Overconfidence, Risk Perception and the Risk-Taking Behavior of Finance Professionals

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Abstract

This paper highlights the role played by overconfidence and risk perception in the risk-taking behavior of finance professionals. We interviewed 64 high-level professionals and show that they are overconfident both in the general and financial domains. Using a recent measure proposed by Glaser *et al.*(forthcoming), we show that respondents are overconfident in forecasting future stock prices. We demonstrate that the risk they are willing to take on is positively influenced by overconfidence, optimism and negatively influenced by risk perception. However, the stock returns volatility anticipated is, in most cases, an insignificant determinant of the risk professionals are ready to take.

JEL Classification: G11

Keywords: Overconfidence, Risk Taking, Risk perception, Finance Professionals, Investors behavior

Introduction

Many empirical studies demonstrate that overconfidence leads to excessive trading (Odean, 1999, Barber and Odean, 2001, 2002 and Glaser and Weber, 2007) and that more overconfident investors choose more risky investments (Barber and Odean, 2001). Overconfidence is common among different categories of professionals including fund managers, analysts and investment advisors (Moore and Healy, 2008, Menkhoff *et al.* 2006, Törngren and Montgomery, 2004).

Nosic and Weber (2010) demonstrate a positive impact of overconfidence and risk perception on the risk-taking behavior of individual investors. They also show that historical returns and volatilities are worse predictors of risk-taking behavior than measures of anticipated risk and return. They obtain these results through the answers of a sample of students to portfolio choice questions.

The main goal of our paper is to extend these results to finance professionals. Overconfidence manifests itself by miscalibration of probabilities, better-than-average effect, illusion of control and unrealistic optimism. In this paper, we focus on the two first types of overconfidence. In this paper we use two different measures of miscalibration. First, we test miscalibration of probabilities by asking confidence intervals for uncertain quantities to a sample of 64 high-level professionals. The degree of miscalibration is measured by the number of answers falling out of the 90% confidence intervals they provide. On average, 5 answers out of 10 fall out the confidence intervals. The second miscalibration measure we use is proposed by Glaser, Langer and Weber (forthcoming). Respondents are asked to propose 90% confidence intervals for the one-year ahead price of stocks. Overconfidence is measured by the difference between 90% and the probability mass induced by the intervals provided by the respondents[1]. The price forecasts allow us to estimate the anticipated standard deviations of returns. Contrary to common wisdom, our results clearly show that risk-taking behavior is not significantly influenced by these estimated standard deviations.

The better-than-average effect (BTA) hints at the fact that people believe they are above average and that individuals have unrealistically positive perceptions of themselves (Taylor and Brown, 1988, Cooper *et al*., 1988). We do not find any significant better-than-average effect in our data at the aggregate level[2]. Moreover, cross-sectional differences in BTA are not significant in explaining risk-taking behavior when controlling for optimism and miscalibration of probabilities.

Section 1 describes the sample and the questionnaire. Section 2 describes our initial results about overconfidence. Section 3 determines the factors that affect the level of risk-taking behavior and stress the quality of respondents' predictions (supplementary results and robustness checks are provided in an Internet appendix). A final section concludes.

1. Sample and questionnaire

We interviewed 64 high-level professionals[3] in May 2011; 61 questionnaires were eventually completed. Professionals in the sample are mainly customers of CCR Asset Management (the main

[1] The ex-post low quality of finance professionals' predictions is illustrated by Ben-David *et al.* (2012).

[2] This result conforms to the findings of Glaser and Weber (2007)

[3] Table A1 in the Internet Appendix provides the set of employers of interviewed professionals.

sponsor of the Behavioral Finance Chair in our University) who accepted to participate in a joint survey on decision under risk by Morningstar and our University. The sample contains 39 fund managers, 12 CFO, 3 CEO, 5 wealth managers, 2 analysts and 3 treasurers. No monetary incentives were provided in order to complete the survey. As respondents accepted the (costly for them) 40-45 minute-length appointment, and as interviewers were Morningstar employees, we expect answers not to be biased by the absence of monetary incentives. Moreover, we informed the participants that the general results of the study are to be made public during a professional event (this event was held in July 2011). We chose face-to-face interviews to be sure that respondents do not have an internet access to check their answers to the knowledge questions.

