Emotional State, Financial Expectations and Overconfidence

Abstract

Although the role of irrationality in the trading choice has been extensively discussed in the literature, individual characteristics, which are equally crucial, have been neglected. The purpose of this paper is to add a different way of looking with finance by focusing on individuals' emotions. In particular, this work emphasizes the role of social life in emotional states. We investigated several possible links between psychological factors and trading choices in a sample of non professional agents, which managed a virtual portfolio pretending to be traders. Using a series of daily surveys over a seven week period as well as introductive inventory surveys, we constructed measures of personality traits and emotional moods and correlate these with subjects' financial choices. Our aim is to find some evidence of the contribution of emotional state to the way to invest, indicating the added value of using an emotional intelligence measure beyond the classic economic theory.

JEL classification*: G11, D81, C92*

Keywords*: financial expectations; behavioural finance; sex and gender*

1. Introduction

Traditional financial literature assumes that individuals are rational agents maximizing the utility function, regardless their emotional state and previous experience.

In the Seventies, Kahneman and Tversky (1979), started to reconsider the role of attitudes, emotions and, in general, behavioral biases in investors' decisions. Agents' preferences are influenced by the way prospects are presented (framing). Decision process consists of an editing stage, when prospects are coded and categorized and complex problems are broken down into simpler sub problems, and an evaluation stage, when prospects with the highest value are chosen. As the editing can lead to different representations, the decision can change accordingly. Framing is at the basis of mental accounting, being the way a problem is subjectively interpreted.

One of the latest developments involve the use of psychology to investigate how emotions and sentiments affect the choice of the utility function and the perception of the state of the world. According to this field of literature, behaviour is dominated by affect rather than rational calculation. Emotions and sentiments have to be considered for decision making process. Thaler (1993) proves that psychological forces play a role in determining asset prices. Damasio (1994) shows how decision making can be extremely difficult for people who have lost the use of the emotional part of their brains. Forgas (1995) show that the computations required for making investment decisions are typically complex, abstract, and involve risk, which are the attributes that are considered to induce people to rely more heavily on their emotions when making a choice Emotions have also been used to explain recent financial crises (Tuckett and Taffler, 2008 and Chick, 2008).

Psychology has also been used to understand traders' decisions. Biais et al (2009) use an experimental approach derived from Plott and Sunder (1988) to test the hypotheses that psychological variables have an influence on traders market behaviour. They show that that mis-calibration reduces and self-monitoring enhances trading performances. Furthermore, the impact of the psychological variables is significant for males but not for females. Lepori (2009) shows that air-quality induced mood changes influence traders' decisions.

Following this stream of literature, in this paper we investigate if financial choices can be influenced by emotional states. We present the results of an experimental approach designed to clarify the interactions between social-emotional life and financial choices. Two were the financial choices considered in our study: first, the attitude to take either a long or a short position in a financial asset; second, the disposition to borrow money in order to pursue financial goals.

With this design we test whether there is any causal relationship between emotional state and financial behaviour. We further investigate if such relationship differ by gender and personality traits.

The paper is organized as follows. In section 2 we present the experimental design. We explain the process of participants' selection, the data we collected through questionnaires, the rule of the game and the methodology we applied to estimate the models. In section 3 we describe and discuss our results. Section 4 concludes.

2. Experimental design. Materials and Methods

2.1. Subjects

As a part of mandatory courses, MSc in Finance students (n = 89; 48 males, 41 females) at Italian Universities (Siena and Bergamo) were asked to participate as volunteers in an experimental trading game to investigate the relationship between financial expectations, risk appetite and investors' mood attitude. Of the total students, 77 provided valid and time compliant responses. 39 were males and 38 females, with age ranging from 19 and 28 and a mean age of 24 years old (32,5% between 19 and 22; 57,1% between 23 and 25; 10,4% between 26 and 28).
Following Bias and Al. (2005) we believed that rewarding participants based on examination grades and their university curricula, as opposed to small amount of money, would induce them to act seriously. We offered two formative credits (ECTS) to add in personal plan of study to all participants who properly complete the questionnaires.[1] As a further inducement to carefully complete the questionnaire, we also offered an airline ticket to London to be extracted among participants at the end of the experiment.
None of the participants in our study had prior professional trading experiences or previous exposure to this kind of experiments. The choice to run the experiment with students, instead than with professional traders, allows us to measure the trading behaviour purifying it from the economic cycle and trend and from the corporate bonus, so that the result would be the pure choice of each investor and her/his emotional status.
This subject population represents an optimal choice for some reasons: (i) MSc in Finance students are familiar with financial risk (minimum uninformed risk); (ii) they are homogeneous in age, educational background, and social status (minimum mystification risk); (iii) they are expected to enter the financial industry, therefore they represent a proxy of professional financial decision makers, without firms' constraints affecting their decisions (minimum representative risk).
The crosstabs show there is no significant difference between the ex-ante orientation of males and females to buy or sell and to borrow money.

[1] The European Credit Transfer and Accumulation System is a student-centred system based on the student workload required to achieve the objectives of a programme, objectives preferably specified in terms of the learning outcomes and competences to be acquired. Credits are allocated to all educational components of a study programme (modules, courses, placements, dissertation work) and reflect the quantity of work each component requires to achieve its specific objectives or learning outcomes in relation to the total quantity of work necessary to complete a full year of study successfully. This is an incentive for our students who are expected to record a pre-defined number of credits (according the Bologna process signed in 1999, the number of credits are 180 for undergraduate courses and 120 for Master of Sciences).

