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Why Would Overconfidence Generate Lower Performance? Insights from an Experimental Study*

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A B S T R A C T

Overconfidence is recognized as one of the most important behavioral biases in decision-making. Using results from a controlled lab experiment we find that participants who *display* more confidence perform worse than other participants, whereas participants who *say* they are confident do not perform worse. We also find evidence that more confident traders also have lower visual attention levels (using an eye-tracking software), lower visual working memory (measured using an "n-back 1" test), and higher physiological arousal (using electro-dermal activity). Although conducted using a small sample of novice traders, our findings represent a first step in explaining how overconfidence and performance are related in financial markets.

Keywords: Overconfidence; Implicit risk tolerance; Visual attention and working memory; Electro dermal activity
JEL Classification: G16

Ⅰ. Introduction

Overconfidence can be defined as the overestimation of one's intuitive ability, which results in a confidence level in one's judgement that is much greater than the objective accuracy of one's judgment (Pallier *et al.* 2002). In financial markets, overconfidence increases risk taking and trading volume, which result in lower returns net of trading fees (Odean 1999; Barber and Odean 2000; Kumar and Goyal 2015). Theoretical advances have incorporated traders' overconfidence to account for these behavioral deviations from rationality (see Daniel *et al.* 1998; Benos 1998; Gervais and Odean 2001, Ouzan and Boyer 2018). Further studies have found evidence of overconfidence amongst mutual fund managers (Puetz and Ruenzi 2011), venture capitalists (Zacharakis and Shepherd 2001), financial analysts (Hilary and Menzly 2006), and retail investors (Barber and Odean 2001; Chuand and Lee 2006; Grinblatt and Keloharju 2009).

Behavioral biases can also explain irrational phenomena such as the difference between investors' portfolio risk and their self-reported risk appetite (Morse 1998). As risk preferences appear to be more accurately measured using an economic task instead of a questionnaire (Harrison and Rutström 2008; Anderson and Mellor 2009), an individual's risk tolerance must be measured using approaches that capture the effect of behavioral biases for both explicit and implicit processes. D'Acunto (2015) and Pikulina *et al.* (2017) propose the use of experimental approaches that seek to study such behavioral biases.

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Different lower-level cognitive processes, such as visual attention and working memory, enter one's decision-making process (Orquin and Loose 2013; Hinson *et al.* 2003). Although the impact of overconfidence on the performance of decision-makers has been thoroughly researched (see the aforementioned related literature, *inter alia*), no study, to our knowledge, has examined the relationship between visual attention, working memory and overconfidence in a financial market setting. Moreover, the interaction between overconfidence and these cognitive processes and traits remains unclear. Since emotions affect the individuals' decisions (Grossberg and Gutowski 1987; Elster 1998; Loewenstein 2000), we also look at the role of physiological arousal on overconfidence to assess the channel through which overconfidence affects a financial market traders' performance.

This paper seeks to increase our understanding of how cognitive functions, and a financial market trader's emotional states, are articulated in the context of overconfidence. We will examine two aspects of individual confidence. The first aspect is that overconfidence determines a trader's ability to perform in a financial trading context. The second aspect will be to examine what individual characteristics, if any, determine an individual's level of overconfidence. The goal is therefore to come up with indicators that would identify the situations during which a market trader is at risk of displaying overconfidence in his own ability to the detriment of his ability to generate positive returns in capital markets. Our research therefore provides some insights for those who seek to combat overconfidence in retail investors.

To achieve our goal, we conduct a small-sample experiment to evaluate the impact of the participants' confidence level on their ability to perform in financial market trading simulations. The tools we shall use to determine how confidence (and over-confidence) affects a participant's trading behavior include an eye-tracking monitor to visual attention and assess visual working memory performance, a risk tolerance psychometric test, and an electrodermal activity (EDA) sensor to measure the participants' physiological arousal during the trading exercise.

The results of our study are the following. First, we find that over-confidence - a measure that we shall define later - leads to under-performance in financial markets. Second, we find that individuals who display more over-confidence tend to be individuals who have worse working memory and are more easily excited or aroused when performing their tasks. Lastly, we find no correlation between risk tolerance and our measure of overconfidence.

