Predicting under-reaction from overconfidence

Hainguerlot Marine, [1] Gajdos Thibault, [3,2] de Gardelle Vincent, [1,2] Vergnaud Jean- Christophe [1,2]

[1]Paris 1 Panthéon- Sorbonne University, [2]CNRS, [3]Aix- Marseille University

1. Introduction

In everyday decisions, people need to integrate subjective and objective information. We define subjective information as the result of an accumulated information process realized by individuals while objective information is given to individuals after being processed by an objective source. In medicine, doctors have to take into account both their clinical diagnosis and the epidemiological data when they examine a patient. In finance, traders use their knowledge about the current situation of markets as well as the public information provided to them before deciding to invest or not. Even for trivial decisions such as deciding whether to take an umbrella or not, people consider both their sense about the weather and the forecast.

In behavioral finance, it has been theoretically documented that people who are overconfident about their subjective information tend to under-react to objective information (Daniel et al., 1998; Odean, 1998). Under- reaction refers to an insufficient adaptation to objective information. The theoretical hypothesis is based on the assumption that overconfidence corresponds to the overestimation of the precision of subjective information (Griffin &Tversky, 1992). They model the underlying mechanism through Bayes' Rule: the more traders overestimate the quality of their subjective information, the less they will take into account the objective information. According to them, this mechanism leads to major predictions for overconfident traders: trading activity increases and financial earnings are impaired. Interestingly, similar predictions could be extended to other domains. For instance, medical errors could be due to doctors who are overconfident in their clinical diagnosis and thus do not fully take into account objective information such as laboratory data. Therefore, the relationship hypothesized between overconfidence and under-reaction to objective information may have important practical implications in finance and other domains.

However, we believe that the mechanism between overconfidence and under- reaction is based on two main hypotheses that could be challenged. First, does overconfidence result from an overestimation of the precision of subjective information? Secondly, do people actually combine subjective and objective information in a Bayesian way?

This paper proposes a new theoretical and experimental methodology that aims to address these two critical issues in order to assess whether overconfidence causes under- reaction to objective information. We decided to apply our method to the perceptual decision framework given that numerous empirical studies in this field have revealed that people do not sufficiently adjust their decision to objective information (Wickens, 1992; Chi & Drury, 1998; Botzer et al, 2010; Wang et al, 2008).

To the best of our knowledge, no similar study has proposed a direct test of this mechanism. Most of the studies in behavioral finance suffer from methodological limitations related to the measurement of overconfidence. First, the suggested measure of overconfidence by the theoretical models is related to the precision of subjective information. More precisely, empirically it corresponds to a calibration- based overconfidence measure which is the difference between a person's mean subjective probability estimate of choosing the correct answer on a test and the mean accuracy. However, a series of studies use a distinct measure of overconfidence which is the overplacement, measured by comparing a person's performance with others' performances (Deaves et al., 2008, Charupat et al.,2005). We believe that the use of another measure to test may not be relevant given that according to Moore& Healy (2008), “the different types of overconfidence are conceptually and empirically distinct”. The second limit arises from the fact that overconfidence is derived from proxy or other tasks. Barber and Odean(2001) use the gender as a proxy for overconfidence. Glaser & Weber (2007) and Biais et al. (2005) derive a calibration measure from a common knowledge task to assess whether or not overconfidence is correlated with trading activity.Even though some studies establish a correlation between individual measures of overconfidence across domains (West &Stanovich, 1997; Bornstein &Zickafoose, 1999) the evidence is still weak (Glaser et al., 2010). Overall, some studies find that overconfidence is related to under-reaction (Barber &Odean, 2001; Deaves et al., 2008; Charupat et al., 2005) whereas others find no relationship (Glaser & Weber, 2007; Biais et al., 2005). Surprisingly, seminal works that hypothesized this mechanism (Daniel et al., 1998; Odean, 1998) remain largely influential in the financial literature even though empirical evidence is scarce and controversial (Olsson, 2014).

We have developed a model based on a Signal Detection Theory approach that has enabled us to: quantify under-reaction, estimate the overestimation of the precision of subjective information, and predict the expected impact of overconfidence on under-reaction by using a Bayesian model. Moreover, our experimental design tries to address the methodological limitations previously mentioned. First, we used a measure of calibration- based overconfidence. Secondly, participants were required to combine subjective and objective information within the same task. Third, we obtained independent behavioral measures of overconfidence and under- reaction. Finally, we describe how our model can be implemented with experimental data and test its predictive power.

