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Gort, C; Wang, M; Siegrist, M

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Originally published at:
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Are Pension Fund Managers Overconfident?

Christoph Gort
Pension Fund City of Zurich, Strassburgstrasse 9, 8026 Zurich, Switzerland. Email: christoph.gort@pkzh.ch
Phone: +41 44 412 5261.

Mei Wang
Swiss Banking Institute, University of Zurich, Plattenstrasse 32, 8032 Zürich, Switzerland. Email: wang@isb.unizh.ch
Phone: +41 44 634 3764

Michael Siegrist
ETH Zurich, Institute for Environmental Decisions (IED), Consumer Behavior
Universitätsstrasse 22, CHN J75.1, CH-8092 Zurich, Switzerland
E-mail: msiegrist@ethz.ch Phone: +41 44 632 6321
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Abstract
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 average the decision makers of Swiss pension plans provide too narrow confidence intervals when asked to estimate the past return of various assets. Their confidence intervals are also systematically too narrow in their forecast of future returns, in comparison with the historical volatility. They are less miscalibrated, however, than our laymen 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 miscalibration is linked to individual characteristics. In our sample younger people with an education from university and with more experience in finance or pension plans are less overconfident than older people without such an education and with less experience.

Key words: Overconfidence, Forecasting, Miscalibration, Confidence Intervals, Pension Plans
1. Introduction

On average people tend to be overconfident. In particular, it is well documented that people exhibit overconfident behaviour 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.¹ So overconfidence might affect not only our participants’ private wealth but also the wealth of every employee in a particular pension scheme. Therefore an additional level of prudence from our participants could be expected. On the other hand, Odean [1998] outlines that possibly exactly those people who are overconfident about their abilities in the domain of financial markets are those who are especially 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 laymen.

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 - education, experience, and age - on overconfidence in the domain of financial markets. We present empirical evidence that younger people with a better education and more experience in financial topics are significantly less overconfident than older participants with less education and less experience. This may help us to gain more insight about the impacts of individual background on overconfidence, and to further develop more accurate models to capture the underlying mechanisms that drive overconfidence. From a practical point of view, this may help us to better assess the qualifications of financial decision-makers in certain positions and to predict better their investment decisions.

¹ A study of the Swiss National Bank SNB [2006] reveals that in 2004 roughly half of all the employee’s wealth in Switzerland, around CHF 500 billion, is managed in the second pillar, i.e. in the hands of decision-makers of Swiss pension plans.
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 clients of an Italian bank in which the people, - who 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 pension 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.²

The remainder of the paper is organized as follows. Section II reviews related research on overconfidence in general and in the domain of financial markets. Section III describes the data, and the methods to measure overconfidence and introduces our linear regression model to measure the relationship between overconfidence and individual characteristics. Section IV presents the results for miscalibration in our sample and for our linear regression analysis. Section V discusses interpretations and practical implications of our results and concludes.

2. Related research on overconfidence

Overconfidence is a complex phenomenon with various facets. For example, Glaser and Weber [2003] differentiate between four different manifestations of overconfidence: miscalibration, better-than-average-effect, illusion of control and overoptimism. We concentrate only on miscalibration in the context of estimating past performance and forecasting future returns of financial assets, because it reflects how people perceive the underlying risk of financial products, which is crucial to investment decisions.