Interviews lasted 28 minutes on average. They were not recorded on tapes because it was problematic for anonymity. Most interviewed professionals are male (women represent 17% of participants), single and hold a university degree. On average, respondents are 44 years old, with 20% (47%) being below (above) the age of 35 (45). They have been in their jobs for an average of 12 years, with 30% (30%) having been there for less (more) than 5 (15) years. Thus, our sample is similar to that used in comparable studies (Gehrig and Menkhoff, 2004, Menkhoff *et al.*, 2006).

The 10 questions[4] cover risk attitude, risk perception and risk-taking, overconfidence and expectations. The structure of the questionnaire is close to the one of Nosic and Weber (2010) but adapted to our sample of professionals. Table 1 presents the variables of interest and provides some descriptive statistics.

The first questions investigate risk perception, risk-taking behavior and risk attitudes outside any market-related context. We refer to standard lotteries or one-year hypothetical investments (see Figure 1, left). Risk perception is measured on a Likert scale ranging from 0 to 10, where 0 (10) represents no (very high) perceived risk[5]. A standard portfolio choice question (proportion of wealth invested in the risky lottery or in 3% risk-free investment) is used to infer risk propensity.

[4] The complete questionnaire in English is available at the end of the Internet Appendix.
[5] Weber and Hsee (1998) and Pennings and Wansink (2004) also used Likert scales to determine individuals' risk perceptions.

A second lottery (B) is offered (Figure 1, right) to assess the risk-taking behavior and risk perception by using certainty equivalents in a power utility framework (Dohmen *et al.*, 2011).

Insert Figure 1

The next questions measure overconfidence and self-evaluation of competences. Two sequences of 10 questions are asked, the first (second) of which contains general (finance) questions. Participants provide the intervals within which they think the right answer is located with a 90% probability. For example, a general question is: "When was Alfred Nobel born?". No constraints were imposed on the length of the interval. The miscalibration score is measured by the number of wrong answers, being given that well-calibrated people should obtain 9 correct answers out of 10.

Participants then guess the number of answers that are contained in the intervals they provided (N_{myself}) and the average number of answers contained in the intervals provided by the other participants (N_{others}). The better-than-average score is the difference $N_{myself} - N_{others}$ (Alpert and Raiffa, 1982, Russo and Schoemaker, 1992).

Final questions investigate expectations about future stock prices. Graphs of three-year time series of the prices of five French stocks (Alcatel, BNP, Peugeot, Thalès and Sanofi-Aventis, from March 2008 to March 2011) are shown[6]. Respondents provide their one-year 90% confidence interval of stock prices as well as a median price forecast. They are then asked to scale their perceptions of the risks of the 5 stocks (from 0 to 10) and to propose a portfolio allocation (between one stock and a 3% risk-free asset). Finally, they evaluate the number of (real) prices that will eventually fall in the intervals they (or the other participants) provided at the horizon of the forecast.

The aforementioned ranges, built with three prices (low, median, high), allow us to estimate the subjective expected returns and volatility of the respondents[7]. We denote the expected return of stock *i*

[6] It is important to note that the scales of the graphs are chosen according to the rules of Lawrence and O'Connor (1993) (i.e. the last price is located in the middle of the graph and the time series covers about 40% of the chart area).
[7] Two starting prices were used to calculated returns. The first one is the end–of–March price appearing on the graph shown to respondents. The second one is the opening price of the day of the interviews (see internet appendix for the results related to the latter starting prices).

for participant j as $r_j^i(x)$, where $x=l$ (low), $x=m$ (median) or $x=h$ (high). Following Keefer and Bodily (1983)[8], we compute the expected subjective returns (denoted ESR_j^i) and the expected subjective volatility (ESV_j^i) of stock j by respondent i as follows[9]:

$$ESR_j^i = 0,63 \times r_j^i(m) + 0,185 \times \left(r_j^i(l) + r_j^i(h)\right)$$

$$ESV_j^i = ([0,185 \times r_j^i(l)^2 + 0,63 \times r_j^i(m)^2 + 0,185 \times r_j^i(h)^2] - [0,63 \times r_j^i(m) + 0,185 \times (r_j^i(l) + r_j^i(h))]^2)^{1/2}$$