We applied our methodology to a perceptual decision framework. In the perceptual task, subjects had to compare the number of dots contained in two circles. The two circles were only displayed for a short fraction of time, about one second, so that it was impossible to count the dots. Subjects had to tell which circle contains the higher number of dots. The observation of these two circles constitutes their subjective information. To measure their overconfidence, we asked them to give their confidence in the choice made. Furthermore, objective information which indicated the correct response with 75% validity was provided to participants before the display of the circles. To obtain two independent measures of overconfidence and under- reaction to objective information, participants came to two sessions: one for confidence and one for objective information.

Our results suggest that there is an empirical link between overconfidence and under- reaction to objective information. Overall, participants deviated from an optimal processing of objective information: they set decision criteria that are twice lower than the ideal one. This inefficient use of information results in a sub-optimal performance: they perform at 51% of what they could have ideally reached. Moreover, we found that overconfidence explains 46% of this loss in performance. These results provide evidence in favor of the two main theoretical hypotheses on which are based the model which predicts the link between overconfidence and under- reaction.

Section 2 describes our theoretical model and tests its implications by simulations. Section 3 describes the experimental design. Section 4 applies the theoretical model to experimental data. Finally, Section 5 discusses the results and the potential applications of our model to other decisional frameworks.

2. Model

We consider a situation where there exists two states of nature: R and L. The subject has to identify the actual state of nature. To form his/her belief about the state of nature, he/she receives two sets of information: an objective prior π about the two states and direct evidence about the state. This direct evidence is to some extent informative about the state of nature but it doesn't permit to identify it with certainty. In our case, the evidence provided is fully informative. However, time pressure does not allow acquiring the complete content of evidence. Following the SDT framework (Green & Swets, 1966), it is assumed that the observation of the evidence leads to the realization of a noisy subjective signal which is distributed according to a Gaussian law with a mean that depends on the state of nature (see Figure 1). More precisely, subjective signal x is generated as follows: on a given observation, x is a random sample from a Gaussian distribution, with unit variance and centered at +d'/2 (for the state of nature $s = R$) or at –d'/2 (for the other state of nature $s = L$), where d' expresses the observer's capacity to accurately discriminate between the two states.

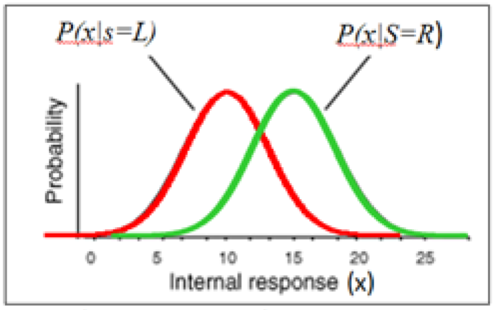

Figure 1

Hereafter, we present our Bayesian approach to describe how overconfidence may cause under-reaction. We will consider as a benchmark the optimal model of integration of both sets of information. We will describe how we model overconfidence defined as being the overestimation of the observer's capacity to accurately discriminate between the two states. We will model how an overconfident observer integrates information. By comparing the integration made by an ideal observer with the one by an overconfident observer, we will be able to quantify under- reaction to the objective prior π. Finally, we will investigate by simulations to what extent does overconfidence impact on under- reaction.

2.1. Information integration by an ideal subject

To integrate information, the subject has to combine an objective prior π about the two states and subjective signal x resulting from the observation of some direct evidence. To present our Bayesian analysis in a simple way, we use a log- odds approach. Ideally, the subject should form beliefs about the two states of nature (R, L) and used them in the following decision variable DV:

$$DV = \log\left[\frac{P(s=R|x,\pi)}{P(s=L|x,\pi)}\right] \qquad \textbf{(1)}$$

If we assume that x is independent from , π, conditionally on the evidence presented, then we can separate the DV into the log- likelihood ratio of the evidence and the log-ratio of the priors:

$$DV = \log\left[\frac{P(x|s=R)}{P(x|s=L)}\right] + \log\left[\frac{P(s=R|\pi)}{P(s=L|\pi)}\right] \qquad \textbf{(2)}$$

Given our SDT framework (see Figure 1), the log- likelihood ratio of the evidence can be inferred from the subjective signal x as follows:

$$\log\left[\frac{P(x|s=R)}{P(x|s=L)}\right] = \log\left[\frac{e^{-1/2\left(x - d'/2\right)^2}}{e^{-1/2\left(x + d'/2\right)^2}}\right] = d'.x \qquad \textbf{(3)}$$