Table 1. Financial Decisions by Gender

Panel A. Expectations/Propensity to buy by gender

			Gender		Total
			Males	Females	
Propensity to buy	Low	Count	26	24	50
		% of Total	66,67	63,16	64,94
	High	Count	13	14	27
		% of Total	33,33	36,84	35,06
Total		Count	39	38	77
		% of Total	100,0%	100,0	100,0

Panel B. Overconfidence/Propensity to indebt by gender

			Gender		Total
			Males	Females	
Propensity to indebt	Low	Count	27	22	49
		% of Total	69,23	57,89	63,64
	High	Count	12	16	28
		% of Total	30,77	42,11	36,36
Total		Count	39	38	77
		% of Total	100,0%	100,0	100,0

2.2. General procedure

We explained the mechanisms and the rules of the games in a two hour session before starting the experiment. All the following communications were done through e-mails. To guarantee as most as possible applicants' privacy, with the first email we sent a random nickname to every one, which served as a unique identifier for each subject.

As a first step of the experiment we asked participants to fill an initial questionnaire aimed at collecting data on students features as described in section 2.1. The initial survey was filled once at the beginning of the experiment (October 3, 2007). Furthermore, the initial questionnaire was intended to identify participants' character using the Five Factor model (Digman, 1990) Test (McCrae and Costa, 1999), a widely used model for dimensionally studying personality. The five factors (Digman, 1997; Griffin and Bartholomew, 1994; John, 1990) are: (i) agreeableness; (ii) conscientiousness; (iii) extroversion; (iv) neuroticism; (v) openness.

The respondent of the test is asked to pick one description (example: do you feel relaxed or anxious) and marks (from the minimum 0 to the maximum of 4) are based on the selected character. Then we divided the quality with regard to the personality treat they refer to. Finally we summed the marks and got a final score for the five factors, which ranges from LOW to HIGH, as shown in table 1.

Table 2: Distribution of Personality Features using the Five Factors Model

Score	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness
Low	16	11	27	54	34
High	61	66	50	23	43
Total	77	77	77	77	77

Agreeableness includes traits like sympathetic, kind, and affectionate. Agreeable individuals are generally perceived as friendly, generous, helpful and with an optimistic view of human nature. the sample is concentrated in the high level, since the self attribution is not an objective way to assess about personality and subjects consider themselves optimistically. Nonetheless, only 4 participants got 3 which, at the end, indicate few persons have a over-consideration of themselves. From a trader's point of view, agreeableness is the trait that makes one able to give people the benefit of the doubt and does not mind giving someone a second chance. This feature makes the investor scarcely depending on conditional temper.

Conscientiousness is related to the way people control and regulate their impulse. People with a high score in conscientiousness tend to show self-discipline, preference for planning rather than spontaneous behaviour. our distribution is shifted to the highest level; that would be a good trait for a trader, because it designs people organized, well planned, reliable, and successful. Self-discipline is a facet of conscientiousness; it relates to how people manage our impulses. We expect self-disciplined people are better able to control and channel their impulses towards goals, not depending on mood factors.

Extroversion captures the way people interact and are related with the external world. Extroverts enjoy being with people, are full of energy, enthusiastic and action-oriented. Introverts are quiet, less involved in the social world, they may be very active and energetic, simply not socially. More than the 60% of the subjects indicate a quite high tendency to be extrovert, outgoing and open to new social experience. We use this specific personality trait to select people who are inclined to social relationships. In this case, emotional components are expected to affect decisions, such as financial ones;

Neuroticism (sometimes reversed and called emotional stability) is characterized by traits like tense, moody, and anxious. Neuroticism is the tendency to assess ordinary situations as threatening, and minor frustrations as hopelessly difficult. People with high score in this trait are often in a bad mood, stressed and anxious. As defined, it is the only "reverse" factor of the Five Factor Model, i.e. a low score equals a positive personality trait; that explains why its quantitative distribution is inverted when compared to the others. Indeed we get the most popular score is 0, which implies people are emotionally stable and mentally together. They are typically calm and relaxed and making others feel secure (Lo, Repin, Steenbarger, 2005). Therefore, we expect a lower reaction to mood issues;

Openness to experience (sometimes called intellect or imagination) distinguishes people who are curious, imaginative, with wide interests from more plain, straightforward, and conventional. The distribution of the sample shows a completely different shape; the subjects assessed themselves quite homogeneously among the scores. Openness to experience is sometimes also referred to intellect, and cognitive ability and intellect are presumably related. Openness to experience should be indicative of creativity and originality; consequently, there may be a direct but unobvious connection to trading performance depending on events affecting emotions.

Students were also asked to fill a daily questionnaire, made of two sections: one related to financial decisions; the other related to the emotional state. The daily questionnaire was filled every working day in the morning (before 10 a.m.) to check the mood of participants, during a period of seven weeks (from October 6 and November 21, 2007).
The financial section of the questionnaire was aimed at estimating, respectively, the propensity to take short positions (SELL) and the propensity to borrow money (NODEBT). To define the SELL variable we asked our participants the following question: "Today, according to your emotional state, would you prefer to buy or sell your financial position?". To define the NODEBT variable we asked our participants the following question: "Today, in case to enhance your financial choices you should borrow money, would you do it?". No other economic or financial fact was provided in order to make participants decisions information-free.
The second section of the daily questionnaire was aimed at defining the emotional state when the financial decisions were declared. We collected eight different mood variables to explain financial decisions, such as short positions and debt increase. The analysis will be estimated for the whole sample and within subgroups both by genre and by psychological factors.

Table 3: Sensitivity of financial decisions (SELL and NODEBT) to psychological factors

PSYCHOLOGICAL	SELL		NODEBT	
FACTORS	LOW	HIGH	LOW	HIGH
Agreeableness	MAX	MIN	MAX	MIN
Conscientiousness	MAX	NO/MIN	MAX	NO/MIN
Extraversion	MIN	MAX	MIN	MAX
Neuroticism	MIN	MAX	MIN	MAX
Openness	MIN	MAX	MIN	MAX

The null hypothesis is that there is no association between the two variables.

