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Are Pension Fund Managers Overconfident?

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Empirical studies show that people tend to be overconfident about the precision of their knowledge, leading to miscalibration. Consistent with this, we found that on overage the decision makers of Swiss pension plans provide too narrow confidence intervals when asked to estimate past returns of various assets. Their confidence intervals are also very narrow in their forecasts of future returns. They are less miscalibrated, however, than our laypeople sample. Individual differences between the participants' degree of overconfidence are large and stable across those two different tasks. In a linear regression model we present evidence that the size of participants' confidence intervals is linked to individual characteristics. In our sample younger people with a degree from university and with more experience in finance provide larger intervals than older people without such an education and with less experience.

Keywords: Overconfidence, Forecasting, Miscalibration, Confidence Intervals, Pension Plans

INTRODUCTION

On average, people tend to be overconfident. In particular, it is well documented that people exhibit overconfident behavior in financial markets. The degree of overconfidence, however, seems to vary across individuals and across different domains of questions. In this paper our contribution to research is twofold. First, we investigate a special group, the decision-makers of Swiss pension plans who not only bear responsibility for their own investments but for the retirement savings of thousands of employees in Switzerland. Therefore an additional level of prudence from those participants could be expected. In contrast Odean [1998] outlines that possibly exactly those people who are overconfident in the domain of financial markets are those who are attracted by jobs that require financial decision making. We shed some light on this question by showing that decision makers of Swiss pension plans are overconfident but to a lesser degree than a sample of laypeople.

Second, we not only confirm the evidence for individual differences in the degree of overconfidence but also show that those differences are related to individual characteristics. In a linear regression model we measure the impact of individual characteristics on overconfidence and we present evidence that younger people with a degree from university and more experience in finance are significantly less overconfident than older participants with less education and less experience.

The remainder of the paper is organized as follows. The second section reviews related research on overconfidence in general and in the domain of financial markets. The third section describes the data and the methods to measure overconfidence and introduces our linear regression model. The fourth section presents the results for miscalibration in our sample and for our linear regression analysis. The fifth section discusses interpretations and practical implications of our results and concludes.

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RELATED RESEARCH ON OVERCONFIDENCE

Overconfidence is a complex phenomenon with various facets. Glaser and Weber [2003] differentiate between four different manifestations of overconfidence: miscalibration, better-than-average-effect, illusion of control and overoptimism. This paper concentrates only on i) miscalibration in the domain of estimating historical returns of financial assets and on ii) forecasting future returns.

People tend to overestimate the precision of their knowledge. As a result, they are miscalibrated in estimating and forecasting by providing too narrow confidence intervals (Lichtenstein, Fischhoff and Philips [1982]). It has been observed that task difficulty and blurred feedback lead to more overconfidence (Lichtenstein, Fischhoff and Philips [1982], Griffin and Tversky [1992]). Odean [1998] argues that forecasting and estimating returns on financial markets are not easy tasks and the available feedback is blurred as the market prices of assets are affected by noise. So the chances to observe overconfident behavior in the domain of financial markets are high.

Current psychological research debates whether miscalibration is a stable human trait or only a statistical illusion (see Gigerenzer, Hoffrage and Kleinbölting [1991], Griffin and Tversky [1992], Erev, Wallsten and Budescu [1994], Brenner, Liberman and Tversky [1996] and Klayman, Soll, Gonzales-Vallejo and Barlas [1999]). As Soll and Klayman [2004] point out the type of question matters and tasks which involve estimations of confidence intervals typically lead to higher measures for miscalibration. It is beyond the scope of this paper to analyze miscalibration in general and with respect to different types of measurement. We focus on the tasks of estimation and forecasting of asset returns, which are similar to tasks the decision makers of Swiss pension plans frequently face in their jobs and which might impact the wealth of Swiss pension plans.

