncertainty concerning the returns. Friedland et al. (1992) show that the level of illusion of control increases in a such environment of stress.

- **the competition** : Langer (1975) shows that illusion of control is positively linked with the competition. Trading is competitive, not only between market actors but also inside the dealing room (i.e. between the traders).
- **the implemented mind set** : Gollwitzer and Kinney (1989) underline the fact that illusion of control is stronger when individuals are focused on goal. Trading is an activity entirely focused on goal. The bonus and targets system accentuates this effect of goal focused activity.
- **the choice, involvement and familiarity** : Langer (1975) finds that the illusion of control is linked with the choice, and is stronger when the involvement and the familiarity is high. Trading is an activity that implies choice and involvement. Moreover, traders tend to develop a familiarity with financial markets.

Fenton O'Creevy et al. (2003) try to measure the consequences of control illusions on the activity of traders. They postulate that such traders tend to ignore feedbacks and thus persist too long with wrong strategies (i.e. they consider trading noise as if it is information).

As a consequence, they try to test if the performance of traders is subject to illusion a control, but also if illusion of control has an impact on other variables, such as the level of market analysis, the risk management, the contribution to profits and the total remuneration of such traders. The contribution to profits, the skill in risk management, the analytical ability and the people skills are variables that are asked to the manager of each trader. Managers are asked, for these four variables, to mark the trader on a linear scale from 0 to 100, representing percentiles (i.e. 60 means that the trader would be better than 60% of other traders).

The total remuneration is the annual salary plus the bonuses. Education variable is measured through the higher educational qualification of each trader (i.e. using a scale from 1=GSCE[23], to 6=PhD). Experience is measured using the number of years in trading activity. Job level is measured using a scale (i.e. 1=trader, 2=trader manager, 3=senior manager).

[23] GSCE is the minimum of UK school qualifications taken at the age of 16.

Fenton O'Creevy et al. (2003) find different implications. First, there is a positive link between both the experiment of traders, their education, their job level and their remuneration. An increase of the education, the job level and the experiment leads to an increase of the remuneration. Results are presented in Table 18.

If we take the dependent variable « Profit contribution », we can see that both education and experience variables are not significant. Job level is significant at the 10% level, and have a positive impact of 0.23. The illusion of control have a negative significant impact (at the 5% level) of -0.33. Thus, Fenton O'Creevy et al. (2003) find that illusion of control bias leads to a lower profit contribution : traders submitted to the illusion of control tend to earn lower returns.

Table 18 : Regressions on remuneration and self-ratings of performance (Fenton O'Creevy et al., 2003)

	Standardized regression coefficients				
			Manager ratings		
	Total annual remuneration (N=107)	Profit contribution (N=103)	Risk management (N=93)	Analytical ability (N=103)	People skills (N=103)
Education	.44***	.18†	.17 ns	.26*	−.04 ns
Experience	.32***	.07 ns	−.01 ns	.08 ns	.03 ns
Job level	.31***	.23*	.17 ns	.14 ns	.24*
Illusion of control	−.23*	−.33**	−.33**	−.21*	−.12 ns
R^2	.30***	.16**	.15*	.10*	.07 ns

†p<.10; *p<.05; **p<.01; ***p<.001.

Fenton O'Creevy et al. (2003) find that illusion of control is also negatively correlated with remuneration, analytical competences, and management of the risk. All coefficients are significant, except for the « people skills » coefficient : the interpersonal performance is not linked with the illusion of control.

To conclude, Fenton O’Creevy et al. (2003) point out the impact of illusion of control on the behavior of professional investors. Indeed, they find a negative impact of the illusion of control bias on the trading performance of financial experts. Illusion of control leads to a decrease of both remuneration, profit contribution, risk management and analytical ability (i.e. as evaluated by managers).

Conclusion

The overconfidence effect on trading behavior of individual investors was widely demonstrated (i.e. Odean 1999, Glaser and Weber 2007) by the literature. Researches that focus on the behavior of professional investors (i.e. funds managers or traders sampled) reached to the same conclusions. Overconfidence bias among financial experts leads to a change in behavior.

Overconfident professional investors tend to have a higher risk taking propensity (i.e. Broihanne et al. 2014), tend to earn less trading returns and to be less competent, in risk management and in their analytical ability (i.e. Fenton O’Creevy et al., 2003).

General Conclusion

Perhaps the most robust finding in the psychology of judgement is that people are overconfident. » (DeBondt and Thaler, 1995, p.389).