Table 4: Independent Mood Variables and Prediction with Financial Expectations and Overconfidence

Variable	Question	Values	SELL	NODEBT
FEELING	How do you feel thinking about the	1 very sad …	- (very happy =buy)	- (very happy higher

	starting day?	5 very happy	+ (sad= buy - consolation)	propensity to borrow)
AWAKE	How did you wake up?	1 very good … 5 very bad	+ (general sickness higher propensity to sell or no to buy)	+ (gen sickness no to borrow, less confidence)
CARE	Did you take care of you this morning?	1 more than usual … 5 less than usual	- (higher care more buy)	-
TODAYIS	Today is expected to be worse or better than yesterday	1 much worse than yesterday … 5 much better than yesterday	- (better expectation higher propensity to buy)	-
THOUGHTS	Do you have any persistent thought which affects your concentration?	0 yes 1 no	?	?
SEX	Do you have any sexual relationship in the last twelve hours?	0 no 1 yes	?	?
HELP	Do you need an help to face today's concerns?	1 nothing … 5 lot of support from a friend/relative	+	+/-
EXPECT	Today, do you expect to be successful?	1 very successful … 5 vey unsuccessful	- (better expectation higher propensity to buy)	- +

For completeness, we ran another statistic test for multicollinearity. Indeed, in some situation, when no pair of variables is highly correlated, but several variables are involved in interdependencies, correlation test might not be sufficient. It is better to use multicollinearity diagnostic statistics produced by linear regression analysis. The collinearity diagnostic statistics are based on the independent variables only, so the choice of the dependent variable does not matter. Afterwards, we examined *Tolerance*.

Table 5: Collinearity diagnostician coefficients.
Dependent Variable: *On the basis of your today emotional condition, do you feel to SELL:*

Model	Tolerance
FEELING	0,764
AWAKE	0,905
CARE	0,927
TODAYIS	0,807
THOUGHTS	0,909
EXPECT	0,878
SEX	0,961
HELP	0,913

Since for each independent variable, *Tolerance = 1 – R-square*, low values indicate high multivariate correlation. There would be as many tolerance coefficients as there are independent. The higher the inter-correlation of the independents, the more the tolerance will approach zero. As a rule of thumb, if tolerance is less than 0.20, a problem with multicollinearity is indicated. In the table above, we can see there are no coefficient values close to this bound.
We checked all the logistic assumptions are verified, thus we could run the regression and examine the outputs. We run multinomial logistic regression for our data, entering the dependent variable one by one and every time all the independent variables.

2.3. Model specification

The empirical analysis presented in this study is restricted to the link between emotional factors and investors' behaviour. We particularly focus how financial expectations and overconfidence can be differently influenced by the mood factors we collected in the daily questionnaire.
Some researches has already been achieved on the relation between personality and traders behaviour, with mixed evidence. Lo, Repin and Steenbarger (2005) show that personality traits are not important for trading. Schwager, 2001 show that traders do the best if they adjust their trading style to match their personality. O'Creevy et. al (2004), who studied 118 professional traders for European investment banks, found that successful traders tend to be emotionally stable introverts who are open to new experiences. Steenbarger (2003) found that high openness and high neuroticism are correlated with trading problems. This literature focused the analysis on personality attributes. Our analysis, vice versa, estimates how financial decisions can be affected by emotions specifically valuated soon before their choice. The experiment was applied, respectively, for all the sample, within gender subgroups, and within personality clusters.

Our tested hypothesis are:
H1: Mood variables do not affect investors' financial decisions, in terms of expectations and leverage options

H2: Mood variables do not affect differently female and male financial decisions
H3: Mood variables do not affect differently financial decisions clusterized by personality features.

Following this reasoning, our empirical analysis involves logit regressions of the following form:

SELL = f (FEELING, AWAKE, CARE, TODAYIS, THOUGHTS, SEX, HELP, EXPECT)

NODEBT = f (FEELING, AWAKE, CARE, TODAYIS, THOUGHTS, SEX, HELP, EXPECT)

where:
SELL is the dummy to measure the investors' expectations through their choice to sell (1) or buy (0).
NODEBT is the dummy to measure the investors' overconfidence through the propensity to invest only their capital (1) or to borrow money (0)

We also added weekly control variables, in order to check both robustness and significance of general outcomes for all the 7 weeks data collected during the experiment.
We apply logistic regressions on data for their non normal distribution; the binary logit was applied since the dependent variables (SELL and NODEBT) were dichotomously defined.
For all the estimates, we computed measures of fit (Akaike Information Criterion, The Schwartz Information Criterion, Pseudo Chi-Square and Pearson Goodness of Fit) and of effect size (Cox and Snell's and Nagelkerke's Pseudo R-Square coefficients).

3. Results

In order to estimate the behaviour of the input variables we computed the cross-tabulation and the chi-square statistics between the factors we supposed to be highly correlated and we composed a basic associational hypothesis using Pearson product-moment correlation coefficients.
Our results confirm those already showed by the literature. We take it as an indication that our method constitutes a true replication of prior works. Referring to the aforementioned social life effects as well as to the discussion of psychological importance of emotional condition in a decision-making context, the main research hypotheses are stated below:
We estimated a model to explain relationships among our variables, using the panel database, including both time series and cross section data.
To ensure no required assumptions would be violated, we applied some cautiousness. The variable coding was done with a logical and conceptual criterion. Linearity was

checked for every model we obtained, even if we do not display the graphs for brevity. From the descriptive analysis stated in the former paragraphs, we recognized our data had too many missing values. We run the experiment for seven weeks (35 trading days).
Since our goal was to understand how the various X variables impact Y using a logistic regression, the presence of multicollinearity would be a problem. We started with examining the correlations between independent variables. We choose a nonparametric (distribution-free) rank statistic proposed by Spearman. As already mentioned, our variables are all non-normally distributed; since they are ordinal data, their distributions is unknown, therefore we can run only nonparametric tests. Table 5 shows that the Spearman correlation between our independent variables should not create significant problems of multicollinearity.