Insert Table 1

Following Glaser, Langer and Weber (forthcoming), we use an overconfidence measure (denoted GLW in the following) based on the implicit probability mass associated to the two extreme prices proposed by respondents. If the probability distribution of returns is denoted R, following a distribution $L(a)$ where a is a vector of parameters, the overconfidence measure of individual i for stock j is defined as:

$$Overconfidence_i^j = 0.9 - P(R \in \left[r_i^j(l); r_i^j(h) \right])$$

Glaser *et al.* (forthcoming) use a perfectly known probability distribution of returns in their experiment. Of course, in our setting, the future probability distribution is unknown. Consequently, we assume a Gaussian distribution of returns with an expectation equal to the estimated expected return and a variance equal to the historical variance[10]. It is the reason why the above measure of overconfidence depends on i and j.

Finally, to capture the role of expectations (neutralized by the preceding parameter choice), we define *Optimism* as the difference between the Expected Subjective Return and the historical return.

2. Initial Results

[8] We also computed our variables with the initial volatility formulation of Pearson and Tukey (1965). The results are very close to the previous ones.
[9] The same methodology is used in Nosic and Weber (2010).
[10] There is in general some persistence in the rankings of volatility across stocks (see table 2 for the stocks considered in this study). No such persistence appears on expected returns.

2.1 Risk-taking behavior

Investing in one of the 5 stocks is perceived as being more risky than playing lottery A (average risk perception of 6.35 against 5.32). On average, participants allocate 34% of their wealth to the risky asset in the choice between stocks and the risk-free asset and 56% in the choice between lottery A and the risk-free asset. This result is not very surprising because the standard deviation of lottery A returns is 15%, the average historical volatility of stock returns is about 40% and the respondents' subjective volatility is 23%. Note however, that for lottery A, the volatility measure is objective because probabilities and outcomes are given, whereas for the stocks, we address expectations. Therefore, we cannot rule out that part of the difference in terms of risk-taking behavior comes from ambiguity aversion and the lack of trust that respondents have in their own expectations.

In lottery B, the certainty equivalent methodology allows us to indirectly evaluate attitudes towards risk. The median certainty equivalent of lottery B is 4,500€ and the median of the risk aversion parameter (power utility) is 0.87. It is worth mentioning that a few respondents are risk-seekers with a risk aversion parameter that is largely above 1.

2.2 Overconfidence

Our first overconfidence variable is the number of wrong answer to the 2 series of knowledge questions. Averages are 5.07 for general knowledge and 5.26 for financial knowledge; these results are far above what is expected from well-calibrated respondents (see Table 1). The cross-sectional correlation between the numbers of wrong answers is 0.5823. Together, these results indicate that respondents are overconfident with respect to their own knowledge. Our results are qualitatively similar to those obtained with students by Russo and Schoemaker (1992) or Nosic and Weber (2010)[11]. However respondents estimate their own expected number of correct answers largely below 9. It is consistent with Gigerenzer (1991) who says that there is no probabilistic justification to the average of 9 correct answers over 10 in a sequence of 10 "one-shot" questions. The right measure of

[11] Moreover, respondents tend to think that their number of correct answers is higher than what it really is. In general knowledge questions (financial), 40 (35) respondents out of 61 overestimate their own number of correct answers, whereas 10 (15) underestimate it and 11 (11) correctly estimate it.

overconfidence should compare the number of correct answers to the self assessment of this number. In our study the average difference is 1.36 for general questions and 1.01 for financial questions.

Calibration errors may arise from too narrow intervals or from the magnitude of the answers. We discriminate between these two explanations by studying the relation between the width of the given intervals and the number of correct answers. For each question *i* and each respondent *j*, we denote:

$$Relativerange_j^i = 2 \times \frac{Upperbound_j^i - Lowerbound_j^i}{Upperbound_j^i + Lowerbound_j^i}$$

Where *Relativerange* is the relative width of the interval defined such that the magnitude of answers is accounted for.