Our results suggest that approaches that seek to determine a capital market trader's type based on his/her measure of risk aversion are missing the mark since visual memory and arousal appear to be more important factor determining an individual's ability to generate positive results in trading financial contracts. The remainder of the paper is organized as follows. In the next section we review a (very small) part of the massive literature related to individuals' cognitive processes, their risk attitudes, and to their apparent physiological arousal when performing tasks. Section 3 presents the five hypotheses we shall test; two hypotheses are related to the impact of over-confidence, whereas the three others are related to the determinants of over-confidence. The methodology and the relatively simple experimental design are presented in Section 4. We present the results of our experiment in Section 5. We discuss our results in Section 6 and conclude with Section 7.

II. Literature Review: Automatic and Controlled Cognitive Processes

The cognitive processes, which are involved in social judgment and behavior, are defined by the dual-process theories that separate cognitive processes into two categories: automatic and controlled processes (Gawronski and Creighton 2013; Kahneman and Frederick 2002). Automatic processes include processes that are effortless, implicit, and associative, while controlled processes include the ones that are controlled and deductive. Dual-process theories also indicate that automatic processes are mainly driven by emotions and past experience, whereas controlled processes touch on conscious and more rational mechanisms. Thus, risk behavior is not only affected by rational processes but also by implicit processes governed by emotions and experience.

A. Cognitive Processes: Visual Attention and Working Memory

Cognitive processes are mechanisms in the brain that allow individuals to learn from, remember, and process the information they receive from the environment in which they live and operate, and (Sternberg and Sternberg 2016) and with which they interact. For instance, memory, attention, perception, and problem-solving abilities are all cognitive processes. The two cognitive processes on which we will focus specifically this study are known as *visual attention* and *visual working memory*.

Visual attention refers to the mechanism that allows individuals to selectively process large amounts of visual information (Carrasco 2011). As argued by Lennie (2003), the large quantity of information captured by the eyes, together with the limited processing capacity of the brain caused by the limited amount of available energy, makes visual attention a selective process. Visual attention can be separated into overt and covert attention (Wright and Ward 2008, Tas *et al.* 2017); overt attention occurs when individuals move their eyes over a specific location, while covert attention occurs when individuals shift their focus to the periphery without moving their eyes. Although mainstream economic models do not include visual attention, evidence suggests that it plays an important role in the decision-making process (Orquin and Loose 2013), especially when decisions need to be made based on information that is collected during intense fixation periods (Krajbich *et al.* 2010).

Visual attention has also been studied in connection with behavioral biases in investments. For instance, Shavit *et al.* (2010) find that investors not only spend more time looking at individual assets rather than their portfolio, they also spend more time looking at assets on which they made gains rather than assets on which they suffered losses. In the same vein, Innocenti *et al.* (2010) observe in an experimental study that overconfident individuals spend less time looking at the stimuli before making trading decisions. They attribute these results to the fact that the time spent examining new visual information is lower for over-confident individuals. In addition, Innocenti *et al.* (2010) note that over-confident individuals have a lower number of fixations when exposed to some visual stimulus. Based on these results, we investigate the participants' visual attention in integrating these cognitive processes in behavioral theories.

In contrast to visual attention, which allows individuals to process information, visual working memory is a cognitive system storing and manipulating temporary information ready to be processed (Miyake and Shah 1999). One's visual working memory is the mechanism by which one retains relevant and discards irrelevant visual information (Olivers et al. 2006). Working visual memory has many components: The visual-spatial sketchpad, memory performance, and memory capacity. All three are essential for reasoning and thus an integral part of the decision-making process (Diamond 2013). The *visuospatial sketchpad* is the component of the working visual memory that is responsible for storing and manipulating visual information (Baddeley 1992). Pattern recognition relies on visual working memory *performance* (Larsen and Bundesen 1978). Working memory *capacity* (see Miller 1956 for an early contribution) is positively correlated with cognitive tasks such as reasoning (Ackerman *et al.* 2005; Kane *et al.* 2005), reading (Daneman and Carpenter 1980; Carretti *et al.* 2009) and decision-making (Hinson *et al.* 2003; Bechara *et al.* 2000). It should therefore be clear that visual working memory in general could be used to predict individuals' performance in cognitive tasks. In particular, Chen and Sun (2003) study working memory capacity as connected to financial decision-making. Juslin *et al.* (2007) attribute the overconfidence to working memory capacity since individuals only use a limited amount of information when performing a task.