Table 6. Spearman's rho correlations
Pearson correlation coefficients for explanatory variables used in the logit regressions. Variables are defined in table 4.

Variable	FEELING	AWAKE	CARE	TODAYIS	THOUGHTS	SEX	HELP	EXPECT
FEELING	1,000							
AWAKE	-0,259**	1,000						
CARE	-0,099**	0,195**	1,000					
TODAYIS	0,383**	-0,226**	-0,053*	1,000				
THOUGHTS	0,098**	-0,216**	-0,168**	0,101**	1,000			
SEX	-0,079**	0,059*	0,047*	0,006	-0,017	1,000		
HELP	0,260**	-0,033	0,013	0,173**	0,061*	-0,025	1,000	
EXPECT	-0,262**	0,134**	0,043	-0,272**	-0,029	0,131**	-0,123**	1,000

* means significantly different from zero at 10% level (two-tail t-test), and ** at the 5% level.

3.1. Financial expectations

Sapienza et al. (2009) show that females are more risk averse than males and this may be explained by variation in salivary concentrations of testosterone.
According to Atkinson, Baird and Grye (2003) male- and female-managed funds do not differ significantly in terms of performance, risk appetite, and other fund characteristics, but net asset flows into funds managed by females are lower than for males.
Ruenzi and Niessen (2009) show that female fund managers are less averse than males. Deaves et al (2008) show that there are no significant differences between male and female in trading activity.
Another factor that may influence the emotional state an so being related to financial choices is the sentimental condition. When asked (at the beginning of the experiment) about their marital status 45 students stated to be single and 32 engaged. Literature on this factor is Hinz et al. (1997), Schubert et al. (1999), Croson and Gneezy (2004), Dohmen et al. (2005), Fellner and Maciejovsky (2007), Lusardi and Mitchell (2008) Marital status and financial decisions: Waite and Gallagher (2000), Lupton and Smith (2003) Gender and marital status: Sundén and Surette

(1998), Jianakoplos and Bernasek (1998), Barber and Odean (2001), Schmidt and Sevak (2006), Zissimopoulos et al. (2008), Guiso and Jappelli (2002), Christiansen et al. (2006).
Our approach is to find out not the marital status impact over financial decisions but emotional factors. Among these, sex activity is expected to affect the mood more than the marital status.
A widespread view is that women are more risk adverse than men. The literature investigated on this topic since it might be seen as the biggest difference among people: what is the gender effect on decision-making choices and financial choices particularly? Several researchers (Sapienza et al., 2009) gave their opinion on this issue, holding the idea that it could be a distinctive trait or argue that individual qualities overpower gender distinction. The perception female are less risk prone give explanation for the discrimination, which diminishes the success of women in financial and labour markets. Women are less trusted than men to make the risky decision that may be necessary for a firm's success. There is evidence that women are less overconfident when the domain is male oriented; therefore, it may be possible that the competence effect will be influenced by gender. Field data seems to support the conjecture that women and men approach financial decision making differently. Given that preconception concerning the risk propensities of men and women seem to affect their financial choices, it is important to examine whether the above stereotype reflects actual economic behaviour.

Women seem to be less prone to indebt to increase their wealth, so they would be more risk adverse than men, confirming outcomes of the previous literature. In spite of this, the Chi-Square statistics show the two variables are not associated, since the statistics is not significant even if we raise the level at 10%. Therefore, we cannot confirm the conjecture that women can handle financial risk differently from men.
In our survey, data gender specific risk attitudes may be confounded with differences in individual opportunity sets, especially when we can manage only a small sample like ours was. We suppose that these sometimes contradictory results may be caused by second order characteristics that influence the behaviour of men and women. Thus, the first hypothesis of gender differences with respect to propensity to invest and to indebt was not supported by any evidence in regard of our data set. A further research would be interesting to investigate the influence of individual characteristics on attitudes toward uncertainty including whether they have a second order effect on gender differences.

To predict financial choices from a combination of several variables, such as perspective feelings or social relations, we used multinomial logistic regression to get complex associational relationships.
We drop independents from the model when their effect is not significant by the Wald statistics. In the third estimation of models, we estimated a logistic regression where we input only the independents chosen in the previous procedure, as say the variables which were significant at the 5% level. In this phase we distinguish between model with all the variables, the model optimized with a forward stepwise selection, and the standard model, which is estimated using the same best group of

independent variables for all the hypothesis we check.
The parameters and tests for first model are showed in the following table.

Table 7: Reduced logistic regression of financial expectations

This table shows binary logit regressions of the negative expectations and subsequent short position decision of investors (SELL). Three equations have been estimated: (i) All the variables collected with the daily questionnaire applied to all the population; (ii) and (iii) the same equation applied by gender (respectively females and males). Heteroschedasticity robust standard errors are reported in brackets. * means significantly different from zero at 10% level (two-tail t-test), ** at the 5% level, and *** at the 1% level.