Studies show that professionals in the financial industry are subject to miscalibration. Russo and Schoemaker [1992] report that money managers tend to formulate too narrow 90% confidence intervals in a questionnaire about meta-knowledge. Participants' subjective confidence intervals in their sample contain the correct solutions only in about half of the cases instead of 90% as required. Graham and Campbell [2003] analyze economic forecasts on the equity risk premium from CFOs in the United States over different time horizons and conclude that the size of the average confidence interval is narrow compared to the volatility of equity markets. Deaves, Lueders and Schroeder [2005] and Glaser, Weber and Langer [2003] present similar evidence in the domain of financial markets as the confidence intervals of the participants in their samples of professionals capture significantly less realized returns for economic forecasts than required. They also notice that the individual degree of overconfidence is stable across different tasks. This result indicates that people are in general overconfident in the domain of financial markets and not just within particular asset classes or particular tasks. It is also in line with the finding of Alpert and Raiffa [1982] who argue that people tend to respond similarly to the same types of questions.

Graham, Campbell and Huang [2006] and Glaser, Weber and Langer [2005] report the level of overconfidence in the domain of financial markets is different across individuals. There is no doubt that individual characteristics affect overconfidence but the evidence about stable relationships is ambiguous. Russo and Schoemaker [1992] report professionals are generally miscalibrated but to a lesser degree than laypeople. In contrast Glaser, Weber and Langer [2003] find that professionals are more overconfident than students about their trend recognition abilities although they do not provide more accurate estimations. In a model from Odean and Gervais [2001], more experience is related to a lower degree of overconfidence. Inexperienced but successful investors are most prone to overconfidence as they self-attribute their success solely to their abilities. Over time more experience will help them to better evaluate their true abilities. Locke and Mann [2001] confirm this theory empirically as they find no indication of miscalibration among highly experienced traders on the Chicago Mercantile Exchange. In light of those results we analyze if individual characteristics such as education or experience increase overconfidence in the domain of financial markets.

Being overconfident can be harmful on financial markets. In a large sample of private investors Odean and Barber [2001] show that overconfidence leads to a higher trading volume and reduces portfolio returns. Guiso and Jappelli [2005] use a sample of Italian bank clients in which the clients, whom the authors suppose to be more overconfident (people with a lower education but a higher self declared knowledge), hold portfolios with lower Sharpe ratios than other clients. However, it is beyond the scope of this paper to evaluate the portfolios and the trading activities of Swiss ension plans and we do not postulate any causal relationships between the degree of overconfidence of our participants and the investments of the corresponding pension plans.[1]

DATA AND METHODS

A total of 584 questionnaires were distributed among decision makers of Swiss pension plans, that is, managers and members of investment committees, and 132 were returned. We refer to it as the professional sample. This corresponds to a response rate of 22.6%. 24 questionnaires contained no confidence intervals and therefore have been excluded from the analysis so the professional sample consists of 108 participants (only 6 participants are female). Fifty-eight persons have a university degree, 36 of them in finance; 65 attended education courses in finance for practitioners. Experience in finance and in pension plans is symmetrically distributed between less than 2 years and more than 25 years, and the respondents are between 25 and 80 years old. A laypeople sample is based on people working for the City of Zurich in several departments not related to financial markets or pension plans but with a self-declared interest in financial topics. In total 104 persons, 19 woman and 85 men, returned a complete questionnaire so the sample size of the laypeople sample is 104 persons (22 questionnaires were incomplete). Of those, 25 have a degree from university but only 16 in finance or economics; 32 have attended courses in finance for practitioners. Two-thirds have no experience in working in financial areas but two-thirds do frequently read newspapers related to financial topics. The participants in the laypeople sample are between 20 and 65 years old.

The questionnaire for the participants in both the professional and laypeople sample consists of two parts. In the first part the respondents provided data about individual characteristics. In the second part the participants were asked to formulate two sorts of 90% confidence intervals.[2] First, 90% confidence intervals for historical annual returns for 6 different asset classes over the last 36 years to estimate the participant's degree of miscalibration. Those questions have been worded the following way: "*In this task you have to provide an upper and a lower boundary for the annual returns of asset class x over the last 36 years. Please choose the boundaries in such a way that 90% of the realized single annual returns of asset class x are within your boundaries.*" Second, 90% confidence intervals for return forecasts for 6 different asset classes for the year 2006 to qualitatively assess how confident the participants are about their forecasting abilities given their confidence intervals. The following wording is used: *"In this task you have to provide an upper and a lower boundary for the return of asset class x in the year 2006. Please choose the boundaries in such a way that the realized return of asset class x in 2006 will be within your boundaries with a probability of 90%."*

The period for returning the questionnaire was May 2006 until the beginning of August 2006. The returns of the different asset classes were volatile over that time period, so the 90% confidence intervals may have been affected. A t-test reveals, however, that there are no differences between the means for 90% confidence intervals from people who handed in their questionnaires before or after mid-June 2006, so there is no need to split our samples.