« *Trading volume is the most robust effect of overconfidence »* Odean, 1998[24] (p.1888)

These two sentences, respectively stated by DeBondt and Thaler (1995) and Odean (1998), can help to sum up this dissertation.

First, psychologists find evidences of biases among individuals. Indeed, individuals do not act as rational as financial theories would have expected. According to financial theories, rational individuals need to maximise their expected utility and respect the rules of probability theories, in their decision-making.

Psychologists point out the fact that the behavior of individuals deviates from these axioms, used in financial theories. Numerous biases were demonstrated, and among them, the overconfidence bias was widely studied by psychological studies. These studies underlined the four components of the overconfidence bias, which were deeply studied in Part I : the miscalibration, the better-than-average effect, the illusion of control and the unrealistic optimism.

Researchers, such as Fischoff et al. (1977), Svenson (1981), Langer (1975) and Weinstein (1980), develop different measures in order to test the overconfidence bias among sampled individuals. These same researchers succeed to find evidences of overconfidence among individuals, using their developed measures.

[24] Odean, T., 1998a. « Volume, Volatility, Price, and Profit When All Traders Are Above Average ». *Journal of Finance*, 53(6). 1887-934.

The work of psychologists is now used in a lot of other fields : one of them is the financial research, through the behavioral finance. Indeed, a large number of financial researchers pointed out the fact that financial markets do not operate the same way as theories had postulated. Various indicators do not support results of classical theories. One of them is the great number of trades and the huge trading volume observed on financial markets. Froot and Thaler (1990), but also Collin-Dufresne and Daniel (2014) and Glaser and Weber (2007), highlight that the number of trades, occurring on financial markets, is very high, and cannot be explained only with rational arguments (i.e. need to rebalance, liquidity or tax reasons).

As a consequence, financial researches focus on the overconfidence bias among investors and its consequences on financial markets. The first step is to find evidences of overconfidence among investors. In order to accomplish that, researchers used the measures constructed by psychologists, and apply these measures to individual and professional investors. A large number of studies find evidences of both miscalibration, better-than-average effect, illusion of control and over-optimism among investors.

The second step is to measure the effects of this overconfidences bias on financial markets. Numerous consequences are found. First, the overconfidence effect leads to a higher trading volume (Odean, 1999). The overconfidence bias also leads to lower returns, by the effect of higher transactions costs, but also by the poor level of stock picking. Finally, overconfidence can lead to higher risk propensity, and thus higher level of risk in individual and professional investors' portfolios.

The overconfidence bias is fundamental in financial markets. The main consequence of this bias is a high level of trading volume. Researches still focus on this bias, in order to quantify more precisely its consequences on financial markets. Moreover, experimental studies, such as the one of Biais et al. (2004), can be interesting in order to measure and to observe the actual behavior of individuals.

The horizon of researches is still large in behavioral finance, but also in other fields, such as corporate finance (i.e. firm managers are demonstrated as overconfident, and it has an impact on the financial structure of firms). Overconfidence can be seen as a matrix in decision-making, and more specifically in financial decision-making.

Bibliography

Books

Broihanne, M., Merli, M., Roger, P., 2004. « *Finance Comportementale* ». Economica.

Kahneman, D., Tversky, A., 1982. « Variants of uncertainty ». In D. Kahneman, P. Slovic, & A. Tversky (Eds.), *Judgment under uncertainty: Heuristics and biases* (509–520). Cambridge, UK: Cambridge Univ. Press.

Lichtenstein, S., Fischhoff, B., Phillips, L. D., 1982. « Calibration of probabilities: The state of the art to 1980 ». In D. Kahneman, P. Slovic, & A. Tversky (Eds.), *Judgment under uncertainty: Heuristics and biases*. 306–334. Cambridge, England : Cambridge University Press.

Mangot, M., 2005. « *Psychologie de l'Investisseur et des Marchés Financiers* ». Dunod.

Articles

Adams, J. K., Adams, P. A., 1961. « Realism of confidence judgments ». *Psychological Review*, 68. 33-45.

Alicke, M. D., 1985. « Global self-evaluation as determined by the desirability and controllability of trait adjectives ». *Journal of Personality and Social Psychology*, 49. 1621-1630.

Alicke, M.D., Klotz, M.L., Breitenbecher, D.L., Yurak, T.J, Vredenburg, D.S., 1995. « Personal Contact, Individuation and the Better-Than-Average Effect ». *Journal of Personality and Social Psychology* , 68(5). 804–825.