B. Risk Behavior and Attitude

With respect to an individual's attitude toward risk, we shall use the notion of risk tolerance, which is defined as the amount of risk an individual can bear. Risk tolerance, which Grable and Joo (2004) describe as a person's willingness to face outcomes that are uncertain and potentially negative (that is, the opposite of risk aversion), is typically measured using self-reported questionnaires.[1] The challenge with self-reported questionnaires that seek to measure risk attitudes is that they involve controlled and planned processes, in a way that the entire exercise is subject to some social desirability bias (Van de Mortel 2008). In particular, Fazio and Olson (2003) feel that ques-

[1] See in particular the Grable and Lytton (1999) questionnaire.

tionnaires fail to capture the contribution of implicit processes in the risk tolerance profile of individuals, which explains why questionnaire-determined risk tolerance measures correlate little with individuals' chosen investment portfolio in simple games (Dow and Werlang, 1992, Morse, 1998, and Gable *et al.* 2018).[2] If we believe that self-assessed risk tolerance questionnaires fail to match the portfolio risk of individuals, then there is a potential important need to develop risk tolerance measures that can identify the importance of implicit processes in risk-taking behavior. Put differently, risk-tolerance profiling needs to consider the implicit component of risk behavior instead of focusing mainly on controlled processes.

Using implicit measures to assess risk tolerance has two advantages compared to explicit measures. The first is that implicit risk tolerance results are difficult to alter or fake because respondents have little time to think before giving answers and, more importantly, respondents have no control over automatically activated evaluations. This is why indirect attitude measures, which Implicit Association Test are but an example, are gaining in importance: They allow assessing implicit cognitions, which are highly relevant in the context of affective decision making.[3] The second is that the purpose of this kind of test is harder to identify, and therefore to manipulate to fit one's intended end result. To assess risk tolerance in such a way, we will make use of implicit association tests (IAT), which have been widely used to measure implicit cognition (Greenwald *et al.* 2009) and to determine individuals' behavior for numerous purposes. IAT has been successfully used to predict anxiety (Egloff and Schmukle 2002), alcohol consumption (Lindgren *et al.* 2013), discriminatory behavior (McConnell and Leibold 2001), and attitudes toward consumer brands (Maison *et al.* 2004). An IAT measuring implicit risk tolerance in a financial context has already been used by Fehr and Hari (2014), who write that it would be "inadvisable to use explicit questionnaires alone to predict investor behavior because they do not cover spontaneous and emotion-driven decision making" (Fehr and Hari, 2014; p60). Although their results show a positive but low correlation between the IAT scores and self-administered questionnaire-determined risk tolerance scores, no attempt has been made, however, to evaluate whether the IAT scores are correlated with the risk of the investor's portfolio. This comes in contrast with the Grable and Lytton (1999) questionnaire, which seems to correlate will with portfolio holdings.

C. Physiological Arousal

Research in the fields of cognitive sciences and behavioral economics indicates that emotions affect rationality in decision-making (Grossberg and Gutowski 1987; Elster 1998; Loewenstein 2000). Schunk and Betsch (2006) find that decision-makers who can be characterized as more rational perform better than those who can be characterized as emotional. Using a lottery-based experiment, they showed that the superior performance of subjects classified as rational is due to a more constant association of the objective value with the subjective one. The relationship between high physiological arousal and lower performance tasks that require cognition and judgment can be explained by higher excitement levels (Lench *et al.* 2011), which limit an individual's ability to concentrate properly on the task itself. Put differently, *enhanced activation* - another name used to refer to higher excitement levels - limits the cognitive processes of individuals. In the same arousal realm, Lo *et al.* (2005) find that traders experiencing more intense emotional reactions were not as effective in financial market trading settings (or simulations or games) as those experiencing less intense emotional reactions.

Ⅲ. Hypothesis Development

A. The Impact of Overconfidence

The main hypothesis we seek to examine in this paper is whether over-confidence leads to lower performance in a financial market context. To test this hypothesis, we build upon the work of Barber and Odean (2000), which shows that the high trading level of overconfident investors leads them to earn significantly lower returns (see also Chuang and Lee, 2006, and Merkle, 2017).

[2] Grable and Joo (2004) contend, however, that risk tolerance measures correlate well with individual choices using a Grable and Lytton (1999) questionnaire.

[3] See in particular Traczyk and Zaleskiewicz (2015) and Metzger and Fehr (2019).