In this paper we use two different methods to judge the participant's confidence intervals. First, following an idea of Hilton [2001], we compare the participants' subjective confidence intervals for annual returns with the distribution of historical annual returns over the last 36 years. We count the number of annual returns over the last 36 years that are included within the participants' 90% confidence intervals. For each asset class we collected the last 36 realized historical annual returns and we simply cut off the 2 highest and lowest returns to approximate a 90% (precisely 88.9%) interval of the annual returns in each asset class. In other words, 90% of the annual returns over the last 36 years are included in those intervals, and this corresponds to 32 annual returns. A miscalibrated participant will provide too narrow 90% confidence intervals and thus captures less than 32 annual returns of the last 36 annual returns.

Second, we analyze the implied volatility of the participants' confidence intervals where we make use of a relationship that Pearson and Tukey [1965] describe. With the term implied volatility we refer to a relationship between the 95% and 5% return quantile (which corresponds to a 90% interval) and the standard deviation as is given in equation (1).

$$\text{Standard deviation} = (95\%\ \text{return quantile} - 5\%\ \text{return quantile})/3.25 \quad (1)$$

Like in the first approach we then compare the participants' answers with historical data, that is, the participants' implied volatilities in their confidence intervals with the historically implied volatility of each asset class based on the annual returns over the last 36 years. Volatility is a popular way to express uncertainty about future returns of an asset class and the higher the volatility the broader is the spectrum in which the realization of the future return will fall with a certain probability. If a participant formulates confidence intervals with very low implied volatilities we interpret this as an indication that he is miscalibrated. The historically implied volatility of the annual returns therefore serves as a guideline to judge the size of the implied volatilities.

We do not apply those two methods to measure miscalibration in the forecasting task because an ex-post comparison between a subject's forecast interval for the return of an asset class in the year 2006 and the accuracy of his answer might be biased and unreliable. The reason is that the measurement is heavily dependent on the future outcome, that is, the realized return in 2006. The annual return in 2006 represents only one single observation, which is not necessarily representative for the participant's true level of overconfidence. Returns close to the historical mean will lead to the conclusion that few participants are miscalibrated whereas extremely positive or negative returns would probably fall out of almost everybody's confidence intervals. Nevertheless forecast intervals provide information about how participants evaluate their own abilities to forecast future returns on financial markets and narrow confidence intervals reflect a high conviction.

To analyze the relationships between confidence interval sizes and individual characteristics we use a linear regression model with 4 predictors. We differentiate between 3 sorts of education: a degree from university, practical financial education, and no such education, resulting in 2 dummy variables. We further apply a predictor for experience – an aggregation of experience in finance and in pension plans – and age. Some of those 4 predictors are positively correlated but never above a level of 0.6. Gender is not included in the regression model as the number of females is too low.