For each individual, the *RelativeRange* average over 10 questions is highly correlated with the number of correct answers (coefficient of 0.787). To illustrate this phenomenon, we present the histograms of the number of correct answers to general and financial knowledge questions and scatter plots of the number of correct answers versus the average individual range in Figure 2. As a conclusion, we observe that the participants with large calibration errors also propose narrow intervals. This result is a good illustration of overconfidence in personal knowledge.

The average GLW measure is equal to 38.8%, thus confirming that respondents provide too narrow intervals.

We compute the BTA (better than average) value for the two sets of questions. No significant BTA effect is found (BTA is always negative in Table 1). Though important individual differences exist (the standard deviations are 1.76 and 0.98), these differences are not sufficient to explain risk-taking behavior when overconfidence and optimism are taken into account. The following section gives more detailed results.

Insert Figure 2

3. Risk taking, risk perception and predictions

Modern financial theory, based on Markowitz's work and the CAPM, suggests that for a given level of risk aversion, the proportion invested in the risky asset is an increasing function of its expected return and a decreasing function of its volatility. In our questionnaire, each stock is presented in a chart. The distributions of past moments may affect the respondents' answers. Table 2 illustrates this point. Panel A (resp B and C) provides the first two moments over the full period of three years (resp. two and one year). Panels D presents the average forecasts revealed by the answers. Expected volatilities are much lower than historical ones. This is an initial indicator of a miscalibration in expectations, whatever the period and the asset. The ex-post realized volatility is also largely above respondents' volatility expectations.

Insert Table 2

Past realized moments are very different from one asset to another and the proportion invested in the risky asset depends on the asset proposed to the respondent. To measure the influence of behavioral biases on risk-taking behavior, we should account for the influence of optimism or pessimism. An "optimistic" individual would be more likely to forecast high returns for all securities and an "overconfident" investor would systematically forecast standard deviations that are too small. Table 3 presents the cross-sectional correlations between forecasts on returns and between forecasts on volatility. In Table 3, most correlations between expected returns are positive and significant (above the diagonal). This is even stronger for volatilities (below the diagonal) with a high degree of significance for all correlations. Therefore, forecasts of moments are more strongly related to individual characteristics than to assets characteristics. Do these individual characteristics influence risk taking?

Insert Table 3

Multivariate analysis

The preceding remarks suggest a more in-depth analysis of the relationship between proportions invested in stocks and their potential determinants in a multivariate setting. The regression equation we use for this purpose is written as:

$$Y = \beta_0 + \sum_{k=1}^{K} \beta_k X_k + \varepsilon$$

where K is the number of independent variables. There are two types of independent variables. Some variables are individual specific (for example risk aversion) and some others are individual and asset specific (for example the GLW overconfidence measure).

We present our results in Table 4. The dependent variable is the proportion of wealth invested in the risky assets. In models 1 to 6, there are four common independent variables: *Better Than Average* measured on the 20 knowledge questions, *Optimism, Risk Aversion*[12] *(Alpha)* and we control for respondents' *Experience* (in years). Models 1 to 6 differ first by the measure chosen for risk perception: risk perception of *Lottery A* declared by respondents or *PCA* which is indirectly estimated by the loadings on the first principal component of a PCA run on the risk perception scores of the 5 stocks. Models 1 to 6 also differ by the chosen overconfidence measure (*Miscalibration* over the two sets of questions or GLW measure) and by the use of *Expected Subjective Volatility* as an independent variable or not.

Insert Table 4

4. Discussion

Our results indicate that risk-taking is decreasing with respect to the two measures of risk perception and/or with respect to risk aversion[13], as well as respondents' experience. The measure of risk perception based on the PCA of risk perception scores for stocks is always significant. This result

[12]Alpha is derived from the assumption of a power utility function and calculated from the certainty equivalent of lottery B.

[13] The positive coefficient means that investment in the risky asset increases with alpha, which is consistent with the power utility function expressed as W^a

confirms the strong role played by the risk perception on stocks on the risk taking behavior like in Nosic and Weber (2010).

Turning to overconfidence measures, we find that the *GLW* overconfidence measure has a strong positive and significant impact on risk taking behavior. Moreover, the negative impact of *miscalibration* (based on knowledge questions) and the positive impact of *BTA* are never significant (consistent with results of Glaser and Weber, 2007). Controlling for risk aversion and individual specificity, the significant impact of the GLW measure confirms that respondents' underestimation of risk plays a crucial role in explaining risk-taking decisions.