The sign of the DV indicates the best choice given the two sets of information: the subject chooses "Right" if and only if the DV is positive. The decision criterion x_c^* is the value of x above which the observer should respond "Right". This criterion depends on both the observer's capacity to accurately discriminate between the two states and on objective prior π:

$$x_c^* = -\log\left[\frac{P(s=R|\pi)}{P(s=L|\pi)}\right].\ \frac{1}{d'} \qquad \textbf{(4)}$$

Let us now study what happens when the integration of information is repeated several times with identical objective prior π. The placement of the decision criterion will directly impact on the overall success rate. For given values of d' and x_c^*, we can quantify the success rate separately in trials in which the state of nature R or the state of nature L was present. Summing the success rates across these two types (weighted by their expected frequencies) produces the following expression for the ideal performance (where Φ denotes the cumulative standard normal distribution):

$$Success^{ideal} = P(s = R|\pi).\left(1 - \Phi\left(x_c^* - \frac{d'}{2}\right)\right) + P(s = L|\pi).\,\Phi\left(x_c^* + \frac{d'}{2}\right) \qquad \textbf{(5)}$$

2.2. Information integration by an overconfident subject

To model overconfidence, we base our approach on the hypothesis that the observer holds a subjective estimate about his capacity to discriminate between the two states, that might deviate from his true capacity. We will note d'_{subj} this subjective estimate. The evidence x is evaluated according to this subjective estimate as follows:

$$\log\left[\frac{P(x|s=R)}{P(x|s=L)}\right] = d'_{subj}\ .x \qquad \textbf{(6)}$$

Moreover, the subjective decision criterion $x_{c,subj}^*$ and the success rate $Success^{subj}$ become:

$$x_{c,subj}^* = -\log\left[\frac{P(s=R|\pi)}{P(s=L|\pi)}\right].\ \frac{1}{d'_{subj}} \qquad \textbf{(7)}$$

$$Success^{subj} = P(s = R|\pi).\left(1 - \Phi\left(x_{c,subj}^* - \frac{d'}{2}\right)\right) + P(s = L|\pi).\,\Phi\left(x_{c,subj}^* + \frac{d'}{2}\right) \qquad \textbf{(8)}$$

Overconfidence is the discrepancy between the subjective and objective discrimination capacities which can be measured by the ratio $\frac{d'_{subj}}{d'}$. Therefore, overconfidence arises when this ratio is greater than one. In other words, overconfident people overestimate their true capacity. Note that our model can also capture under-confidence when the ratio is lower than one.

2.3. Theoretical predictions and Simulations

By comparing the integration made by an ideal subject with the one by an overconfident subject, we will be able to quantify under- reaction to the objective prior π. From Equation (4) and Equation (7), we can predict how overconfidence will impact on under- reaction to informative priors $\left(\log\left[\frac{P(s=R|\pi)}{P(s=L|\pi)}\right] \neq 0\right)$. More precisely, overconfidence ($\frac{d'_{subj}}{d'}$>1) implies an insufficient adaptation of the decision criteria $\left(\left|x^*_{c,subj}\right| < |x^*_c|\right)$ and a suboptimal performance ($Success^{subj}$<$Success^{ideal}$). Conversely, under-confidence implies over- reaction and a suboptimal performance.

The effect of overconfidence (or under-confidence) on the performance depends on two dimensions: the objective capacity to discriminate and the informativeness of the prior. We are interested in evaluating the gain in success from adaptation, defined as being the adaptation gain, that is to say the gap between the subjective success and the success without adaptation (setting the decision criterion xc at 0). Simulations (see Figure 2) show how each dimension impacts on the adaptation gain. First, Figure 2A presents the simulations for various levels of objective capacity to discriminate (d') with a fixed prior at $P(s = R|\pi) = 0.75$. Similarly, Figure 2B presents the simulations for various levels of prior ($P(s = R|\pi)$) with a fixed objective capacity to discriminate (d'=1). Overall, results show that adaptation gain is optimal when the ratio $\frac{d'_{subj}}{d'}$ is equal to one, otherwise it is impaired. Figure 2A suggests that the lower the objective capacity to discriminate, the greater is the negative impact of overconfidence on the adaptation gain. Figure 2B suggests that the higher the informativeness of the prior, the greater is the negative impact of overconfidence on the adaptation gain. Note that the model predicts that when the prior is uninformative $P(s = R|\pi) = 0.50$, adaptation gain is not impaired by overconfidence or under-confidence. Moreover, the effect of under- confidence seems to present a different pattern.