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

² For an approach about how overconfidence is related to investment strategies of fund managers see Menkhoff and Schmidt [2005]
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 behaviour in the domain of financial markets are relatively 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 task 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 financial professionals 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. The participants’ subjective confidence intervals in their sample contain the correct solutions only in roughly half of the cases instead of 90% as required. 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. Graham and Campbell [2003] analyze economic forecasts on the equity risk premium from CFOs in the USA over different time horizons and conclude that the size of the average confidence interval is very narrow compared to the volatility of equity markets. This is no direct observation for miscalibration because they undertake no ex post...
comparison between a subject’s confidence interval and the accuracy of his answers. Nevertheless we interpret this information as an indirect indication of miscalibration because the participants express a surprisingly high confidence about their abilities to forecast returns on financial markets. There is no doubt that individual characteristics affect overconfidence but the evidence about the relationship between those individual characteristics of a person and its degree of overconfidence is ambiguous. Russo and Schoemaker [1992] report evidence that professionals in their sample are in general miscalibrated but to a lesser degree than laymen. In contrast Glaser, Weber and Langer [2003] find that professionals are more overconfident than a sample of students about their trend recognition abilities although they do not provide more accurate estimations. Graham, Campbell and Huang [2006] and Glaser, Weber and Langer [2005] present evidence that the degree of overconfidence in the domain of financial markets is different among individuals. In a model from Odean and Gervais [2001] more experience is related to a smaller 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 (CME). Heath and Tversky [1991] show that people prefer to bet on their own judgment if they feel comfortable in a domain than on chance-matched lottery and vice-versa. In light of those results the question is if individual characteristics such as education or experience increase overconfidence in the domain of financial markets.

3. Data and Methods

3.1 Respondents and questionnaire

In total 584 questionnaires have been distributed among decision-makers of Swiss pension plans - we refer to this sample as the professional sample - and 132 have been returned. This corresponds to a response rate of 22.6%. Twenty-four questionnaires contained no confidence intervals and therefore have been excluded from the analysis so the professional sample consists of 108 partici-
pants (Only 6 participants are female). 58 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 laymen 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. 25 of them have a degree from university but only 16 in finance or economics and 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 laymen sample are between 20 and 65 years old.

The questionnaire for the participants in both the professional and laymen sample consists of two parts.\(^3\) 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. First, 90% confidence intervals for historical annual returns for 6 different asset classes over the last 36 years. Second, 90% confidence intervals for return forecasts for 6 different asset classes for the year 2006. This allows us to estimate the participant’s degree of miscalibration in two distinct aspects of financial markets and to analyze whether there are any differences between those two tasks. In the analysis of confidence intervals for return forecasts we include all participants whereas in the analysis of confidence intervals for historical returns we only include those from 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 profes-

\(^3\) The questionnaire contained also other parts but those are not relevant for this paper.
sional 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.

The period for handing in the questionnaire was from May 2006 until August 2006. As the returns of the different asset classes were volatile over that time period it might be the case that the 90% confidence intervals were 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 of June 2006. In the laymen sample the questionnaires were all handed in within the end of May and the end of June 2006.

3.2 Methods

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. The focus on confidence interval sizes allows us to analyze the risks the participants perceive in different asset classes since overconfidence may lead to a wrong perception of risks on financial markets.

More concretely 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 may 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).
Standard deviation = (95% return quantile – 5% return quantile) / 3.25  \hspace{1cm} (1)

Like in the first approach we then compare the participants’ answers with historical data, i.e. the participants’ implied volatilities in their confidence intervals with the historical annual 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 overconfident. The historical volatility of annual returns over the last 36 years therefore serves as a guideline to judge the size of the implied volatilities.

We acknowledge one caveat in the approaches in this paper as an estimation error due to the comparison of confidence intervals with historical annual returns could arise. By definition we only have 36 observations for annual returns over the last 36 years and in total we cut off 4 annual returns in each asset class to approach a 90% interval. So the measurement of miscalibration with a comparison between the size of historical return intervals and subjective confidence intervals depends on the highest and lowest historical annual returns. The difference between the highest and the lowest annual return that are included in our 90% interval and those 4 annual returns that are excluded could matter. However we notice that our results are not materially influenced by changes of the historical return intervals that we use to construct historical intervals and that the volatilities of annual returns in different asset classes are realistic.\(^4\)

To analyze the relationships between overconfidence and individual characteristics we use a linear regression model with 6 predictors. We differentiate between 4 mutually exclusive sorts of education: non-finance education from university, finance education from university, education in finance from courses for practitioners, and no such education, resulting in 3 dummy variables. In case a person has both a degree from university and an additional education in finance for practitioners we

\(^4\) The reason is that the differences between subjective confidence intervals and historical annual returns are much larger than the differences between included and excluded historical annual returns. The largest difference between an included and an excluded return occurs in the USD-CHF exchange rate with 8.9% and the average difference is 3.9%.
only considered the university degree to mitigate double counting. We further use two types of experience – experience in finance and experience in pension plans – and age as predictors which can take values from 1 to 7 reflecting more or less experience and a lower or higher age respectively. Some of those 6 predictors are positively correlated but never above a level of 0.6. The only exception is the highly negative correlation between the 2 different variables for financial education. As those variables are both dummies we expect them not to distort the regression model. Gender is not included in the regression model as the number of females in the professional sample is too low.