Looking at expectations, we observe that *Optimism* enhances risk-taking whereas *Expected Subjective Volatility* has a negative impact on it. It is worth to recall that *Expected Subjective Returns* have a significant impact on risk-taking in all models via the *Optimism* variable. It is not the case for *Expected Subjective Volatility* as expected according to traditional finance theory. The first interpretation of this last result pertains to the interconnection between the forecasted volatility and the level of risk aversion because preferences and expectations are not independent. In our sample, the correlation between the direct level of risk aversion and the average subjective expected volatility (for the 5 stocks) is 0.298 (p = 1.96%).

The second interpretation for the lack of statistical significance of forecasted volatility is related to the low quality of the standard deviation as a measure of risk[14]. In the Internet Appendix, table A.2 gives the same results as table 4, except that the starting price used to calculate anticipated returns is the opening price on the day of the interview. This robustness check is necessary because we cannot exclude the fact that respondents closely follow the evolution of the stocks under consideration. In such a case, the respondent has in mind the current prices (at the time of the interview) and not the end-of-March prices appearing on the graphs shown to the respondents[15].

The results are globally unchanged, but the significance of the GLW measure is lower, compensated by the variable *Optimism* which is much more significant. As a robustness check, we also performed

[14] For example, Mitton and Vorkink (2007) or Barberis and Huang (2008) show that skewness is an important feature of the probability distribution of returns that influences portfolio decisions and risk perception.

[15] We thank an anonymous referee for suggesting this robustness check.

the same analysis in the spirit of Nosic and Weber (2010) who do not introduce risk aversion and risk perceptions in the same regression (table A.3). The results deteriorate a little bit even if the same basic variables like *Optimism,* risk aversion and the GLW measure are still significant.

Ex-Post Realizations vs. Ex-Ante Predictions

Following Ben-David *et al.* (2012), we calculated the performance of the respondents one year after the forecasts had been issued. Despite the fact that we only have 305 predictions (61 individuals times 5 stocks), our results are in line with those of Ben-David *et al.*, who benefit from a large sample of more than 13,000 predictions of S&P500 returns over a 10-year period. They find that only 36% of predictions lie in the 80% confidence interval provided by the CFOs participating in the survey. In our more modest sample, we find that 44.3% of predictions lie in the 90% confidence interval provided by the respondents. Our results are therefore quite comparable. A more careful examination of the results reveals that there are large differences between stocks. The percentages of "good answers" for the individual firms are 26.23%, 26.23%, 16.39%, 91.80% and 60.66%. Note that the five stocks (Alcatel, BNP, Peugeot, Thales and Sanofi-Aventis) are large firms in different industrial sectors. What is really meaningful in this result is that the best performance is obtained for stocks with low subjective expected volatility. Given that anticipated volatility comes from the 90% confidence index, this result seems surprising at a first glance. In fact, it is not because interviews were conducted by Morningstar employees, that is by people who are also viewed as finance professionals. To be consistent with the requested 90% interval, the respondents should have provided quite large intervals; however, as mentioned by Kahneman (2011, p262), "a wide confidence interval is a confession of ignorance, which is not socially acceptable for someone who is paid to be knowledgeable in financial matters."

Looking more closely at the stocks at hand reveals that the first three were highly volatile in recent years; however, it is difficult for any finance professional to say "Well, maybe BNP could be down 70% or up 50% next year".

Conclusion

Based on interviews of 64 high-level professionals, our results show that financial professionals are overconfident both in the general and financial domains. The errors made by the professionals are related to the amplitude of their confidence intervals, which reinforces our conclusion. Concerning risk perception and forecasted volatility, the results indicate the presence of intrinsic individual characteristics. Using the GLW measure allows us to show that risk perception and overconfidence strongly impact the risk-taking behavior of professionals. Finally, the stock return volatility anticipated by professionals in our sample is, in most cases, an insignificant determinant of the risk they are ready to take in buying stocks. This last result, which is contradictory to standard financial theory, questions the quality of the standard deviation as a measure of risk.

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