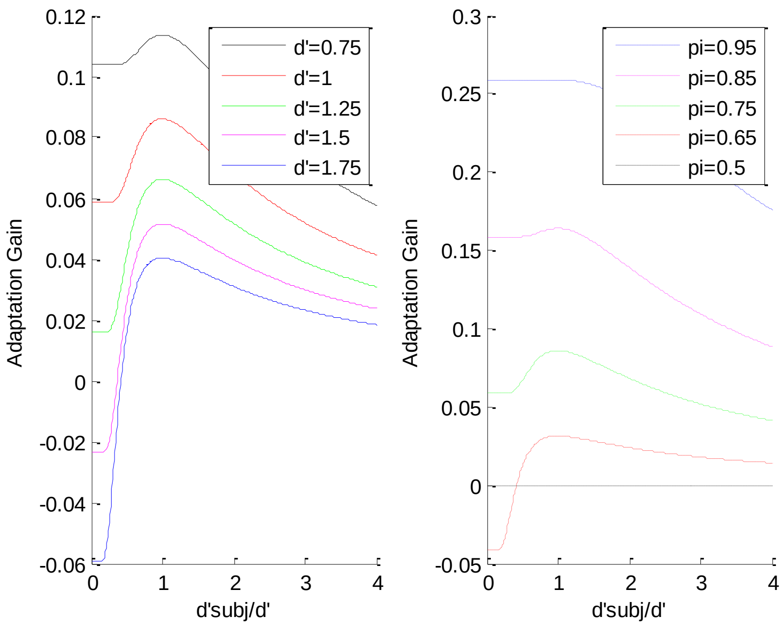

Figure2 (légende? exemple)

3. Experimental design

Summary of experimental design

In the perceptual task, subjects had to compare the number of dots contained in two circles. The two circles were only displayed for a short fraction of time, about one second, so that it was impossible to count the dots. Subjects had to tell which circle contains the higher number of dots. The observation of these two circles constitutes their subjective information. In both sessions, the decisional problem was repeated 512 times.

In a first session (see Figure 3A), objective information was provided to participants before the display of the circles[1]. The prior indicated the correct response with 75% validity or it was non predictive. Subjects were fully informed about the meaning of the prior. They were instructed to optimally combine in each trial the stimulus information with the prior information. Response accuracy was incentivized.

In a second session (see Figure 3B), participants had to indicate after each decision their subjective probability that the decision was correct, on a scale from 50% to 100% by steps of 10. To encourage

[1] We replicated the experimental design of Rahnev et al. (2011)

participants to truthfully reveal their subjective probability of success *p,* we incentivized these confidence ratings using the Probability Matching Rule (see Massoni, Gajdos and Vergnaud (2014) for details).

We decided to organize two distinct experimental sessions in order to obtain two independent measures of overconfidence and under- reaction. Otherwise, we believe that the measure of overconfidence would have been influenced by the prior information provided. As a consequence, we need to extrapolate overconfidence from one session to the other one to assess its potential impact on under- reaction. Thus we suppose that overconfidence is constant across the two sessions. In addition, the prior preceded the stimuli in order to rule out several other potential cognitive biases that may arise from the presentation of the prior after seeing the stimuli such as the confirmation bias or the premature closure (Berner & Graber, 2008).

Participants

69 individuals (39 female; mean age= X ± SD) with normal or corrected-to-normal vision were recruited through the LEEP (Laboratory of Experimental Economics in Paris) research pool. Participants gave informed consent to participate in two experiments administered on separate days, with a four days interval, in a counterbalanced order across participants. They received a show-up fee of 13 Euros plus an incentivized bonus as described below (mean bonus= X ± SD).