They find that more active investors earn lower expected returns. The under-performance of active investors comes from the trading costs, which include commissions, fees, and the so-called bid-ask spread. Barber and Odean (2000) also report that the 20% most active investors had an average turnover of more than 150% a year; this means that an investor having $100,000 invested in capital markets at the beginning of the year would enter transactions worth $150,000 in the year.[4] Grinblatt and Keloharju (2009), Glaser and Weber (2007) and Statman *et al.* (2006) find similar results.

Before analyzing the relationship between overconfidence and visual attention, visual working memory, implicit risk tolerance, and arousal, we need to verify that overconfidence is indeed linked to inferior performance in our study. This leads us to state our first testable hypothesis:

Hypothesis 1: Overconfident traders perform worse.

The second hypothesis we seek to examine is whether overconfidence affects the participants' ability to concentrate on the task that needs to be accomplished; that is, we are interested in seeing whether overconfidence is related to visual attention. To our knowledge, only Innocenti *et al.* (2010) examine whether visual attention (or gaze) is affected by overconfidence. They find that, with respect to information provided on the screen, overconfident participants have both a lower average duration time of first fixation and a lower number of fixations before making a choice. Thus, if participants in our study are overconfident, they should look less often at the visual stimulus, and for a shorter time. This leads us to state our second hypothesis:

Hypothesis 2: A) Overconfident traders examine information stimuli less often; and B) Overconfident traders examine information for a shorter amount of time.

B. The Determinants of Overconfidence

The second set of hypotheses we examine seeks to determine which individual characteristics, apart from socioeconomic and educational characteristics (if any), are associated with overconfidence in a capital market trading context. We will focus on three such dimensions: Working memory, Risk tolerance, and Arousal. We expect overconfidence to be negatively related to working memory, and positively related to risk tolerance and arousal.

Juslin *et al.* (2007) show that the limited capacity of **working memory** is positively linked to the presence of overconfidence because only limited working memory information can be used. By having less-than-full information at their disposal, individuals must rely on the little information they have. Using an experimental approach, Hansson *et al.* (2008) find that increasing task experience is insufficient to eliminate overconfidence because of working memory limitations. This means that individuals with more limited working memory should also be more overconfident. We state this as our third hypothesis:

Hypothesis 3: Low visual working-memory performance is positively related to overconfidence.

Overconfidence is an emotional bias linked to more risk-taking (Odean 1998; Hirshleifer and Luo 2001; Nosić and Weber 2010). We expect that traders with higher **risk tolerance** should also be more overconfident. Assuming that risk tolerance can be measured using implicit association test (IAT) scores (as in Greenwald *et al.* 2009), we are able to test Hypothesis 4:

Hypothesis 4: Greater risk tolerance (and low IAT scores) is positively related to overconfidence.

According to Schunk and Betsch (2006), rational decision-makers perform better than emotional decision-makers due to a more constant association of the subjective value with the objective one. Additionally, Lo *et al.* (2005) find that traders experiencing more intense emotional reactions while trading performed worse than traders with less intense emotional arousal. As overconfidence is a bias associated to emotions (Chu *et al.* 2012), we expect traders having higher arousal characteristics to also be more overconfident:

Hypothesis 5: Arousal is positively related to overconfidence.

[4] This may be due to rotating half of the assets (or $50,000) in his portfolio three times a year (say in the months of May, September, and December), or entering transactions worth $12,500 each month.

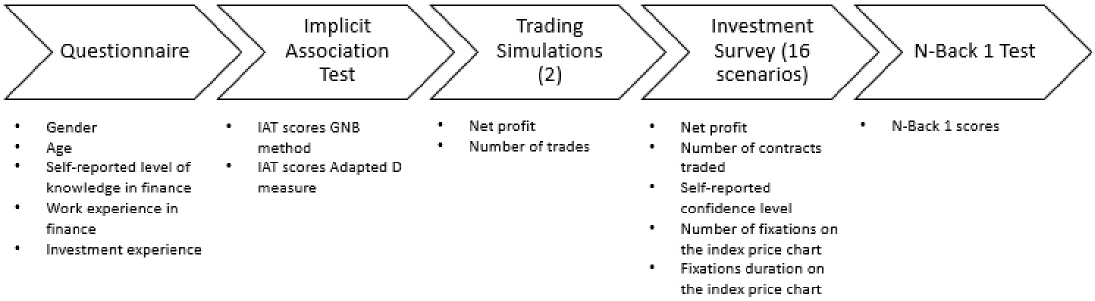

Figure 1. Experiment Flow Chart

Ⅳ. Methodology and Experimental Design

To test our hypotheses, we conducted a within-subjects lab experiment that took 60 minutes to complete on average. Thirty participants took part in the experiment. Each participant received a $20 gift card at the university's bookstore as fixed compensation. An additional $200 gift card was given in the form of a lottery with the incentive that a participant's winning probability was a function of his/her performance and involvement in tasks. The study was reviewed and accepted by our institution's Research Ethics Board.