Explaining variables	All the variables	Females	Males
FEELING	-0,121***	-0,130**	-0,163**
	(0,021)	(0,036)	(0,086)
AWAKE	0,015**	0,044*	0,026**
	(0,033)	(0,032)	(0,021)
CARE	0,043**	0,040***	-0,012**
	(0,041)	(0,009)	(0,091)
TODAYIS	-0,359**	-0,243**	-0,242*
	(0,029	(0,066)	(0,348)
THOUGHTS	0,021*	-0,036*	0,003**
	(0,093)	(0,104)	(0,087)
SEX	-0,391***	-0,434**	-0,679***
	(0,142)	(0,162)	(0,129)
HELP	0,36	0,294	0,343
	(3,192)	(3,170)	(3,166)
EXPECT	0,680**	0,628*	0,704**
	(0,182)	(0,256)	(0,181)
INTERCEPT	1,002***	2,336**	2,577**
	(0,214)	(0,303)	(0,290)
Observations (N)	2695	1330	1365
Prediction % correct	88,203	83,411	83,844
AIC	1834,786	199,584	200,230
BIC	1894,280	222,204	216,382
Pearson Chi-Square	1232,933	73,014	74,791
Sig.	0,123	0,029	0,056
Cox and Snell Pseudo R2	0,079	0,028	0,056
Nagelkerke Pseudo R2	0,109	0,040	0,050

As expected, the variable FEELINGS is negatively correlated to the propensity to sell: happiness level makes the investor more oriented to take long positions instead to sell. On the other side, the AWAKING conditions affect the selling orientation of our participants: the positive sign of regressor stands for a correlation between sickness and the propensity to sell. TODAYIS stands for general expectations compared with the day before: the better is the expectation the higher is the buying inclination. A similar result is generated by EXPECT, which assesses the successful or unsuccessful expectations. SEX is the factor about the sexual activity during the last 12 hours: the negative sign stands for a higher disposition to take long positions

in the financial markets.
The last step of this process consisted in running the logistic in both the independent variables cases with the same regressors choice.
The motive of this regressors selection is partly based on the fact these are the common variables between the two preceding calculated models, and partly on the correlation matrix we have discussed in the former section. Indeed, the Spearman's rho correlation matrix revealed significant presence of correlation between the variables; we supposed this correlation may influence the results, since the computed regressions take into account only main effects, not interactions between covariates. As we will note later, this choice was successful and we found two good explanatory models of our data set. Table 8 shows how the equation behaves within psychological factors.

Table 8: Reduced logistic regression for financial expectations by psychological factors
This table shows binary logit regressions of the negative expectations and subsequent short position decision of investors (SELL) in five cohorts, by personality features: Agreeableness, Consciousness, Extraversion, Neuroticism, Openness. The standard model has been estimated. Heteroschedasticity robust standard errors are reported in brackets. * means significantly different from zero at 10% level (two-tail t-test), ** at the 5% level, and *** at the 1% level.

Explaining variables	AGREEABLENESS		CONSCIOUSNESS		EXTRAVERSION		NEUROTICISM		OPENNESS	
	Low	High	Low	High	Low	High	Low	High	Low	High
FEELING	-0,140	-0,156	-0,134	-0,153	-0,145	-0,129	-0,111	-0,100	-0,121	-0,144
	(0,019)	(0,017)	(0,031)	(0,022)	(0,043)	(0,028)	(0,012)	(0,006)	(0,027)	(0,042)
AWAKE	0,002	-0,021	0,000	-0,003	0,006	-0,015	0,016	0,022	0,009	0,006
	(0,032)	(0,057)	(0,054)	(0,048)	(0,069)	(0,038)	(0,006)	(0,016)	(0,036)	(0,050)
CARE	0,016	0,012	0,009	0,017	0,009	0,018	0,061	0,074	0,029	0,029
	(0,074)	(0,055)	(0,059)	(0,047)	(0,050)	(0,075)	(0,021)	(0,024)	(0,042)	(0,076)
TODAYIS	-0,395	-0,389	-0,367	-0,390	-0,385	-0,367	-0,339	-0,339	-0,388	-0,384
	(0,049)	(0,031)	(0,032)	(0,046)	(0,040)	(0,065)	(0,003)	(0,008)	(0,064)	(0,053)
THOUGHTS	-0,002	0,010	-0,014	0,006	0,004	-0,002	0,026	0,040	0,017	-0,003
	(0,109)	(0,126)	(0,113)	(0,122)	(0,093)	(0,117)	(0,067)	(0,090)	(0,106)	(0,105)
SEX	-0,416	-0,388	-0,403	-0,410	-0,402	-0,416	-0,369	-0,371	-0,397	-0,421
	(0,158)	(0,155)	(0,167)	(0,161)	(0,143)	(0,141)	(0,116)	(0,113)	(0,173)	(0,180)
HELP	0,334	0,346	0,328	0,341	0,342	0,363	0,365	0,372	0,331	0,327
	(3,203)	(3,200)	(3,211)	(3,198)	(3,222)	(3,191)	(3,184)	(3,171)	(3,194)	(3,227)
EXPECT	0,655	0,649	0,667	0,679	0,670	0,678	0,691	0,708	0,657	0,646
	(0,205)	(0,206)	(0,195)	(0,214)	(0,210)	(0,206)	(0,179)	(0,145)	(0,197)	(0,202)
INTERCEPT	0,967	0,972	0,988	0,985	0,983	0,987	1,005	1,034	0,993	0,981
	(0,245)	(0,226)	(0,233)	(0,236)	(0,237)	(0,229)	(0,214)	(0,207)	(0,215)	(0,245)
Observations (N)	560	2135	385	2310	945	1750	1890	805	1190	1505
Prediction % correct	54,4	73,4	59,8	71,2	62,7	68,6	55,9	81,6	58,4	60,3
AIC	1834,8	1834,8	1834,7	1834,8	1834,7	1834,8	1834,8	1834,8	1834,8	1834,8
BIC	1894,3	1894,3	1894,3	1894,3	1894,3	1894,2	1894,3	1894,3	1894,3	1894,2
Pearson Chi-Square	1232,9	1232,9	1232,9	1232,9	1232,9	1232,9	1233,0	1233,0	1232,9	1232,9
Sig.	0,095	0,097	0,113	0,104	0,087	0,115	0,121	0,137	0,119	0,088
Cox and Snell Pseudo R2	0,049	0,072	0,053	0,053	0,064	0,071	0,104	0,110	0,065	0,076