To analyze 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. 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 D values indicate no significant effects of outliers.

4. Results

4.1 Estimation of historical returns

The first row in Table 1 shows that, except for CHF bonds and gold, the median lower boundaries of 90% intervals estimated by the professional sample are above the historical lower boundaries (seventh row). On the other hand the median estimated upper boundaries are below the historical upper boundaries for all asset classes except for the USD-CHF exchange rate. In other words, on average the professional sample underestimates both the downside risk and the upside potential. Not surprisingly the medians for 90% confidence intervals from the professional sample (second row of Table 1) are narrower than the historical 90% intervals for annual returns over the last 36

\(^5\) Both predictors for experience can take 7 different values which range from 1 (no experience) to 7 (more than 25 years experience). Age can also take values from 1 (below 25 years) to 7 (above 65 years).
years in all asset classes. The laymen sample provides even narrower boundaries and intervals for all asset classes which is a sign of a higher degree of miscalibration. (Insert Table 1 here)

The median subjective 90% confidence intervals only capture around 60%~80% of the past annual returns in the professional sample and around 50%~70% in the laymen sample (oil is the exception) as can be seen in the tenth and eleventh row of Table 1. This is evidence that both samples are miscalibrated on average because the participants’ confidence intervals were meant to contain 90% of the annual returns over the last 36 years. We also note that the professional sample provides on average broader confidence intervals than the laymen except for world equities, which implies that professionals were less miscalibrated than the laymen sample.

Another indication for miscalibration is given by a comparison of the implied volatilities embedded in the confidence intervals (row 3 and 6 of Table 1) and the volatility of historical annual returns (row 9). We see that the implied volatilities in both samples are significantly lower than the historical volatilities in all asset classes except for gold and the USD-CHF exchange rate in the professional sample. Further evidence for miscalibration is given in rows twelve and thirteen in Table 1 as a majority of all participants in both samples provide 90% confidence intervals which are narrower than the historical intervals on each asset class.

An interesting result is the fact that the participants in the professional as well as in the laymen sample 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 (bottom two rows in Table 1). Those ratios are calculated by dividing the historical intervals by the median of the subjective confidence intervals. This leads to the conclusion that the professional and the laymen sample are both well informed about the relative risk of each asset class.

The professionals provide larger intervals than the laymen on average so they are less miscalibrated. A Mann-Whitney test however reveals that the differences between the confidence interval sizes are not significant except for gold and the USD-CHF exchange rate (second and fourth row in Table 1).
Further we note that the confidence intervals in the professional sample contain more annual returns over the last 36 years, fewer participants provide narrow intervals compared to historical intervals and the confidence-interval to historical-interval ratios are higher in most of the asset classes but never on a significant level according to Mann-Whitney tests.

4.2 Return forecasts

We now focus on the participants 90% confidence intervals for return forecasts in different asset classes for the year 2006. As we know from almost every brochure of an asset manager past performance is no indicator for future performance. Therefore we take into account that a good knowledge of the past is not necessarily related to good return forecasts but it seems plausible that good knowledge of the the distribution of historical annual returns in different asset classes is related to a higher level of awareness for potential risks in the future.

Table 2 lists in the first 6 rows the median boundaries, the 90% confidence intervals and the implied volatilities for the return forecasts for 6 different asset classes in the year 2006 for the professional and the laymen sample. Like in section 4.1 we count the number of annual returns that fall into the participant’s confidence intervals for forecasts to analyze the degree of miscalibration in our samples and we compare the implied volatilities with historical volatilities. Rows 8 and 9 show that only around 20% of the annual returns of Swiss equities and CHF bonds would be included in the confidence intervals of the professionals and the numbers for the laymen are even lower. This is evidence that both of our samples are significantly miscalibrated in the domain of forecasting returns on financial markets. The medians for the implied volatilities are much lower than the historical volatilities for Swiss equities and CHF bonds over the last 36 years (rows 3 and 6).