Barber, B.M., Odean, T., 2000. « Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors ». *Journal of Finance*, 55. 773-806.

Barber, B., Odean, T., 2001. « Boys will be boys: gender, overconfidence, and common stock investment ». *Quarterly Journal of Economy*, 116. 261–292.

Barber, B., Odean, T., 2002. « Online Investors: Do the Slow Die First?». *The Review of Financial Studies*, 15(2). 455-487.

Baumhart, R., Holt, Rihenart, Winston, 1968. « Ethics in business. Business & Economics ». 248 p.

Greenwald, A. G., 1980. « The totalitarian ego: Fabrication and revision of personal history ». *American Psychologist*, 35. 603-618.

Benassi, V.A., Sweeney, P.D., Drevno, G.E. 1979. « Mind over matter: Perceived success at psychokinesis ». *Journal of Personality and Social Psychology*, 37, 1377-1386.

Benos, Alexandros V. , 1998. « Aggressiveness and Survival of Overconfident Traders ». *Journal of Financial Markets*, 1(3–4). 353-83.

Bernoulli D., 1738. « Exposition of a New Theory on the Measurability of Wealth ». *Econometrica*. 1958. 503-546.

Biais, B., Hilton, D., Mazurier, K., Pouget, S., 2004. « Judgmental overconfidence, self-monitoring and trading performance in an experimental financial market ». IDEI Working Papers.

Black F., Scholes M., 1973. « The Pricing of Options and Corporate Liabilities ». *Journal of Political Economy,* 81(3). 637-659.

Brad, M.B., Odean, T., 2013. « The Behavior of Individual Investors ». *Handbook of the Economics of Finance.* 1533-1569.

Broihanne, M.H., Merli, & M., Roger, P. 2014. « Overconfidence, Risk Perception, and the risk-taking behavior of finance professionals ». *Finance Research Letters* (11). 64-73.

Brown, T. A., Shuford, E. H. 1973. « Quantifying uncertainty into numerical probabilities for the reporting of intelligence ». (Report R-1185-ARPA). Santa Monica: The RAND Corp.

Brown, J. D., 1986. « Evaluations of self and others: Self-enhancement biases in social judgments ». *Social Cognition*, 4. 353-376.

Burger, J.M., 1986. « Desire for control and the illusion of control: The effects of familiarity and sequence of outcomes ». *Journal of Research in Personality*, 20. 66-76.

Caballé, J., Sákovics, J., 2003. « Speculating against an overconfident market ». *Journal of Financial Market*s, 6. 199-225.

Camerer, Colin et Dan Lovallo, 1999. « Overconfidence and Excess Entry: An Experimental Approach ». *American Economic Review*, 89(1). 306-318.

Collin-Dufresne, P., Kent, D., 2014. « Liquidity and Return Reversals ». Columbia GSB working paper.

Chuang, W. I., Lee, B. S., 2006. « An empirical evaluation of the overconfidence hypothesis ». *Journal of Banking and Finance*, 30. 2489-2515.

Daniel, K., Hirshleifer, D., 2001. « Overconfidence, arbitrage and equilibrium asset pricing ». *Journal of Financ*e, 56(3). 921-965.

Daniel, K., Hirshleifer, D. 2015. « Overconfident Investors, Predictable Returns, and Excessive Trading ». *Journal of Economic Perspectives* (29): 61-88.

Deaux, K., Farris, E., 1977. « Attributing causes for one's own performance: the effects of sex, norms, and outcome ». *Journal of Research in Personality*, 11. 59-72.

Deaves, R., Lüders, E., Luo, R. 2003. « An Experimental Test of the Impact of Overconfidence and Gender on Trading Activity ». Working Paper, McMaster University.

Dorn, D., Huberman, G., 2002. « Who trades? ». Working Paper, Columbia University.

Dorn, D., Huberman, G., 2005. « Talk and Action: What Individual Investors Say and What They Do ». *Review of Finance*, 9. 437-481.

Dow, J., Gordon, G., 1997. « Stock Market Efficiency and Economic. Efficiency: Is There a Connection? ». *Journal of Finance*, 52(3). 1087-1129.

Erev, I., Wallsten, T. S., Budescu, D. V., 1994. « Simultaneous over- and underconfidence: The role of error in judgment processes ». *Psychological Review*, 101. 519–528.