Participants were recruited from a registered research panel and from our university's student population. Of the 30 participants, 22 were male and 8 were female, and were aged between 18 and 42 years (average age of 24.6 years). No participant had any diagnosed neurological, psychiatric or health problem, and they were all able to work on a computer without the need for corrective lenses or glasses. Moreover, since we study the behavior of novice traders, participants needed to have completed a maximum of three university-level finance courses. Upon their arrival at the lab participants were told that they would take part in an experiment studying decision-making in a trading context. After signing an informed consent form, a research assistant installed and calibrated the apparatus.

A. Experimental Approach

The experiment we conducted has five separate tasks (see Figure 1).

The first two tasks consist in a short questionnaire on the participants' socio-economic background and knowledge[5] about finance, and in his/her participation in an implicit association test (IAT).[6] We replicate the IAT task for the financial domain developed by Fehr and Hari (2014) and simply changed the currency displayed (dollars instead of euros).

The third task consists of two five-minute simulations using the Rotman Interactive Trader (rit.rotman.utoronto.ca) platform. Participants are asked to trade future contracts based on a fictitious market index created for the experiment. The only information provided to participants is the price chart of the index for the duration of the simulation. No historical or fundamental data are provided, and no statistics are displayed, but participants receive information on trading limits, position limits, and transaction costs. The price of the index changes every second.

For the fourth task, participants are asked to answer questions based on price charts related to the same fictitious index as in the trading simulations they had just completed. Half of the charts are directly taken from simulations already seen by each participant. Each scenario seen is created using one-fifth of the price path used for a given trading simulation. The other scenarios have not been seen, but are conceived similarly to the ones taken from the simulations. We include scenarios seen in the investment survey so that participants who remember how the index behaved during the trading simulations can benefit from a more aggressive investment position, similar to so-called technical traders in financial markets (Kirkpatrick and Dahlquist 2010). For each scenario, a chart displays

[5] We measure financial knowledge even though Fernandes et al. (2014) find that such knowledge does not seem to lead to better financial behavior.

[6] See also https://meade.wordpress.ncsu.edu/freeiat-home/.

the price movement of the fictitious index, and participants have to make an investment decision, which consists in choosing the number of contracts they wanted to buy or sell, and their confidence level (on a Likert scale). For simulation-based scenarios, the trader's performance is calculated using the simulation's price 15 seconds after the last price presented in the scenario. For new scenarios, a predetermined end price of the same order of magnitude as the scenarios already seen is set. Participants do not receive any feedback after completing a scenario, and there is no time constraint. Scenarios are presented randomly. As in the trading simulations, participants are given the objective to generate the highest possible profit to increase their probability of winning 200 dollars.

For the last task, participants are presented a "n-back" test to measure their visual working-memory performance. This test shows a series of 30 small white squares appearing in one of the 15 different locations on a screen. Participants must determine if the square shown is in the same place as the previous square. Squares are presented for 1,000 milliseconds. Between each square, a number appears in the center of the screen for 500 milliseconds, which a participant must report to the lab instructor to prevent him/her from fixating on the previous square's location. After being given instructions on how to perform the n-back test participants perform a practice run, followed by the real test.

B. Instruments and Apparatus

A Biopac MP150 amplifier (Biopac Systems Inc, Goleta, United States) with a sampling rate of 500 Hz is used to record participants' electro-dermal activity (EDA). EDA is recorded using two electrodes placed on the palm of the non-dominant hand for the duration of the experiment. An SMI RED250 (SensoMotoric Instruments, Berlin, Germany) infrared pupil reflection system with a sampling rate of 60 Hz is used to record participants' eye movement on the screen.