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 and a comparison with semiannual volatility might be fairer. But even in comparison with semiannual volatilities (16.72% for Swiss equities and 3.78% for CHF bonds) the implied volatilities in Table 2 look very low. We interpret this as a clear indication that the participants in both of our samples are
miscalibrated in the domain of forecasting returns on financial markets. The participants’ confidence intervals for the four types of pension plan returns are also all very narrow but those asset classes are difficult to compare to reasonable benchmarks. However we have the strong impression that the confidence intervals for those forecasts are also very narrow compared to the distribution of historical returns and also indicate overconfidence in our sample. (Insert Table 2 here)

Similar to the estimation task in the previous section, the degree of miscalibration is also bigger among laymen because they provide narrower confidence intervals than the professionals and the differences are significant in all asset classes (Table 2). Mann-Whitney tests confirm that the laymen provide significantly higher values for the lower boundaries of their confidence intervals in all asset classes. A comparison between the upper boundaries of the two samples however shows that the laymen are more optimistic but the difference is only significant for 3 asset classes (CHF bonds, pension plan CHF bonds and average pension plans). So the professionals express a more conservative view with respect to downside risk but expect a comparable upside potential in each asset class.

It is worth to note that the participants in the professional as well as the laymen sample express very stable answering patterns within both types of tasks. The average correlation in the professional sample (laymen sample) for forecast intervals is 0.80 (0.64) and ranges from 0.72 to 0.92 (0.47 to 0.89). For the historical intervals the average is 0.60 (0.56) and 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). Those findings are evidence that the sizes of a participant’s confidence intervals across all tasks in the questionnaire are very stable. Providing narrow confidence intervals seems to be a stable trait across individuals regardless of the asset class and the type of estimation (forecast or historical).

We can summarize our results by saying that the decision-makers of Swiss pension plans are miscalibrated when forecasting future returns as well as when estimating historical returns on financial markets but to a lesser degree than a sample of laymen and with more conservative expectations.

We also note that both samples have a good sense for the relative risk of different asset classes but
are roughly equally miscalibrated across all asset classes with a high stability across individuals. The next section addresses the relationships between individual characteristics and overconfidence and suggests an explanation for those findings.

4.3 Linear regressions

In this section we show that individual characteristics of our participants can explain the individual stability in our participant’s answering patterns. Table 3 contains all results of our regression models segregated into four different panels (A, B, C, and D). (Insert Table 3 here)

Panel A and B contain the results of linear regression analysis of the individual characteristics on the participants’ confidence intervals for historical returns of different asset classes for both samples respectively. Our regression model works pretty well for the professional sample with an average $R^2$ of 28.8% over all asset classes (second row from the bottom in Table 3) but cannot relate our predictors to the 90% confidence intervals for historical returns in the laymen sample equally well as the average $R^2$ is not above 10% except for gold and oil.

The dummy variable general education from university is significantly related to broader confidence intervals in all asset classes. The other predictors related to education are not significant for most of the asset classes but also show always positive values. On the other hand older age is always related to narrower confidence intervals. This indicates that older people with less education are more miscalibrated than younger people with more education. In line with the model from Odean and Gervais [2001] the two variables for experience tend to reduce overconfidence as people with more financial or pension plan experience provide broader confidence intervals for historical returns, but the effects are not significant for most of the asset classes.

In panels C and D we analyze the 90% confidence intervals for return forecasts in both samples. The regression model shows a comparable explanatory power in both the professional and the laymen sample as the average $R^2$ are 15.9% and 16.8% respectively. The panels present evidence that general education from university has again a significant positive influence on the sizes of the fore-
cast intervals in the professional as well as the laymen sample. Like in the model for historical confidence intervals, the other predictors for education are positive most of the times but rarely at significant level. In line with previous evidence older people provide significantly narrower forecast intervals than younger people, but the effect is stronger in the laymen sample than in the professional sample. More experience either in pension plans or in finance is also related to broader forecast intervals as most of the standardized Beta coefficients in panels C and D are positive and the influence is significant in 4 (3) cases in the professional (laymen) sample.