Fama, E., 1972, « Components of Investment Performance ». *Journal of Finance*, 27(3). 551-67.

Fenton O'Creevy, M., Nicholson, N., Soane, E., Willman, P., 2003. « Trading on Illusions; Unrealistic perceptions of control and trading performance ». *Journal of Occupational and Organisational Psychology*, 76. 53-68.

Friedland, N., Keinan, G., Regev. Y. 1992. « Controlling the uncontrollable: effects of stress on illusory perceptions of controllability ». *Journal of Personality and Social Psychology*, 63(6). 923-31.

Froot, K.A., Thaler., R.H., 1990. « Anomalies: Foreign Exchange ». *Journal of Economic Perspectives,* 4(3). 179–92.

Gervais, S., Odean, T., 2001. « Learning to be overconfident ». *Review of Financial Studies*, 14. 1-27.

Gigerenzer, G., Hoffrage, U., Kleinbolting, H., 1991. « Probabilistic mental models:A Brunswikian theory of confidence ». *Psychological Review*, 98. 506–528.

Glaser, M., Weber, M., 2004. « Which Past Returns Affect Trading Volume? ». Working Paper, University of Mannheim.

Glaser, M., Langer, T., Weber, M., 2005. « Overconfidence of Professionals and Lay Men: Individual Differences Within and Between Tasks? ». Working Paper, University of Mannheim.

Glaser, M., Weber, M. 2007. « Overconfidence and trading volume ». *Geneva Risk Insur Rev* (32). 1-36.

Goethals, G. R., Messick, D. M., Allison, S. T., 1991. « The uniqueness bias: Studies of constructive social comparison ». *Social comparison: Contemporary theory and research*. 149–176.

Gollwitzer, P.M., Kinney, R.F. 1989. « Effects of deliberative and implemental mind-sets on illusion of control ». *Journal of Personality and Social Psychology*, 56, 531-542.

Griffin, D., Tversky, A., 1992. « The weighing of evidence and the determinants of confidence ». *Cognitive Psychology*, 24(3). 411-435.

Harris, M., Raviv, A., 1993. « Differences of Opinion Make a Horse Race ». *Review of Financial Studies*, 6(3). 473-506.

Heath, C.H., S., Lang, M., 1999. « Psychological Factors and Security Option Exercise ». *Quarterly Journal of Economics*, 114(2). 601-27.

Heine, S. J., Lehman, D. R., 1997. « The cultural construction of self-enhancement: An examination of groupserving biases ». *Journal of Personality and Social Psychology*, 72. 1268–1283.

Heisler, J., 1994. « Loss Aversion in a Futures Market: An Empirical Test ». *Review of Futures Markets*, 13(3). 793-822.

Hendin, H. M., Cheek, J. M., 1997. « Assessing hypersensitive narcissism: A re-examination of Murray's narcissism scale ». *Journal of Research in Personality*, 31. 588–599.

Hirshleifer, D., Luo, G.Y., 2001. « On the survival of overconfident traders in a competitive security market ». *Journal of Financial Markets*, 4 (1). 73–84.

Hoch, S.F, 1985. « Counterfactual Reasoning and Accuracy in Predicting Personal Events ». *Journal of Experimental Psychology: Learning, Memory and Cognition*, 11. 719-731.

Keefer, D.L. Bodily, S.E., 1983. « Three-Point Approximations for Continuous Random Variables ». *Management Science*, 29(5). 595-609.

Klayman, J., 1995. « Varieties of confirmation bias ». In J. Busemeyer, R. Hastie,& D. L. Medin (Eds.), *Psychology of Learning and Motivation*.

Klayman, J., Soll, J. B., Gonzalez-Vallejo, C., Barlas, S., 1999. « Overconfidence: It depends on how, what, and whom you ask ». *Organizational Behavior and Human Decision Processes*, 79. 216–247.

Koriat, A., Lichtenstein, S., Fischhoff, B., 1980. « Reasons for confidence ». *Journal of Experimental Psychology: Human Learning and Memory*, 6. 107–118.

Kruger J, Dunning D., 1999. « Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments ». *Journal of Personality and Social Psychology*, 77. 1121-1134.

Kyle, Albert S., Wang, F. Albert., 1997. « Speculation Duopoly with Agreement to Disagree: Can Overconfidence Survive the Market Test? ». *Journal of Finance*, 52(5). 2073-90.