C. Variable Operationalization

Answers to the sociodemographic questionnaire provide information on the participants' gender, age, self-reported financial knowledge, work experience in finance, and investment experiences. We obtain data on the participants' net profit and the number of trades for each trading simulation. The n-back test provides a measure of the participants' visual working memory capacity (Kramer *et al.* 2014; Kirchner 1958). In summary, the variables we use are defined as:

- **Overconfidence** is measured using 1-the number of trades during the simulations, 2- the number of contracts traded in the chart-recollection exercise, and 3- and a self-reported confidence level regarding their investment decisions during the recollection exercise.
- **Performance** is the net profit the trading simulations and recollection exercise.
- **Visual attention** is measured as the number of fixations and their duration on an area of interest (AOI) during the recollection exercise. Separating the price charts in areas of interest (AOI) allows us to compute eye-fixation data. This exercise yields the number of fixations and their duration for each AOI.
- **Visual working memory** capacity is measured by the n-back score.
- **Arousal** is measured by the participant's EDA amplitude during the recollection exercise. We take the average of each participant's EDA.
- **Risk tolerance** is measured by the two scores generated from the IAT using either the GNB or the adapted-D scores (Greenwald *et al.* 2003; Gattol *et al.* 2011). IAT scores are bounded between -2.00 and +2.00.[7] A negative IAT score indicates high risk tolerance, while a positive IAT score implies low tolerance.

V. Results

The results we present are two-fold. First, we present results related to the performance of the participants during the trading simulation (task number 3), then we present

[7] According to the GNB method (resp. adapted-D measure) the participants' risk tolerance ranged from 0.1353 to 1.3426 (resp. -0.0803 to 1.4030), with an average of 0.7798 (resp. 0.8454) and a standard deviation of 0.3154 (resp. 0.3805). The implicit risk tolerance scores for the GNB method are in line with previous research (Fehr and Hari 2014).

Table 1. Estimates of the Independent Variables for the RITC Market Simulation (Task #2, with *n* = *60*)

Panel A: Coefficient estimate of overconfidence for net profit (H1)

Explanatory variable	Net profit	
	Estimate	*p-value*
Number of trades	-17.7900	0.0062***

Panel B: Coefficient estimate of working memory capacity for overconfidence (H3)

Explanatory variable	Number of trades	
	Estimate	*p-value*
NBACK	-10.5664	<.0001***

Panel C: Coefficient estimates of risk tolerance for overconfidence (H4)

Explanatory variable	Number of trades	
	Estimate	*p-value*
IAT(IA) score	-22.7738	0.0322**
IAT(AD) score	-17.0547	0.0538**

Panel D: Coefficient estimate of arousal capacity for overconfidence (H5)

Explanatory variable	Number of trades	
	Estimate	*p-value*
Arousal		

Legend*: Only the estimates of the main independent variables of interest are presented. NBACK = n-back score; IAT(IA) = IAT GNB score using the "improved algorithm"; IAT(AD) = IAT GNB score using the "adapted-d measure". P-values are two-tailed, with * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.*

the results of the chart-recollection exercise (task number 4). By construction, only hypotheses 1, 3, 4, and 5 can be tested using the trading simulation since the participants' self-reported level of confidence was asked only for the recollection exercise. We perform independent linear regressions to test our hypotheses (*n* = *60*). A summary of the results for the trading simulation follows in Table 1.

1- The effect of the number of trades, which we use as the level of confidence as reported by Barber and Odean (2000), on net profit (H1) suggest a significant negative relationship, thus **supporting H1** ($\beta = -17.7900$; $p = 0.0062$; two-tailed).
2- There is a significant negative relationship between confidence, as measured by the number of trades, and visual working memory performance, thus **supporting H3** ($\beta = -10.5664$; $p < 0.0001$; two-tailed), suggesting that participants with higher visual working memory trade less often, which may mean that they are less overconfident.
3- There is a significant negative relationship between confidence, as measured by the number of trades, and a participant' risk tolerance using either the GNB-improved AIT algorithm ($\beta = -22.7738$; $p = 0.0322$; two-tailed) or the adapted-D AIT measure ($\beta = -17.0547$; $p = 0.0538$; two-tailed), thus **supporting H4**. This would indicate that with higher risk tolerance (or lower risk aversion) trade more and are thus more likely to be overconfident.

Table 2, in which we display the coefficients and p-values of the explanatory variable for each regression, shows the results for the recollection exercise. As for the results presented in Table 1, no control variable (gender, age, financial knowledge, experience) is significant in any regression (and not shown).

The results from the independent linear mixed-model regressions tell us that:

1- The effect of confidence on net profit (H1) suggests a significant negative relationship between the number of contracts traded and net profits, thus **supporting H1** ($\beta = -20.5751$; $p = 0.0037$; two-tailed), even though the impact of self-reported confidence on net profits is not significantly different from zero.