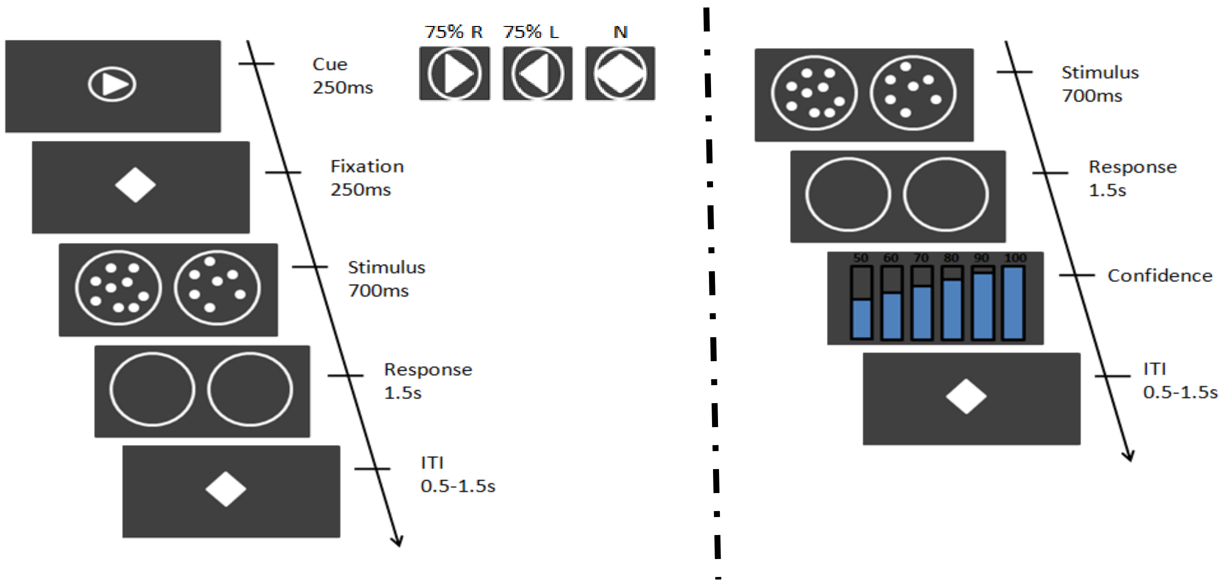

Figure 3

4. Empirical application

In the following section, we apply our model to experimental data in order to assess its predictive power. First, we computed the optimal decision criteria. It enabled us to quantify the extent to which each subject under- reacts to the prior information. Moreover, we assess how this under- reaction impairs the adaptation gain that each subject could have reach when the prior information was predictive. Secondly, to test the hypothesis that overconfidence may cause under- reaction, we need to propose a method to estimate the ratio of overconfidence. This method is applied to experimental data gathered during the confidence session. Third, we use our model of information integration by an overconfident subject to predict the expected under- reaction to prior informative and the expected adaptation gain given the estimated degrees of overconfidence. Finally, we assess the goodness of fit of our model.

4.1. Quantification of under- reaction

First, we propose to define under- reaction as being the difference between the optimal decision criterion and the actual criterion. To do so, optimal decision criteria are computed (see Equation 4) from the actual observer's capacity to accurately discriminate between the two states (d'). In addition, we decided to infer the observer's capacity from experimental data when the prior was non- informative[2]. We take the non- informative situation as a reference to predict how subjects should set their decision criteria when the prior is informative given his capacity to discriminate. A subject should set a Left decision criterion given the prior predictive of Left and a right decision criterion given the prior predictive of Right such that ideally the difference between the two is:

$$x_L^* - x_R^* = \frac{1}{d'}.\,2\log(3)\ (\mathbf{9})$$

Actual decision criteria are derived from experimental data when the prior was informative[3]. Overall, results show that human participants do not sufficiently adjust their decision criteria (mean= 0.9761, var= 0.6396) given the informativeness of the prior compared to the optimal adjustment (mean= 1.9562, var=0.4843).

Secondly, we assess how this under- reaction to prior information impacts on performance. Thus, we computed the ideal success rate from Equation 5. We found overall a good correlation across

[2] When the prior is non- informative, the decision criterion is nullthus the success rate is simply: $Success = 0.5.\left(1 - \Phi\left(0 - \frac{d'}{2}\right)\right) + 0.5.\,\Phi\left(0 + \frac{d'}{2}\right)$ thus $d' = 2 * InvNorm(Success)$

[3] Actual decision criterion is computed from Hit and False Alarm Rate as follows: $x_{c,obs}^*$= $InvNorm(HitRate)$ - $InvNorm(FalseAlarmRate)$ where Hit Rate is the correct detection rate when the actual state was R and False Alarm Rate is the incorrect detection rate when the actual state was L.

participants between the ideal and observed success rates (r= 0.6702, p=3.0074e-10), but there was also a clear gap between the two measures: overall participants performed significantly worse than the ideal observer (average success rate: 76.60 % vs. 80.15%, T(68)= 7.8880, p=3.5006e-11). On average, subjects could ideally have gained 7.25 % (var =7.5964e-04) by taking optimally into account the informativeness of the prior whereas their adaptation gain only increased by 3.70% (var=0.0019).