Nagelkerke Pseudo R2	0,094	0,085	0,100	0,072	0,096	0,104	0,118	0,140	0,100	0,097

3.2. Overconfidence

As proved by Hackbarth (2008), overconfident managers choose higher debt levels and issue new debt more often but need not follow a pecking order. We then studied the relation between debt propensity (as a proxy of overconfidence) and the emotional state.

Huang and Kisgen (2009) examine whether males and females differ in corporate financial decisions. They conclude that the latter group of people undertakes greater scrutiny and exhibit less hubris in acquisition decisions. Female CFOs decide to issue debt less frequently, and debt and equity issuances have higher announcement returns for firms managed by female CFOs. However, female CFO capital decisions are no more likely to move a firm toward its target leverage. Agarwal et al. (2009) study the relation between financial decision making in debt markets and age, showing a pronounced U-shape curve by age, showing that the relatively young and old have annual percentage rates of loans and line of credit that can be fifty basis points or more higher than the middle-aged.

The parameters and tests for the second model are showed in table 9.

Table 9: Reduced logistic regression of overconfidence

This table shows binary logit regressions of the overconfidence of investors and subsequent decision not to borrow money (NODEBT). Five equations have been estimated: (i) All the variables collected with the daily questionnaire applied to all the population; (ii) and (iii) the same equation applied by gender (respectively females and males). Heteroschedasticity robust standard errors are reported in brackets. * means significantly different from zero at 10% level (two-tail t-test), ** at the 5% level, and *** at the 1% level.

Explaining variables	All the variables	Females	Males
FEELING	0,421**	-0,110***	-0,169**
	(0,127)	(0,049)	(0,102)
AWAKE	0,029	0,014	0,034
	(0,802)	(0,841)	(0,748)
CARE	-0,208*	-0,227**	-0,203*
	(0,108)	(0,110)	(0,126)
TODAYIS	0,118**	-0,277***	-0,273*
	(0,198)	(0,018)	(0,348)
THOUGHTS	0,097*	0,103*	0,082*
	(0,199)	(0,191)	(0,238)
SEX	-0,208**	-0,464**	-0,754**
	(0,238)	(0,112)	(0,139)
HELP	0,342	0,363	0,371
	(3,192)	(3,197)	(3,134)
EXPECT	0,024	0,045	0,026
	(1,874)	(1,907)	(1,924)
INTERCEPT	-4,139**	2,371***	2,549**
	(0,425)	(0,386)	(0,216)

Observations (N)	2695	1330	1365
Prediction % correct	89,900	92,103	78,174
AIC	1912,422	199,850	201,206
BIC	1992,153	224,899	219,134
Pearson Chi-Square	1089,365	73,760	75,452
Sig.	0,012	0,007	0,036
Cox and Snell Pseudo R2	0,061	0,045	0,034
Nagelkerke Pseudo R2	0,083	0,079	0,067

The second model shows which are the explanatory variables for the indebt orientation of financial players. Higher level of happiness (FEELING) generates higher disposition to borrow money in order to increase the capital to invest. Moreover, the better is the expectation change (TODAYIS) the higher is the inclination to make a debt. The assessment of personal CARE shows that people who lack of desire are more conservative and reduce their debt. Finally, SEX shows that subjects who had sex are more inclined to borrow money.
Table 10 confirms the expected correlations as predicted in table 3.

Table 10: Reduced logistic regression for overconfidence by psychological factors

This table shows binary logit regressions of the overconfidence and subsequent decision not to borrow money to increase financial exposures (NODEBT) in five cohorts, by personality features: Agreeableness, Consciousness, Extraversion, Neuroticism, Openness. The standard model has been estimated. Heteroschedasticity robust standard errors are reported in brackets. * means significantly different from zero at 10% level (two-tail t-test), ** at the 5% level, and *** at the 1% level.