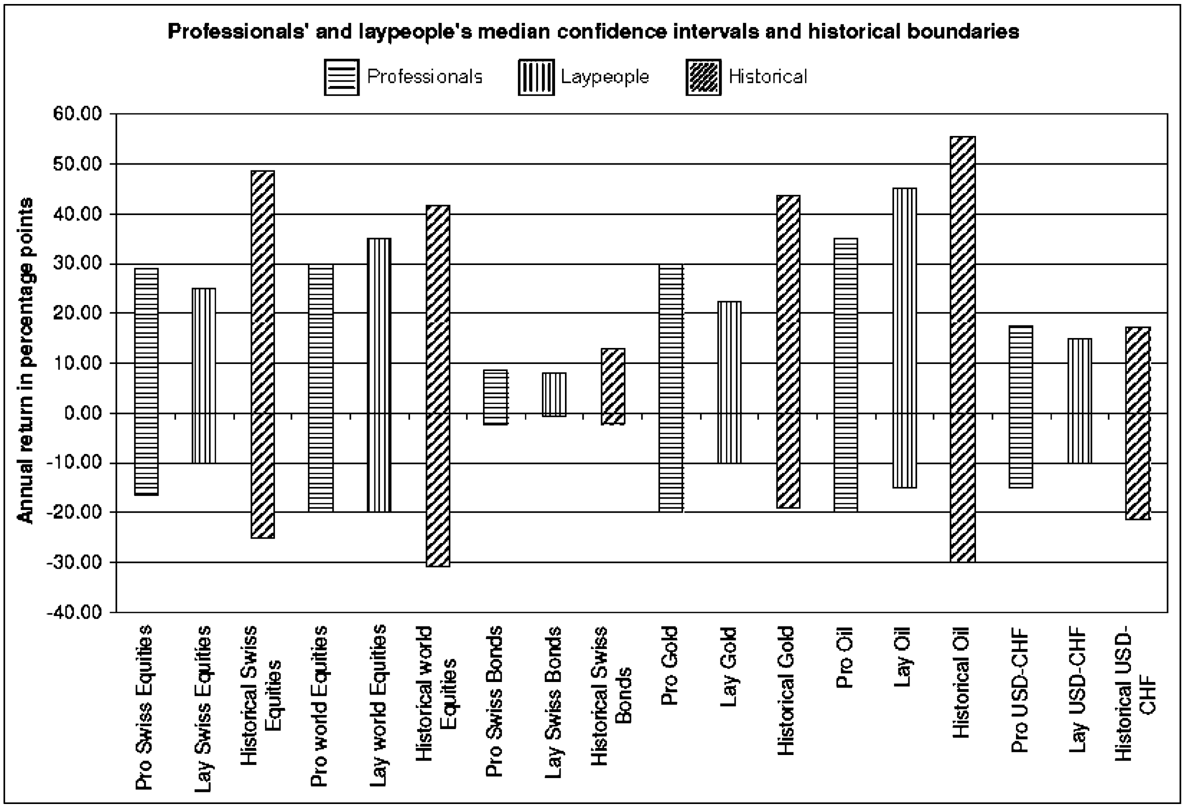

FIGURE 1 Confidence Intervals for Historical Returns. Figure 1 shows the median lower and the median upper boundaries for the confidence intervals in the professional and the laypeople sample for historical return estimates of 6 different asset classes as well as the upper and lower boundaries of the realized return of those asset classes over the last 36 years.

In the analysis of confidence intervals across all participants we present median values as there are a few outliers that have big impacts on the mean. In the application of the linear regressions analysis we use the logarithm of the confidence intervals and the corresponding boundaries to mitigate such outlier effects. However, the results do not substantially change if we analyze the non-transformed data. To aggregate confidence intervals of different asset classes we normalize the data by calculating the z scores of the participants log intervals. We report R^2 to provide information about the amount of variance our regressions explain. No significant interaction effects have been identified within the variables for our regression model so we do not include interaction variables. Cooks Distance values (Cooks D) indicate no significant effects of outliers.

RESULTS

Estimation of Historical Returns

The median 90% confidence intervals of professionals only capture around 60–80% of the past annual returns in each asset class.[3] This is evidence that professionals in our sample are miscalibrated in the median because their confidence intervals were meant to contain 90% of the annual returns over the last 36 years. The laypeople sample provides even narrower boundaries for almost all asset classes so laypeople are more miscalibrated than professionals. A Mann-Whitney test however reveals that the differences between the confidence interval sizes are not significant except for 2 asset classes. The bars in Figure 1 show the median lower and the median upper boundaries for the confidence intervals in the professional and the laypeople sample for historical return estimates in 6 different asset classes. Those are Swiss and world equities, CHF bonds, gold, oil and the CHF-USD exchange rate. The bars with the diagonal lines represent the distribution of 90% of all annual returns over the last 36 years for those 6 asset classes and serve as a guideline to judge the size of the participants' confidence intervals. It can be seen that in the median the professionals and the laypeople underestimate the downside risk but also the upside potential in almost all asset classes. That explains why medians for 90% confidence intervals from both samples are narrower than the historical 90% intervals for annual returns over the last 36 years.[4]

Further indication for miscalibration is given by a comparison of the implied volatilities embedded in the confidence intervals and the implied volatility of historical returns. Table 1 shows the implied volatilities of the confidence intervals from the professionals and the laypeople respectively for historical returns for each asset class. We see that the implied

TABLE 1
Implied Volatilities of Confidence Intervals.