4.2. Estimation of overconfidence

In this section, we develop a method, based on our model, which enables us to estimate overconfidence from experimental data gathered during the confidence session. The participant was required to indicate not only his choice but also his belief that this choice was correct. The participant was informed that stimulus R and stimulus L were presented with equal probability. Confidence data are used to infer how subjects subjectively evaluate their capacity to discriminate between both states of nature. According to our model, when the subject receives evidence *x* he reports subjective probabilities (see Equation 6: $\log\left[\frac{P(s=R|x)}{P(s=L|x)}\right] = x\,.\,d'_{subj}$) that depend on his subjective estimate of his capacity to discriminate (d'_{subj}). However, the objective probabilities are given by Equation 3: $\log\left[\frac{P(s=R|x)}{P(s=L|x)}\right] = x\,.\,d'$). Overconfidence corresponds to an overestimation of the predictive power of the given evidence. Therefore, by combining the two equations above, we can formulate a calibration curve that relates the objective evaluation and the subjective evaluation made by the observer:

$$\log\left[\frac{P_{subj}(s=R|x)}{P_{subj}(s=L|x)}\right] = \log\left[\frac{P_{obj}(s=R|x)}{P_{obj}(s=L|x)}\right].\frac{d'_{subj}}{d'} \qquad (\mathbf{10})$$

As experimenters, we don't directly observe the subjective signal x at each trial, but we can evaluate both the objective and subjective probabilities for each conjunction of a response and a confidence rating given by the observers. By fitting a regression line through this calibration curve, we can obtain an estimation of overconfidence (d'_{subj}/d') for each observer. To illustrate our analysis, we plot in Figure 4A this regression for a representative participant. Overall, we found that the values of d'_{subj} were systematically greater than the actual d' values (see Figure 4B; average d': 2.2655 vs. 1.1118, T(68)= 8.7863, p=8.2131e-13). Participants were thus overconfident, but this overconfidence was quite heterogeneous across observers, as there was no correlation between d'_{subj} and d' (r= 0.0383, p=0.7544).

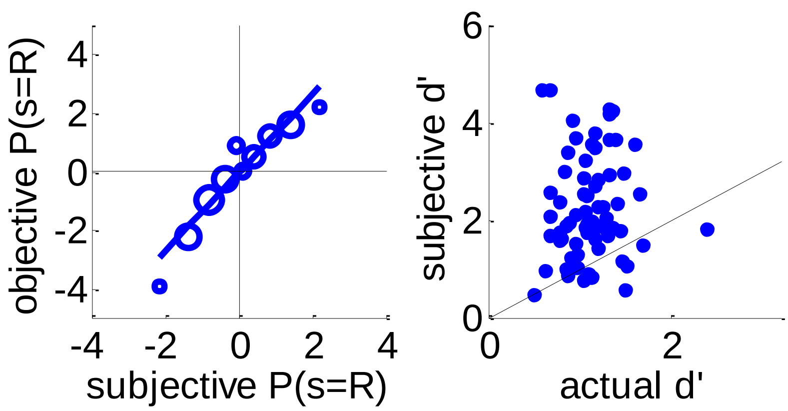

Figure 4

4.3. Test of theoretical predictions

Our model of information integration by an overconfident subject (see Section 2.2) enables us to predict the expected under- reaction to an informative prior and the expected adaptation gain. We apply this model to the estimated degrees of overconfidence from experimental data. Finally, to test the predictive power of our model we compare how well the predictions fit the observed behaviors.

According to our model (see Equations 7 and 8), decision criterion and success depend on the observer's subjective estimate about his capacity to discriminate between the two states (d'_{subj}). As we previously argued, we assume that overconfidence (d'_{subj}/d') is constant between the confidence session and the information integration session, such that we can extrapolate the value of d'_{subj} in the information integration session, given the objective d' measured in this session.

Overall, Figures 5A and 5C show that predictions with our model of information integration by an overconfident subject are closer to the observed behaviors than the predictions from the ideal subject's model. Indeed, the prediction error, corresponding to the absolute value of the difference between predicted and observed values, is significantly lower for both: the decision criteria adjustment (average: 0.7979 vs. 1.1776, T(68)= -3.7419, p= 3.7758e-04) and the adaptation gain (average: 0.0316 vs. 0.0397, T(68)= -3.9811, p=1.6931e-04). On average, our model of an overconfident subject predicts that subjects will under-react to the prior information (mean= 1.1887, var= 0.5257) compared to the optimal adjustment (mean= 1.9562, var=0.4843). Interestingly, the predicted under-reaction is not far from the observed under- reaction (mean= 0.9761, var= 0.6396). Figure 5B presents the distribution of the distance between the two decision criteria for ideal, overconfident and real subjects. In addition, we observe that overconfidence impairs the adaptation gain: the model predicts a mean gain of 5.63 % (var=7.9664e-04) while ideally the mean adaptation gain could have attained 7.25% (var= 7.5964e-04). Remind that the mean observed adaptation gain is 3.70 % (var=0.0019). Overall, overconfidence explains 1.62 % of the loss in adaptation gain, out of a total observed loss of 3.55%. Figure 5D presents the distribution of the adaptation gain for ideal, overconfident and real subjects.