Langer, E.J., 1975. « The illusion of control ». *Journal of Personality and Social*, Psychology, 32. 311-328.

Langer, E. J., Roth, J., 1975. « Heads I win, tails it's chance: The illusion of control as a function of the sequence of outcomes in a purely chance task ». *Journal of Personality and Social Psychology*, 32. 951-955.

Larwood, L., Whittaker, W. 1977. « Managerial myopia: Self-serving biases in organizational planning ». *Journal of Applied Psychology*, 62.194-198.

LeRoy, S.F., Porter, R.D., 1981. « The Present-Value Relation: Tests Based on Implied Variance Bound ». *Econometrica,* 49. 555–574.

Lundeberg, M., Fox, P.W., Puncochar, J., 1994. « Highly confident, but wrong: Gender differences and similarities in confidence judgments ». *Journal of Educational Psychology*, 84. 114-124.

Malmendier, U., Taylor, T., 2015. « On the Verges of Overconfidence ». *Journal of Economic Perspectives* (29): 3-8.

Markowitz H., 1952. « Portfolio Selection ». *Journal of Finance*, 7(1). 77-91.

Menkhoff, L., Schmidt, U. and Brozynski, T., 2006. « The Impact of Experience on Risk Taking. Overconfidence and Herding of Funds Managers: Complementary Survey Evidence ». *European Economic Review*, 50. 1753-1766.

Miller, D. T., Ross, M., 1975. « Self-serving biases in attribution of causality: Fact or fiction? ». *Psychological Bulletin*, 82. 213-225.

Modigliani F., Miller M., 1958. « The Cost of Capital, Corporation Finance and the Theory of Investment ». *American Economic Review*, 48(3). 261-297.

Moore, D., Healy, P. J. 2008. « The trouble with overconfidence ». *Psychological Review,* 115, 502–517.

Murphy, A. H., 1973. « A new vector partition of the probability score ». *Journal of Applied Meteorology*, 12. 595–600.

Murphy, A. H., Winkler R., 1984. « Probability forecasting in meteorology ». *Journal of the American Statistical Association*, 79. 489–500.

Oberlechner, T., Osler, C.L. 2003. « Overconfidence in Currency Markets ». Working Paper.

Odean, T., 1998a. « Volume, Volatility, Price, and Profit When All Traders Are Above Average ». *Journal of Finance*, 53(6). 1887-934.

Odean, T., 1998b. « Are Investors Reluctant to Realize Their Losses? ». *Journal of Finance*, October, 53(5). 1775-98.

Odean, T., 1999. « Do Investors Trade Too Much? ». The American Economic Review, 89(5). 1279-1298.

Oskamp, S., 1965. « Overconfidence in case-study judgments ». *The Journal of Consulting Psychology*, 29. 261–265.

Perloff, L. S., Fetzer, B. K.,1986. « Self-other judgments and perceived vulnerability of victimization ». *Journal of Personality and Social Psychology*, 50. 502-510.

Pitz, G., 1974. « Subjective probability distributions for imperfectly known quantities ». In G. W. Gregg (Ed.), Knowledge and cognition. New York: Wiley.

Plott, C.R., Sunder, S. 1988. « Rational Expectations and The Aggregation of Diverse Information in Laboratory Security Markets ». *Econometrica*, 56(5). 1085-1118.

Presson, Paul K., and Victor, A. Benassi, 1996. « Locus of Control Orientation and Depressive Symptomatology: A Meta-Analysis ». *Journal of Social Behavior and Personality*, 11. 201–212.

Proeger, T., Meub, L. 2014. « Overconfidence as a Social Bias: Experimental Evidence » . *Economics Letters,* 122, 2, 203–207.

Puri, M., Robinson, D.T., 2006a. « Dispositional optimism and life expectancy miscalibration ». Working paper, Duke University.

Puri, M., Robinson, D.T., 2007. « Optimism and economic choice ». *Journal of Financial Economics*, 86. 71-99.

Régner, I., Hilton, D., Cabantous, L., Vautier, S. 2004. « Overconfidence, Miscalibration and Positive Illusions ». Working Paper, University of Toulouse.

Renner, B., Knoll, N., Schwarzer, R., 2000. « Age and body make a difference in optimistic health beliefs and nutrition behaviors ». *International Journal of Behavioral Medicine*, 7. 143-159.

Rosenberg, M., 1965. « Society and the adolescent self-image ». Princeton, NJ, P*rinceton University Press*.