Asset class	Swiss equities	World equities	CHF bonds	Gold	Oil	USD-CHF
Implied volatility professionals	13.08%***	15.38%***	3.23%***	15.85%	18.46%	9.23%
Implied volatility laypeople	12.31%***	15.18%***	2.77%***	10.77%	15.38%	7.69%
Historically implied volatilily	22.62%	22.30%	4.62%	19.26%	26.22%	11.84%
Ratio of professionals' implied volatility vs. historically implied volatility	0.58	0.69	0.70	0.82	0.70	0.78
Ratio of laypeople's implied volatility vs. historically implied volatility	0.54	0.69	0.60	0.56	0.59	0.65

Table 1 shows the implied volatilities of the confidence intervals from the professionals and the laypeople respectively for historical returns for each asset class. It also contains the historically implied volatility in each asset class over the last 36 years and the ratio of the participants' implied volatilities and historically implied volatilities. The stars indicate if the differences between implied volatilities from participants' confidence intervals are significantly different than the historically implied intervals in each asset class.
*significant at 10% level.
**significant at 5% level.
***significant at 1% level.

volatilities in both samples are lower than the historically implied volatilities in all asset classes and the difference is highly significant for equities and bonds. Another evidence for miscalibration is given by the fact that more than 70% of the professionals and 75% of the laypeople provide 90% confidence intervals which are narrower than the historical intervals on each asset class.

An unexpected but interesting result is the fact that the professionals as well as the laypeople have a good feeling for the relative risk of each asset class. The ratios between the historical intervals and the subjective confidence intervals are close to 0.7 and 0.6 respectively in all asset classes as the last two lines in Table 1 show. Those ratios are calculated by dividing the historically implied volatility by the median implied volatility of the participants' confidence intervals. So both the professional and the laypeople sample are well informed about the relative risk of each asset class or in other words are equally miscalibrated across the historical returns of different asset classes.

Return Forecasts

Now we turn to the participants 90% confidence intervals for return forecasts for the year 2006. We asked for return forecasts in Swiss equities, CHF bonds, the participants' own pension plan, and the average Swiss pension plan. The implied volatilities of our professional sample for Swiss equities (3.1%), CHF bonds (1.2%) and the two types of pension plan returns (1.5% for each forecast) are difficult to compare to reasonable benchmarks but we have the impression that those confidence intervals are very narrow relative to the historically implied volatilities in Table 1. So the

TABLE 2
Linear Regression Models on Confidence Interval Sizes.

Dependent variables	Professionals' aggregated forecast interval size	Laypeople's aggregated forecast interval size	Professionals' aggregated historical interval size	Laypeople's aggregated historical interval size
Predictors	Standardized Beta Coefficients and T values for 90% confidence interval sizes			
University Degree	0.344	0.316	0.432	0.125
	2.600**	3.427***	2.641**	0.741
Practical finance education	0.160	0.050	0.235	−0.057
	1.210	0.530	1.460	−0.324
Experience	0.209	0.143	0.360	−0.028
	1.953*	1.401	2.845***	−0.142
Age	−0.226	−0.334	−0.465	−0.077
	−2.111***	−3.360***	−3.641***	−0.418
R-square	0.139	0.190	0.329	0.031
F	3.234**	5.642***	5.754***	0.285

Table 2 shows the standardized Beta and T values of the predictors in our linear regression models for professionals' and laypeople's forecasts and historical estimations as well as R^2 and F values for the our 4 different linear regression models.
*significant at 10% level.
**significant at 5% level.
***significant at 1% level.

participants in our sample express a high conviction about their own forecasting abilities because they choose very narrow upper and lower boundaries in their forecasting intervals.[5] Similar to the estimation of historical returns laypeople provide narrower confidence intervals than professionals but in the forecasting task Mann-Whitney tests confirm that the confidence interval sizes are significantly different. So the professionals express less confidence into their own forecast abilities than the laypeople and on average they share a more conservative view with respect to downside risk but expect a comparable upside potential.