Explaining variables	AGREEABLENESS		CONSCIOUSNESS		EXTRAVERSION		NEUROTICISM		OPENNESS	
	Low	High	Low	High	Low	High	Low	High	Low	High
FEELING	0,405	0,394	0,415	0,421	0,390	0,386	0,457	0,445	0,407	0,401
	(0,148)	(0,133)	(0,154)	(0,142)	(0,152)	(0,126)	(0,129)	(0,100)	(0,147)	(0,162)
AWAKE	0,007	0,024	0,024	0,023	0,020	0,031	0,038	0,038	0,009	0,020
	(0,828)	(0,802)	(0,801)	(0,838)	(0,826)	(0,820)	(0,782)	(0,794)	(0,831)	(0,837)
CARE	-0,235	-0,234	-0,218	-0,236	-0,224	-0,243	-0,199	-0,191	-0,239	-0,215
	(0,142)	(0,129)	(0,138)	(0,115)	(0,126)	(0,135)	(0,089)	(0,107)	(0,132)	(0,143)
TODAYIS	0,086	0,113	0,085	0,106	0,094	0,104	0,148	0,139	0,094	0,098
	(0,229)	(0,233)	(0,235)	(0,223)	(0,220)	(0,228)	(0,187)	(0,193)	(0,233)	(0,215)
THOUGHTS	0,081	0,082	0,078	0,074	0,086	0,100	0,127	0,098	0,094	0,084
	(0,215)	(0,210)	(0,198)	(0,198)	(0,197)	(0,221)	(0,170)	(0,185)	(0,203)	(0,225)
SEX	-0,214	-0,247	-0,227	-0,208	-0,238	-0,220	-0,208	-0,180	-0,219	-0,231
	(0,261)	(0,252)	(0,245)	(0,247)	(0,252)	(0,268)	(0,210)	(0,236)	(0,248)	(0,266)
HELP	0,319	0,326	0,316	0,310	0,328	0,325	0,363	0,366	0,335	0,315
	(3,224)	(3,207)	(3,221)	(3,201)	(3,200)	(3,215)	(3,158)	(3,163)	(3,208)	(3,211)
EXPECT	-0,006	0,005	0,009	-0,008	0,023	0,014	0,024	0,036	0,014	-0,011
	(1,908)	(1,904)	(1,878)	(1,886)	(1,903)	(1,896)	(1,877)	(1,859)	(1,907)	(1,909)
INTERCEPT	-4,161	-4,176	-4,156	-4,157	-4,165	-4,173	-4,113	-4,122	-4,136	-4,150
	(0,439)	(0,450)	(0,448)	(0,453)	(0,427)	(0,452)	(0,426)	(0,387)	(0,462)	(0,440)
Observations (N)	560	2135	385	2310	945	1750	1890	805	1190	1505
Prediction % correct	58,0	58,4	81,7	59,3	65,4	90,2	65,1	83,2	69,2	87,8
AIC	1912,4	1912,4	1912,4	1912,4	1912,4	1912,4	1912,4	1912,4	1912,4	1912,4
BIC	1992,1	1992,1	1992,1	1992,1	1992,1	1992,1	1992,2	1992,2	1992,1	1992,1
Pearson Chi-Square	1089,3	1089,4	1089,3	1089,4	1089,3	1089,3	1089,4	1089,4	1089,4	1089,3
Sig.	-0,018	0,002	0,009	-0,005	0,009	0,003	0,035	0,046	-0,022	-0,026
Cox and Snell Pseudo R2	0,045	0,043	0,028	0,058	0,032	0,043	0,080	0,068	0,041	0,052
Nagelkerke Pseudo R2	0,058	0,071	0,052	0,079	0,081	0,066	0,104	0,114	0,074	0,069

4. Conclusions

This paper provides an empirical step in establishing the role of emotions in a financial decision making environment. In particular, we focused on the impact of daily mood on choice behaviour in a self-assessment experiment.

This experiment of non professional agents was designed to identify a relationship between emotional state and attitude to financial choices. We measured individuals' personality traits and attitudes to socialize and used them to explain a financial decision context. We found that some variables are of special importance for the explanation of trading decisions: assessment of perspective feelings, day expectations and wish of social relations can explain tendency to sell or to indebt.

We started with a descriptive analysis, which offered a complete view of our data and allowed us to set them in order to achieve the most fittable database for our regressions. In fact, we had to code the variables and remove part of the observations. At the end of this process, we obtained a sample composed of 73 subjects and daily observations for a period of 25 days. Since the variables were not normally distributed and in many cases we had ordinal variables, we choose the multinomial logistic regression, whose assumptions are not violated by our data set.

To find a good fitting explanatory model, we ran several times multinomial logistic regressions. For two of the dependent variables we got interesting findings; the remaining were not possible to explain with a logistic regression probably because of the complexity of their content. For the investment choice variable and the indebt choice variable, we obtained four models, that we compared through significance and goodness of fit statistical tests, which allowed us to choose the best. The subsequent procedure was applied on the *SELL* and *NODEBT* variables one by one as dependent.

The first method we used was a logistic regression with all the available regressors; the result was obviously not enthusiastic, but it made us able to select the significant independent variables to use in the following steps, using the Chi-Square significance criterion. Then, we computed the regression applying the stepwise backward elimination method; this automatically remove from the model variables which overcome a minimum level of p-value significance, settled at 5%. The next step was to apply the logistic with only the independent variables accepted by the stepwise method; since this time the choice is not made by an algorithm, the outputs are different. Finally, we excluded from the regressors the variables which have shown some correlation in a preceding correlation analysis.

Then we made a comparison among the models; Akaike information criterion, Bayesian information criterion, Chi-Square and likelihood ratio test were used to choose the best explanatory regression coefficients. By parsimony criterion, the final model was chosen to be the last we computed for both the variables. These variables are assessments of instant feelings, perspective view of the day and wish of social relationships. From psychological and sociological literature, we know people do not have a good expectation about the new coming day or prefer to stay alone might have a pessimistic view even about things should not infer in private life. That is exactly the case of an investor from the behavioural economists point of view. From our findings, we can conclude that in fact there is a relationships between these two

sides of the human life: emotions affect financial choices.
In addiction, our research was pointed to find whether if gender and personality play an important role in explanation of trading choices. Our preliminary hypothesis imply that individual characteristics, like gender, marital status, personal habits and personality traits, may have effects that are distinctive to group membership or social affiliation. As mentioned, our study examined the interaction of individual characteristics with gender and personality.

References

Agarwal, B. and Vercelli, A. (2005), *Psychology, Rationality and Economic Behaviour*, Palgrave MacMillan.

Aiken, L.R. (1997), *Questionnaires and Inventories, Surveying opinions and assessing personality*, John Wiley & Sons: New York, NY.

Bandura, A. (1986), *Social foundations of thought and action: A social cognitive theory,* Englewood Cliffs, NJ Prentice-Hall.