Ross, S. A., 1976. « The Arbitrage Theory of Capital Asset Pricing ». *Journal of Economic Theory*, 3. 343-362.

Sandroni, A., Squintani, F., 2004. « A Survey on Overconfidence, Insurance and Self-Assessment Training Programs ». Kellogg School of Business.

Scheinkman, J., and Wei, X., 2003. « Overconfidence and speculative bubbles ». *Journal of Political Economy*, 111. 1183–1219.

Sharpe, W., 1964. « Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk ». *Journal of Finance*, 19(3). 725-742.

Shefrin, H., Statman, M., 1985. « The disposition to sell winners too early and ride losers too long – Theory and Evidence ». *Journal of Finance*, 40(3). 777-790.

Shiller, R.J., 1999. « Human Behavior and the Efficiency of the Financial System ». *Handbook of Macroeconomics*, J. Taylor and M. Woodford (Eds.), Amsterdam: Elsevier Science. 1305-1340.

Smith, V., Suchanek, G., Williams, A., 1988. « Bubbles, Crashes, and Endogenous Expectations in Experimental Spot Asset Markets ». *Econometrica*, 56 (5). 1119-1151

Snyder, C. R., Shenkel, R. J., Lowery, C. R., 1977. « Acceptance of personality interpretations: The « Barnum effect » and beyond ». *Journal of Consulting and Clinical Psychology*, 45. 104-114.

Statman, M., Thorley, S., Vorkink, K., 2006. « Investor overconfidence and trading volume ». *Review of Financial Studies*, 19. 1531-1565.

Soll, J. B., 1996. « Determinants of overconfidence and miscalibration: The roles of random error and ecological structure ». *Organizational Behavior and Human Decision Processes*, 65. 117–137.

Soll, J. B., Klayman, J., 2004. « Overconfidence in interval estimates ». *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 30(2). 299-314.

Tversky, A., Kahneman, D., 1974. « Judgment under uncertainty: Heuristics and biases ». *Science*, 185. 1124-1131.

Wang, F. A., 1998. « Strategic trading, asymmetric information and heterogeneous prior beliefs ». *Journal of Financial Markets*, 1. 321-352.

Weinstein, N. D., 1980. « Unrealistic optimism about future life events ». *Journal of Personality and Social Psychology*, 39. 806-820.

Wenglert, L., Svenson, O., 1982. « Self-image and predictions about future events. ». *Scandinavian Journal of Psychology*, 23. 153-155.

Wenglert, L., Rosen, A.S., 2000. « Measuring optimism-pessimism from beliefs about future events ». *Personality and Individual Differences*, 28. 717-728.

Other sources

http://www.institut-numerique.org/11-definitions-et-caracteristiques-de-lexces-de-confiance-4e09fc266ff00

http://overconfidence.behaviouralfinance.net

http://www.investopedia.com/university/behavioral_finance/behavioral9.asp

The impact of the overconfidence bias on financial markets

Résumé

Le biais de surconfiance peut-il avoir un impact sur les marchés financiers ? Ceci est un aspect clé des recherches en finance comportementales. Comme le volume de trading, mesuré sur les marchés financiers, est trop élevé en comparaison des prévisions des théories financières traditionnelles, les chercheurs ont tenté de trouver des explications à ce volume de trading. L'objectif de cette étude est de définir la surconfiance et de résumer les principales conséquences de ce bias sur les marchés financiers. La surconfiance est principalement caractérisée par quatre composantes : la « miscalibration », le « better-than-average » effet, l'illusion de contrôle et l'optimisme irréaliste. Les chercheurs en finance ont prouvé que la surconfiance entraîne un plus important volume de trading, mais également des rendements plus faibles et un plus haut risque.

MOTS-CLÉS : finance, surconfiance, psychologie, volume de transactions

Abstract

Does the overconfidence bias have an impact on financial markets ? This is a key aspect in behavioral finance researches. As the trading volume, measured on financial markets, is too high compared to expectations of traditional financial theories, researchers try to find explications for this great level of trading volume. This study aims at defining what overconfidence is and summing up the principal consequences of this bias on financial markets. Overconfidence is principally characterized by four components : miscalibration, better-than-average effect, illusion of control, and unrealistic optimism. Financial researchers find that overconfidence leads to higher trading volume, but also to lower returns and higher risk.

KEYS-WORDS : finance, overconfidence, psychology, trading volume