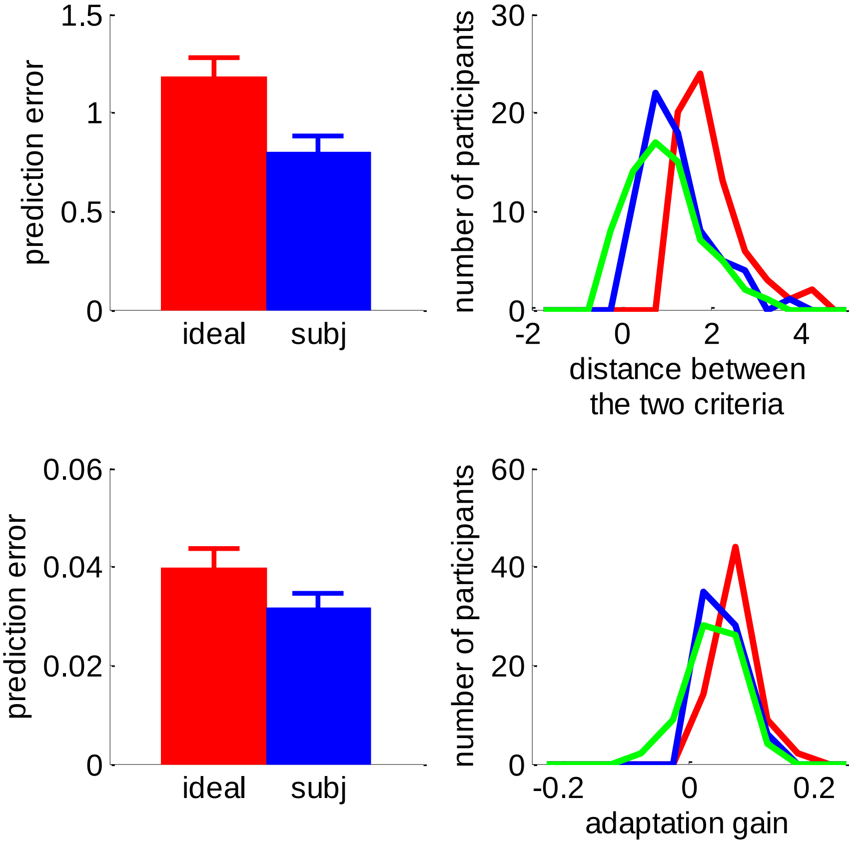

Figure 5 (légende)

Discussion

To summarize, we developed a theoretical model of information integration by an overconfident subject which can be estimated and empirically tested. We define overconfidence as the overestimation of the precision of an subjective signal. We propose to model the precision of the subjective signal by using a Signal Detection Theory approach. We compare information integration by an overconfident subject and an ideal subject to quantify the impact of overconfidence on under-reaction. We provide a method to estimate overconfidence and under- reaction from experimental data. We apply our theoretical model to experimental data to test its predictive power. Overall, we provide evidence in favor of a link between overconfidence and under- reaction. Our methodology enabled us to quantify under- reaction: subjects only increased their performance by 3.7% while they could have gained 7.25% from optimally taking into account objective information. Moreover, we showed that overconfidence explains 46% of this loss.

Is our measure of overconfidence relevant? We compare our measure with usual measures of overconfidence. We observe that our measure is well correlated with a simple measure of overconfidence defined as the difference between the mean confidence and the mean accuracy (r=0.8546, p=9.6480e-21). On the other hand, we found no correlation with gender which is commonly considered as a proxy of overconfidence (r= 0.0494, p= 0.6867). This result suggests that one should be careful when considering overconfidence as a psychological trait.