Those findings are evidence for the fact that individual characteristics like education, experience and age influence a person’s degree of miscalibration in the domain of financial markets. We discuss the aspects of our results in the next section.

5. Discussion and 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. They are miscalibrated because they provide very narrow confidence intervals for estimating historical and future returns of different asset classes. This finding seems interesting to us because decision-makers of pension plans are not only responsible for their own wealth management but also for the retirement payments of most of the employees in Switzerland. We expect such a sample to consist of rather prudent investors because of the high responsibility level they bear but still we find evidence for overconfidence. We asked all participants to express their personal views in our questionnaire and not the corporate views of their pension plans. So we can not relate the answers of the decision-makers in our professional sample to the investments of any particular pension plan. Also there is no direct link between a participant’s degree of overconfidence and his investment behaviour in our sample. However we want to emphasize two practical issues related to our findings. The first addresses the strategic asset allocation and the second deals with its implementation.

There is evidence that decision-makers of Swiss pension plans on average underestimate the historical volatility and the historical downside risk of different asset classes. Moreover, they express
very low implied volatilities with their confidence intervals for return forecasts. Such an overconfi-
dently biased perception of low risks in a volatile asset class like for example equities could in-
crease the perceived Sharpe ratio of that asset class and makes it look more attractive. This might
then result in an overweight of that asset class in a pension plan’s asset allocation, might lead to an
increased overall volatility of the portfolio and exposes it more to downside risks but the overconfi-
dent 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 be-
liefs (like for example miscalibrated investors) can not only survive in the market but can also earn
higher expected returns. However such noise traders take excessive risk and gain less expected util-
ity than rational investors. Having said that we point out that the participants in our sample provide
too narrow confidence intervals for all asset classes and not only for more volatile ones so we can-
not generalize the argument that high risk assets are overweighted. Further research is needed to
address the relationship between miscalibration and the weighting of risky asset in a strategic asset
allocation. Nevertheless excessive portfolio risk due to miscalibration is an issue for every inves-
tor’s portfolio and not only for pension plans, but in the latter case the effects are particularly seri-
ous. Higher portfolio volatility and more exposure to downside risk put a pension plan’s coverage
ratio at a higher risk and might reduce the pension plans’ ability to guarantee future retirement
payments in general. It is not a healthy signal to the market – neither the labour market nor the fi-
nancial market - if a company reports a severe reduction in the coverage ratio of its pension plans
and has to increase its contributions. Therefore we recommend pension plans to take a cautious
view on assumptions about risk-return-profiles of different asset classes. Further we encourage de-
cision-makers of pension plans to conduct sensitivity analysis with very bad scenarios when defin-
ing the strategic asset allocation to develop a better intuitive feeling and a higher degree of aware-
ness for potential downside risks in a portfolio.

The second issue addresses an issue for overconfident decision-makers in the implementation of the
strategic asset allocation. It is related to present findings of other authors who demonstrate that
overconfidence can have an impact on trading decisions of investors. In most of those studies over-confi-
dence 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]). Decision-
makers might overconfidently perceive opportunities to exploit market inefficiencies because cur-
rent market prices deviate from their subjective (and as presented very narrow) forecast intervals
and might lead them to increase tactical trading. Tactical trading always generates additional trans-
action costs that have to be compensated by higher returns. Academic research presents few indica-
tions that tactical trading, often referred to as timing, pays off in general (see for example Daniel,
Grinblatt, Titman and Wermers [1997] who analyze a sample of mutual funds and find no success
with timing in most of the funds or Blake, Lehman and Timmermann [1999] who report that UK
pension plans have on average no timing skills). If this was also true for Swiss pension plans there
might be some room to increase returns by reducing trading costs caused by tactical trading due to
overconfident forecasting. However further research is needed to analyze in depth the relationship
between pension plan investments and the degree of overconfidence of the decision-makers.