In line with the observation of Alpert and Raiffa [1982], the participants in both samples express stable answering patterns when providing 90% confidence intervals for different asset classes. The correlation in the professional sample (laypeople sample) for forecast intervals ranges from 0.72 to 0.92 (0.47 to 0.89) and for the historical intervals the range lies between 0.33 and 0.92 (0.44 and 0.77). Even the correlations between forecasts intervals and historical intervals are always positively correlated with an average of 0.32 (0.18). Providing narrow confidence intervals seems to be a stable trait across individuals regardless of the asset class and the type of estimation.

We can summarize our results so far by saying that the decision-makers of Swiss pension plans as well as a sample of laypeople are miscalibrated when estimating historical returns on financial markets. They also express a high conviction in their forecasting abilities as they provide very narrow confidence intervals for future returns but the effect among professionals is less extreme than across laypeople and professionals have more conservative expectations. Furthermore the participants in both samples are roughly equally miscalibrated across all asset classes and express stable confidence interval patterns when forecasting returns on financial markets. The next section addresses the relationships between individual characteristics and the degree of miscalibration with a linear regression model.

Linear Regressions

Across all asset classes in both tasks not only correlations but also Cronbach Alphas are very high. For the professionals (laypeople) forecast intervals they are at 0.88 (0.86) and for the historical intervals at 0.84 (0.84). That allows for an aggregation of the confidence intervals of the different asset classes in each task to define the dependent variables in our linear regression models.[6] The dependent variables are the normalized log values of the participants' 90% confidence intervals for forecasts and historical returns divided into professional and laypeople samples. The first two predictors are mutually exclusive dummy variables for the different types of education, that is, holding a degree from university or attendance of practical financial education. Participants with both a university degree and a practical finance education were considered as people with university degree to mitigate double counting. The third predictor reflects a participants' experience in finance or pension plans and can take values from 1 (no experience) to 7 (more than 25 years of experience). The last predictor can also take values from 1 (below 25 years) to 7 (above 65 years) and reflects the range of a participants' age. The last two rows contain the R^2 of the regression models for each type of confidence interval as well as its F-value.

Our regression model works well for the professional sample with a R^2 of 13.9% for the forecast intervals and 32.9% for the historical intervals. It also explains 19% of the variation in the confidence intervals for laypeople's forecasts but it fails to relate our predictors to the 90% confidence intervals for historical returns in the laypeople sample. Having a degree from university is significantly related to broader confidence intervals in all asset classes. In contrast practical financial education is not significantly related to the interval sizes. In line with the model from Odean and Gervais [2001] the variable for experience tends to reduce overconfidence as professionals with more financial or pension plan experience provide significantly broader confidence intervals. Age is related to narrower confidence intervals as older people provide significantly narrower confidence intervals.

To summarize, our regression analysis indicates that older people without a degree from a university and with little experience in finance or pension plans provide significantly narrower confidence intervals for returns on financial markets than younger people with a degree from university and more experience.

CONCLUSION

We confirm that people are overconfident in the domain of financial markets but provide new evidence that this is also the case in a sample of decision-makers of Swiss pension plans. So we want to emphasize two practical issues related to overconfidence in the domain of financial markets that might apply to several pension plans and other investors.

First, an overconfidently biased perception of low risks in a volatile asset class like for example equities could increase its perceived attractiveness. This might then result in an overweight of that asset class and exposes a pension plan's portfolio more to downside risks but the overconfident decision-makers might be unaware of that risk. De Long, Shleifer, Summers and Waldman [1990] present a theoretical model to demonstrate that noise traders with erroneous stochastic beliefs (like for example miscalibrated investors) take excessive risk and gain less expected utility than rational investors. Having said that we point out that the participants in our sample provided too narrow confidence intervals for all asset classes and not only for more volatile ones so we cannot generalize the argument that high risk assets are overweighted. Further research is needed to address the relationship between overconfidence and the weighting of risky asset in a strategic asset allocation.