Table 2. Estimates of the Independent Variables for the Chart-Recollection Exercise (Task #3, with *n = 480*)

Panel A: Coefficient estimates of overconfidence for net profit (H1)

Explanatory variable	Net profit	
	Estimate	*p-value*
Self-reported confidence	7.1629	0.5056***
Number of contracts	-20.5751	0.0037***

Panel B: Coefficient estimates of overconfidence for visual attention (H2)

Explanatory variable	Number of fixations		Fixation duration	
	Estimate	*p-value*	*Estimate*	*p-value*
Self-reported confidence	-0.1098	<.0001***	-0.1216	<.0001***
Number of contracts	-0.0320	0.0066***	-0.0399	0.0017***

Panel C: Coefficient estimates of working memory capacity for overconfidence (H3)

Explanatory variable	Self-reported confidence		Number of contracts	
	Estimate	*p-value*	*Estimate*	*p-value*
NBACK	-0.1637	0.0846*	-0.1418	0.1787

Panel D: Coefficient estimates of risk tolerance for overconfidence (H4)

Explanatory variable	Self-reported confidence		Number of contracts	
	Estimate	*p-value*	*Estimate*	*p-value*
IAT(IA) score	-0.3899	0.4505	-0.2838	0.6153
IAT(AD) score	-0.2456	0.5678	-0.0872	0.8526

Panel E: Coefficient estimates of arousal for overconfidence (H5)

Explanatory variable	Self-reported confidence		Number of contracts	
	Estimate	*p-value*	*Estimate*	*p-value*
Arousal	0.0747	0.0086***	0.0530	0.0934*

Legend*: Only the estimates of the main independent variables of interest are presented. NBACK = n-back score; IATIA = IAT GNB score using the "improved algorithm"; IATAD = IAT GNB score using the "adapted-d measure". P-values are two-tailed, with * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.*

2- The effect of the two over-confidence levels on the number of fixations and their duration shows a significant negative relationship in the two cases. Both the self-reported confidence level ($\beta = -0.1098$; $p < 0.0001$; two-tailed) and the number of contracts traded ($\beta = -0.0320$; $p = 0.0066$; two-tailed) are negatively related to the participants' reported level of confidence, thus **supporting H2**. The same directional relationship is found for the fixation duration that is negatively related to the self-reported confidence level ($\beta = -0.1216$; $p < 0.0001$; two-tailed) and the number of traded contracts ($\beta = -0.0399$; $p = 0.0017$; two-tailed). As a result, we can say that the more often and with more intensity a participant looks at the charts, the less confident he is in making an investment decision.

3- The effect of the visual working memory performance on both measures of confidence shows a negative relationship, but only marginally significantly so for the self-reported confidence level ($\beta = -0.1637$; $p = 0.0846$; two-tailed). It is therefore not clear that **H3** is supported because, even though participants with higher visual working memory trade less contracts and report a lower level of confidence, the impact is not significant at the usual statistical levels.

4- The relationship between risk tolerance and confidence, however, measured, is insignificant for both IAT measures. We thus find **no support for H4**, which tells us that risk tolerance is not correlated with the participants' level of over-confidence.

In the last panel of Table 2, we test the relationship between a participant's arousal and his/her level of confidence. We find positive relationships for arousal with the two measures of confidence, but only with the self-reported level of confidence is the relationship significant ($\beta = 0.0747$; $p < 0.0086$; two-tailed); the positive relationship with the number of contracts traded is only marginally significant at the 10% level ($\beta = 0.0530$; $p < 0.0934$; two-tailed). We can thus say that we find **support for H5**, which means that participants who experience a higher level of arousal are likely overconfident as well.

Ⅵ. Discussion

The purpose of our study was to determine the relationship between traders' overconfidence and their cognitive processes and traits. More precisely, we attempted to determine the relationship between overconfidence and visual attention, visual working memory performance, implicit risk tolerance and physiological arousal. To do this, we conducted a correlational study involving trading simulations and investment scenarios. We aimed to explain through which cognitive processes overconfidence is related to increased trading volume and reduced performance.

H1 stated that overconfidence reduces traders' performance. We find evidence supporting this hypothesis for both the investment survey and trading simulations. We find that higher trading volumes result in a lower net profit, as indicated by overconfidence in previous studies (Barber and Odean 2000; Grinblatt and Keloharju 2009; Glaser and Weber 2007; Statman *et al.* 2006). We can thus conclude that overconfidence is likely associated with reduced performance from traders.