Is our method necessary to empirically test the link between overconfidence and under-reaction? Indeed, one could restrict this study to the use of direct behavioral measures. Thus we compare our results with the ones obtained from a simple behavioral analysis by assessing to what extent the simple measure of overconfidence explains the observed success rate when the prior was informative. By regressing observed success rate on the simple measure of overconfidence, we found that 1% increase in overconfidence leads to a significant reduction of success rate by 0.0927% (pvalue=0.0553) Given that the average value of this behavioral measure amount to 8.32%, we can estimate that the overall impact of overconfidence on under-reaction is 0.77%. Comparing with our analysis, this estimated effect is more than twice lower. Moreover, such behavioral analysis doesn't allow a quantification of under- reaction with respect to optimality.

A common practice within the Signal Detection Theory framework is to introduce the possibility of a bias in the decision criterion to better fit behavioral data. As a matter of simplicity, we do not take into account the presence of this potential bias but it could be introduced in the model and estimated. In particular, we also performed the all analysis with a bias and results were unchanged.

This paper introduces a new and general method to empirically test the link between overconfidence and under- reaction. We believe that it could be replicated to other domains. For instance, in medical decisions, one could wonder if overconfidence influences the way doctors integrate their clinical diagnosis with epidemiological data. Hereafter, we list the conditions that seem to be necessary for a replication of our proposed methodology to other decisional frameworks. First, the method has been so far elaborated for situations of uncertainty that deal with only two possible states of nature. Secondly, the decisional problem that would have to be considered is the identification of the actual state of nature. Third, to obtain a robust estimation of overconfidence and under- reaction, it is required to sufficiently repeat the decisional problem.

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Appendix

Stimuli and task

Two white circles (diameter 5.1) were presented on a gray background for 700ms, on the left and right of a central fixation (eccentricities of ± 8.9°). Both circles contained small white dots (diameter 0.4°), with 100 dots in one circle and 100+*X*dots in the other circle. Participants had to indicate whether the left or right circle contained more dots, by pressing on the corresponding arrow key on the keyboard. They received no feedback about response accuracy, but responses times shorter than 200ms or longer than 2200ms (from stimulus onset) were discouraged by presenting a "too fast" or "too slow" message. The fixation cross appeared 250 ms before the stimulus and after the response the inter-trial interval was jittered between 0.5s and 1.5s.The experiment was run using MATLAB (MathWorks) and Psychtoolbox (Brainard, 1997), on screens (resolution 1024 X 768) viewed at normal distance (about 60 cm).

Procedure

Calibration phase: Both experiments included an initial calibration phase, in which we adjusted the value X (that is, the difference in number of dots between the two circles) using a 2-down 1-up psychophysical staircase (Levitt, 1971). We used two independent and interleaved staircases (150 trials each), one adjusting the value Xr in the right circle to obtain 70% of "right" responses and the other one adjusting the value Xc in the left stimulus to obtain 70% of "left" responses. Stepsize was initially set to 20 and reduced to 16, 8, 4 and 2 at trials 12, 24, 60 and 80, respectively. At the end of this calibration, for each participant we fit a psychometric curve (EQX) and estimated the values Xr and Xc that were used in the experiment.

Session 1 ("Information integration"): Here, a visual prior was presented for 250ms before each trial. The prior indicated the correct response with 75% validity (triangle pointing to the left or to the right) or it was neutral (diamond). Subjects were fully informed about the meaning of the priors. They were instructed to optimally combine in each trial the stimulus information with the prior information. Response accuracy was incentivized: participants gained 1 point for each correct response and lost 1 point for each error (where 1 point= 0.02 Euros). A training phase with feedback on accuracy (96 trials) was included, before the main phase without feedback (512 trials).

Session 2 ("Confidence"): After each decision, participants had to indicate their subjective probability that the decision was correct, on a scale from 50% to 100% by steps of 10%, using the numerical keys (1, 2, 3, 4, 5, 6), on the top-left of the keyboard. To encourage participants to truthfully reveal their subjective probability of success p, we incentivized these confidence ratings using the Probability Matching Rule (Massoni, Gajdos, and Vergnaud, 2014). After giving a level of confidence P, a random number $L1$ is drawn between 40 and 100. If $P \geq L1$, the reward depends on response accuracy (+1 point if correct, -1 point if incorrect). If $P<L1$, the reward is randomly determined with probability $L1$: a new random number $L2$ is drawn between 0 and 100, and one point is earned if $L1 \geq L2$ and one point is lost if $L2<L1$. Points were converted to payments (1 point= 0.02 Euros). The mechanism was presented to participants as a way to maximize their earnings, by providing accurate confidence ratings. Instructions, examples, and a training phase with feedback (40 trials) were provided, to make sure that participants understood the intuition behind this mechanism. Participants then performed the main phase (512 trials) without feedback.