The second issue is related to present findings of other authors who demonstrate that overconfidence influences trading decisions of investors. In those studies overconfidence is a drag on performance either because of higher transaction costs due to an increased trading volume (Odean [1999]) or because investors misperceive the true probabilities of market situations and over- or underreact (Daniel, Hirshleifer and Subrahmanyam [1998]). Tactical trading always generates additional transaction costs that have to be compensated by higher returns but so far academic research rejects the thesis that tactical trading, often referred to as timing, pays off in general. Daniel, Grinblatt, Titman and Wermers [1997] report no systematic timing success for mutual funds and Blake, Lehman and Timmermann [1999] report that UK pension plans have on average no timing skills.

To put our results into perspective Yaniv and Foster [1997] argue that there is a trade-off between accuracy and informativeness when providing confidence intervals. Narrow confidence intervals usually provide more information than large but accurate intervals. We can not rule out that the participants in both of our samples want to provide very informative confidence intervals, especially in the forecasting task, knowing that those might not be totally accurate. We also take in to account that we can not relate the answers of our professionals to the investments of a particular pension plan because we asked all participants to express their personal views in our questionnaire and not the views of their pension plans.

More in depth research is needed to model the relationship between individual characteristics and overconfidence but one straightforward thesis to explain why people tend not to be homogenously miscalibrated is the effect of perceived task difficulty. Task difficulty can not be measured in our questionnaire on an absolute basis. But it might be the case that older people with less education and less experience find it more difficult to come up with appropriate confidence intervals for asset returns on financial markets than younger people with a better education and more financial experience. According to Lichtenstein, Fischhoff and Philips [1982] a higher level of task difficulty is linked to a higher level of miscalibration and this is in line with our observations. However, the unexplained variance in our model indicates that other factors are necessary to explain individual differences in miscalibration in the domain of financial markets, which needs further exploration.

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NOTES

1. Menkhoff and Schmidt [2005] address how overconfidence might be related to investment strategies of mutual fund managers.
2. A full version of the questionnaire -either in German or in French - can be obtained from the first author of this paper.
3. In the analysis of confidence intervals for historical returns we only include participants who provided negative lower boundaries in the confidence intervals for the asset class world equities. The reason is to not bias the study with respondents who might have misunderstood the question (i.e. provided a 90% confidence interval for the annualized mean return over the whole 36 years instead of a 90% confidence interval for all annual returns in that period). In total 56 participants from the professional sample are included. If we included the confidence intervals from all the participants, miscalibration would appear to be much higher but arguably may be spurious. In the analysis of confidence intervals for return forecasts we include all participants.
4. We acknowledge that an analysis of only the size of the participants’ confidence intervals does not provide any information about the accuracy, that is, how much the lower and upper boundaries of a subjective confidence interval deviate from the historical intervals. Mann-Whitney tests show that the professional sample provides significantly more accurate boundaries for every asset class than the laypeople.
5. We acknowledge that the participants provided their answers between May 2006 and August 2006 and it might be the case that they already used the available information for the year 2006. But even then the upper and lower boundaries are on average very close to each other.
6. All linear regressions with single asset classes as dependent variables are available on request.

REFERENCES

Alpert, M. and H. Raiffa. “A Progress Report on the Training of Probability Assessors.” In P. Slovic (Ed), *Judgement Under Uncertainty: Heuristics and Biases*. New York: Cambridge University Press, 1982.

Blake, D., B. Lehman and A. Timmermann. “Asset Allocation Dynamics and Pension Fund Performance.” *The Journal of Business,* 72, (1999), pp. 429–461.

Brenner, L., V. Liberman and A. Tversky. “Overconfidence in Probability and Frequency Judgements: A Critical Examination.” *Organizational Behaviour and Human Decision Processes,* 65, (1996), pp. 212–219.

Daniel, K., M. Grinblatt, S. Titman and R. Wermers. “Measuring Mutual Fund Performance with Characteristic Benchmarks.” *Journal of Finance,* 52, (1997).

Daniel, K., D. Hirshleifer and A. Subrahmanyam. “Investor Psychology and Security Market Under- and Overreaction.” *Journal of Finance,* 53, (1998), pp. 1839–1885.