There is an explanation for an individuals’ proneness to overconfidence that seems relevant in our
context as it puts the aforementioned two practical issues in perspective. It is based on a trade-off
described in Yaniv and Foster [1995]. When providing confidence intervals participants face a
trade-off between accuracy and informativeness because narrower confidence intervals are usually
more informative but less accurate. The formulation of narrow confidence intervals might be on
purpose as participants eventually put a lot of weight on informativeness and little weight on accu-
racy. When guessing how many championships Michael Jordan has won in his stellar career an in-
terval of 4-5 times is more helpful than an interval 0-15 times. However only the second interval
contains the correct number of 6 championships. Narrower forecast intervals provide more informa-
tion than large forecast intervals and Cesarini, Sandewall and Johannesson [2003] argue that espe-
cially professionals are keen on demonstrating their knowledge with informative (and therefore nar-
row) confidence intervals. We can not exclude the possibility that the participants in our samples want to express informative views knowing that those might not be accurate in 90% of the cases but simply put more weight on informative confidence intervals instead of accurate intervals.

In light of this argument we acknowledge that an analysis of only the size of the participants’ confidence intervals does not provide any information about the accuracy, i.e. how much the lower and upper boundaries of a subjective confidence interval deviate from the historical interval boundaries. We measure those deviations as the log-transformed sum of the absolute differences between the participants’ boundaries and the historical boundaries for each asset class. The closer a participant’s lower and upper boundaries to the historical interval boundaries the lower are his deviations and the more accurate are his confidence intervals in an asset class. We have no benchmark to compare the absolute deviations of the participants’ intervals so we cannot comment on the absolute results but we can compare our professional sample with the laymen sample. Mann-Whitney tests show that the professional sample provides more accurate boundaries for every asset class. The difference is significant on the 5% level for Swiss equities, gold, oil, the USD-CHF exchange rate and also the average over all asset classes. Knowing the past performance of some asset classes is no guarantee of predicting future returns correctly or defining more appropriate asset allocations for pension plans but at least the participants in the professional sample are better informed about the distribution of historical annual returns than a sample of laymen which might help to be more aware of future risks. This is good news for the second pillar in Switzerland because the three aforementioned issues are probably better addressed by our professional sample than by our laymen sample.

We also want to emphasize that average levels of miscalibration in our sample are bad predictors for an individual’s degree of miscalibration. With this paper we take the miscalibration research one step further as we demonstrate that people tend not to be homogenously miscalibrated but that individual differences are significant and stable across the tasks in our questionnaire. Observable personal characteristics like education, experience and age seem to influence a person’s degree of miscalibration. Our findings suggest that a better education may reduce overconfidence and that older
people with less experience in finance or pension plans tend to be more overconfident than young people with more experience. Age, however, seems not to be a good proxy for experience in the domain of financial markets. From a theoretical point of view, it is a curious question to ask why and how these demographic variables affect miscalibration. Potentially age, education, and experience may be related to financial literacy, the ability to learn from feedback, and other factors. Future research may distinguish these alternative interpretations. Our findings also have certain implications in practice, for example, regarding the screening of fund managers, the voting for the board of trustees of pension plans, and the designing of professional training programs.

The significant influence of age in our linear regression model might also be related to the regulation in Switzerland, which our samples are subjected to. Swiss regulation implies an asymmetric sharing of pension plan portfolio risk between current employees and pensioners. In case a pension plan is underfunded, the employees’ future retirement payments can be reduced and their current contributions to the pension plan can be increased whereas the payments to current pensioners are guaranteed and fixed. Therefore older people in Switzerland might care less about downside risks in financial markets because they will only participate on the upside (receive higher pensions) but not on the downside with their pension plans. However this argument is not applicable in the professional sample as the older decision-makers of Swiss pension plans not only bear the responsibility for themselves but for the overall pension plan. In addition we asked the participants for their personal views and underestimating downside risk would put older people’s private investments at risk, too.