Cramer, J.S. (1991), *The Logit Model: an introduction for economists*, Edward Arnold.

Damasio, A.R. (1994), *Descartes' Error*, New York, G. P. Putnam's Sons.

Deaves R., Luders E. and Luo G. Y., An Experimental Test of the Impact of Overconfidence and Gender on Trading Activity, Review of Finance (2008), 1–21

Digman, J. M. (1997). Higher-order factors of the Big Five. *Journal of Personality and Social Psychology, 73,* 1246-1256.

Ebbeson, E.B. and Konecni, J.J. (1980), *On the External Validity of Decision-Making: What Do We Know about Decisions in the Real World? Cognitive processes in choice and decision behaviour,* Hillsdale.

Elster, J. (1989), "When rationality fails", in Cook K.S. and Levi M., *The Limits of Rationality*, Cambridge University Press.

Elster, J. (1998), "Emotions and economic theory", *Journal of Economic Literature* 36, 47-74.

Glasser, W. (1998), *Choice Theory: A New Psychology of Personal Freedom*, HarperCollins Publishers.

Greene, W.H. (2000), *Econometric analysis*, Englewood Cliffs, Prentice Hall International.

Griffin, D. W., & Bartholomew, K. (1994). The metaphysics of measurement: The case of adult attachment. In K. Bartholomew & D. Perlman (Eds.), *Advances in personal relationships* (Vol. 5, pp. 17-52). London: Jessica Kingsley.

Gysler, M.; Kruse, J.B. and Schubert, R. (2002), *Ambiguity and Gender Differences in Financial Decision Making: An Experimental Examination of Competence and Confidence Effects*, Swiss Federal Institute of Technology.

Hira, T.K. and Mugenda, O. (2000), *Gender Differences in Financial Perceptions, Behaviors and Satisfaction*, Journal of Financial Planning 13, no. 2: 86–92.

John, O. P. (1990). The "Big Five" factor taxonomy: Dimensions of personality in the natural language and in questionnaires. In L. A. Pervin (Ed.), *Handbook of personality: Theory and research* (pp. 66-100). New York: Guilford.

Kahneman, D. and Tversky, A. (1979), "Prospect Theory: An Analysis of Decision Making Under Risk." *Econometrica* 47, no. 2: 263-291.

Kahneman, D.; Knetsch, J. L. and Thaler, R. H. (1986), "Fairness and the Assumptions of Economics", in Hogan R.M. and Reder M.W. (eds.), *Rational Choice*, The University of Chicago Press.

Kahneman, D.; Slovic, P. and Tversky, A. (1982), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Lo, A.W. (2005), *Reconciling Efficient Markets with Behavioural Finance:The Adaptive Markets Hypothesis*, MIT Sloan School of Management.

Lo, A.W.; Repin, D.V. and Steenbarger, B.N. (2005), *Fears and Greed in Financial Markets: A Clinical Study of Day-Traders*, MIT Sloan School of Management.

McBurney, D.H. (1986), *Metodologia della ricerca in psicologia*, Il Mulino, Bologna.

McCrae, Robert R., and Paul T. Costa. 1999. A Five-Factor Theory of Personality. In Handbook of Personality: Theory and Research, edited by L. Pervin and O. P. John. New York: Guilford Press

O'Connell, A.A. (2005), "Logistic regression models for ordinal response variables", Thousand Oaks, CA, *Quantitative Applications in the Social Sciences* 146.

O'Creevy F., Nicholson M., Soane N. and Willman E., 2004. Traders; Managing Risks and Decisions in Financial Markets, Oxford University Press.

Rachlin, H. (1989), *Judgment, decision and choice*, W. H. Freeman and Company.

Sapienza P., Zingales L., Maestripieri D., 2009, Gender differences in financial risk aversion and career choices are affected by testosterone

Schubert, R.; Brown, M.; Gysler, M. and Brachinger, H.W. (1999), "Financial Decision Making: Are Women Really More Risk-Adverse?", *The American Economic Review* 89, no. 2: 381-385.

Schwager J. D., 1991, Stock Market Wizards: Interviews with America's Top Stock Traders, HarperCollins Publisher, New York

Shefrin, H. (2001), *Behavioral finance Volume I*, Elgar Reference Collection.

Shefrin, H. (2002), *Beyond Greed and Fear,* Oxford University Press.

Simon, H. A. (1955), "A Behavioral Model of Rational Choice", *Quarterly Journal of Economics* 69, 99-118.

Simon, H.A. (1986), "Rationality in Psychology and Economics", in Hogan R.M. and Reder M.W. (eds.), *Rational Choice*, The University of Chicago Press.

Stanley M. Atkinson, Samantha Boyce Baird, Melissa B. Frye, Do Female Mutual Fund Managers Manage Differently?, Journal of Financial Research, 2003, vol. 26, issue 1, 1-18

Steenbarger, B. (2003), *The Psychology of Trading*, John Wiley and Sons: New York, NY.

Stock, J.H. and Watson, M.W. (2003), *Introduction to Econometrics*, Pearson International Edition.

Sumit Agarwal, John C. Driscoll, Xavier Gabaix, and David Laibson, The Age of Reason: Financial Decisions over the Life-Cycle with Implications for Regulation, MIMEO, August 31, 2009

Tversky A. and Kahneman D. (1986), "Rational Choice and the Framing of Decisions", in Hogan R.M. and Reder M.W. (eds.), *Rational Choice*, The University of Chicago Press.

Wright, R.E. (1995), "Logistic regression". in L.G. Grimm & P.R. Yarnold, (eds.), *Reading and understanding multivariate statistics*. Washington, D.C., American Psychological Association.