De Long, B., A. Shleifer, L. Summers and R. Waldman. “Noise Trader Risk in Financial Markets.” *Journal of Political Economy,* (1990), pp. 703-738.

Deaves, R., E. Lueders and M. Schroeder. “The dynamics of overconfidence: Evidence from stock market forecasters.” ZEW Discussion Paper No. 05-83, 2005.

Erev, I., T. Wallsten and D. Budescu. “Simultaneous Over- and Underconfidence: The Role of Error in Judgment Process.” *Psychological Review,* 101, (1994), pp. 519–527.

Gigerenzer, G., U. Hoffrage and H. Kleinböltin. “Probabilistic Mental Models. A Brunswikia Theory of Confidence.” *Psychological Review,* 98, (1991), pp. 506–528.

Glaser, M. and M. Weber. “Overconfidence and Trading Volume.” *Geneva Risk Insurance Review*, 32, (2007), pp. 1–36.

Glaser, M., T. Langer, and M. Weber. “On the Trend Recognition and Forcasting Ability of Professional Traders” *Decision Analysis,* 4, (2007), pp. 176–193.

Glaser, M. and M. Weber. “Overconfidence and trading volume.” *Geneva Risk Insurance Review,* 32, (2007), pp. 1–36.

Graham, J. and H. Campbell. “Expectations of Equity Risk Premia, Volatility and Asymmetry.” Working Paper, 2003.

Graham, J., H. Campbell and H. Huang. “Investor Competence, Trading Frequency and Home Bias.” NBER Working Paper, W11426, 2006.

Griffin, D. and A. Tversky. “The Weighing of Evidence and the Determinants of Confidence.” *Cognitive Psychology,* 24, (1992), pp. 411–435.

Guiso, L. and T. Jappelli. “Information Acquisition, Overconfidence and Portfolio Performance.” CEPR Discussion Paper, 5901, 2005.

Hilton, D. “The Psychology of Financial Decision-Making: Applications to Trading, Dealing and Investment Analysis.” *The Journal of Psychology and Financial Markets*, 2, (2001), pp. 37–53.

Klayman, J., J. Soll, C. Gonzales-Vallejo and S. Barlas. “Overconfidence: It Depends on How, What and Whom You Ask.” *Organizational Behaviour and Human Decision Processes,* 79, (1999), pp. 216–247.

Lichtenstein, S., B. Fischhoff and L. Philips. “Calibration of Probabilities.” In D. Slovic (Ed.), *Judgement Under Uncertainty: Heuristics and Biases*. Cambridge, MA: Cambridge University Press, 1982.

Locke, P. and S. Mann. “House Money and Overconfidence on the Trading Floor.” *AFA 2002 Atlanta Meetings*, 2001.

Menkhoff, L. and U. Schmidt. “The Use of Trading Strategies by Fund Managers: Some First Survey Evidence.” *Discussion Paper*, 314, 2005.

Odean, T. “Volume, Volatility, Price and Profit When all Traders are above Average.” *The Journal of Finance,* 53, (1998), pp. 1887–1934.

Odean, T. “Do Investors Trade Too Much.” *The American Economic Review,* 89, (1999), pp. 1279–1298.

Odean, T. and B. Barber. “Boys Will be Boys: Gender, Overconfidence and Common Stock Investment.” *The Quarterly Journal of Economics*, 116, (2001), pp. 261–292.

Odean, T. and S. Gervais. “Learning to be Overconfident.” *The Review of Financial Studies,* 14, (2001), pp. 1–27.

Pearson, E. and J. Tukey. “Approximate Means and Standard Deviations Based on Distances Between Percentage Points and Frequency Curves.” *Biometrika,* 52, (1965), pp. 533–546.

Russo, E. and P. Schoemaker. “Managing Overconfidence.” *Sloan Management Review,* 33, (1992), pp. 7–17.

Soll, J. and J. Klayman. “Overconfidence in Interval Estimates.” *Journal of Experimental Psychology,* 30, (2004), pp. 299–314.

Yaniv, I. and D. Foster, D. “Precision and Accuracy in Judgmental Estimation.” *Journal of Behavioral Decision Making,* 10, (1997), pp. 21–32.