H2 stated that overconfidence should decrease the time spent looking at a chart before making an investment decision increases. We find that both the number of fixations and their duration are lower when confidence measures are high, supporting this hypothesis. These results are in line with previous findings on overconfidence and visual attention (Innocenti *et al.* 2010). We thus conclude that overconfidence correlates with a decrease in time spent looking at the chart. A possible explanation for this result is that overconfident participants see a pattern in the chart (which isn't there), thus shortening the time spent analyzing the visual stimuli and precipitating their decision.

H3 stated that traders with lower visual working memory performance would be more overconfident. Our results support this hypothesis for both the investment survey and trading simulations; however, only the self-reported confidence estimate is significant for the investment survey. Since participants can take as much time as they need to answer the investment survey, they are probably better able to manage the cognitive load. This provides a likely explanation for why we find no link between the number of contracts traded and the participants' visual working memory performance. These results also support previous studies indicating that limited working memory capacity makes individuals overconfident (Juslin *et al.* 2007; Hansson *et al.* 2008). We thus propose that participants with lower visual working memory are also likely to be overconfident.

H4 stated that participants with higher risk tolerance are likely overconfident as well since they are more affected by their emotions and impulsions. We find significant results regarding the implicit risk tolerance only for the trading simulations. One possible reason for these insignificant coefficients comes from the difference in the type of tasks. Since the investment survey is a task where participants have time to think before deciding, they were more likely to rely more on their controlled processes than their automatic processes. On the other hand, we see significant results for the trading simulations, which is a time-paced task where participants need to react quickly and thus have little time to think before acting. In addition, the results are similar for both IAT scores. Implicit risk tolerance seems to correspond to traders' risk tolerance in situations where there is insufficient time to engage controlled processes, like high-volatility trading sessions, market bubbles and crashes. Using an implicit risk tolerance task test jointly with a typical risk tolerance questionnaire should improve risk tolerance profiling issues.

H5 stated any participant's overconfidence is positively correlated with his/her emotional arousal. We find such a positive correlation in support of our fifth hypothesis. These results are also supported by previous findings on emotional levels experienced (Lo *et al.* 2005; Schunk and Betsch 2006; Chu *et al.* 2012). Since arousal is linked to overconfidence, it may be useful for traders to be able to regulate their emotions in order to perform better.

Ⅶ. Conclusion

In conclusion, the results presented in our study suggest that many cognitive processes play a role in explaining why overconfident traders perform less well than non-overconfident traders. We found in particular that traders who display overconfidence fixed the chart less often and for shorter periods. Also, lower visual working memory performance and higher implicit risk tolerance seem to be correlated with overconfidence. The same can be said of participants with higher arousal: They displayed more overconfidence and thus, lower returns.

This study contributes to existing literature in two ways. First, this is the first study that draws a comprehensive understanding of how cognitive functions and emotional states of traders are articulated in the context of overconfidence. As such, our study contributes to our understanding of which cognitive processes are associated with overconfidence, which leads to lower performance. Second, the methodology we develop appears useful in testing novices as well as more senior traders and experienced investors in a financial context.

This study has three important limitations. First, since we do not manipulate the cognitive processes, we are only able to determine that visual attention, visual working memory and implicit risk tolerance are correlated with overconfidence, which itself results in lower performance. The second limitation of our study is our sample size. Although our results are original, future research using a larger sample of more senior traders and experienced investors would allow one to reach conclusions that are more relevant to capital market participants. Increasing the sample size would allow more robust inferences, especially for the trading simulations. Since our participants were only novice traders, we cannot draw any conclusions about professional traders so that our findings may only apply to novice traders and are less significant for experts. Third, and finally, our results are more correlates than the result of a clear cause-and-effect experiment.

Future research on overconfidence should seek to confirm the relationships we highlighted in this study in addition to determining their causality. For example, future research could examine how performance varies when a trader's working memory is loaded. Another approach could be to have different conditions where traders need to try to regulate or follow their emotions. Moreover, multivariate analyses can be performed to determine the respective weights of visual attention, visual working memory and implicit risk tolerance on overconfidence. Future research on risk tolerance should study whether the combination of the IAT score and risk tolerance questionnaire can explain the risk behavior of investors. In conclusion, this study confirms that the behavior of overconfident traders is linked to their cognitive processes and emotional states.

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