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 deserves further exploration in the next step. It would also be interesting to investigate other facets of overconfidence like illusion of control or overoptimism, and the interaction of these phenomena with individual characteristics.
Acknowledgement

We would like to thank Ulf-Dietrich Reips, Klaus Jonas, Vera Kupper, Jürg Tobler, Christian Fitze, Thomas Häfliger and Andreas Reichlin for valuable comments and discussions. Financial Support from the members of the University Priority Program “Finance and Financial Market” at the University of Zurich is gratefully acknowledged. We also thank Ulf-Dietrich Reips, ASIP, Watson Wyatt and PPC Metrics for their technical support.

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Table 1. 90% confidence intervals for historical returns in the professional and laymen sample

Rows 1 to 3 contain the boundaries of the confidence intervals, the intervals themselves and the corresponding implied volatilities according to Pearson and Toksvig (1969) in the professional sample. Rows 4 to 6 show the same numbers for the laymen sample and rows 7 to 9 for the historical values. Rows 10 and 11 contain the percentage of annual returns the median interval includes for the professionals and the laymen and rows 12 and 13 show how many participants in each sample provided narrower confidence intervals than the historical intervals. Rows 14 and 15 contain the ratio of the participants’ median confidence intervals divided by the historical intervals.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Asset class</th>
<th>Switzerland</th>
<th>World equities</th>
<th>CHF bonds</th>
<th>Gold</th>
<th>Oil</th>
<th>USD/CHF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Interval</td>
<td>Interval</td>
<td>Interval</td>
<td>Interval</td>
<td>Interval</td>
<td>Interval</td>
<td>Interval</td>
</tr>
<tr>
<td></td>
<td>Professional median boundaries</td>
<td>-16.50%</td>
<td>29.00%</td>
<td>-20.00%</td>
<td>30.00%</td>
<td>-5.00%</td>
<td>8.50%</td>
</tr>
<tr>
<td></td>
<td>Professional median interval</td>
<td>42.50%</td>
<td>50.00%</td>
<td>10.50%</td>
<td>15.58%</td>
<td>60.00%</td>
<td>30.00%*</td>
</tr>
<tr>
<td></td>
<td>Implied volatility of median</td>
<td>13.08%^**</td>
<td>15.38%^**</td>
<td>3.23%^**</td>
<td>15.65%</td>
<td>18.48%^**</td>
<td>9.23%</td>
</tr>
<tr>
<td></td>
<td>Laymen median boundaries</td>
<td>-10.00%</td>
<td>25.00%</td>
<td>-20.00%</td>
<td>35.00%</td>
<td>-5.00%</td>
<td>8.00%</td>
</tr>
<tr>
<td></td>
<td>Laymen median interval</td>
<td>40.00%</td>
<td>50.00%</td>
<td>9.00%</td>
<td>35.00%*</td>
<td>60.00%</td>
<td>25.00%*</td>
</tr>
<tr>
<td></td>
<td>Implied volatility of median</td>
<td>12.31%^**</td>
<td>15.38%^**</td>
<td>2.77%^**</td>
<td>10.77%^**</td>
<td>15.98%^**</td>
<td>7.69%^**</td>
</tr>
<tr>
<td></td>
<td>Historical boundaries</td>
<td>-26.01%</td>
<td>48.52%</td>
<td>-30.74%</td>
<td>41.73%</td>
<td>-2.22%</td>
<td>12.79%</td>
</tr>
<tr>
<td></td>
<td>Historical interval</td>
<td>73.53%</td>
<td>72.47%</td>
<td>15.01%</td>
<td>62.58%</td>
<td>85.21%</td>
<td>36.45%</td>
</tr>
<tr>
<td></td>
<td>Historical volatility of annual returns</td>
<td>20.65%</td>
<td>22.50%</td>
<td>5.85%</td>
<td>26.68%</td>
<td>41.86%</td>
<td>12.85%</td>
</tr>
<tr>
<td></td>
<td>Percentage of included annual returns in prof. sample median</td>
<td>63.89%</td>
<td>72.22%</td>
<td>69.44%</td>
<td>80.36%</td>
<td>33.33%</td>
<td>72.22%</td>
</tr>
<tr>
<td></td>
<td>Percentage of included annual returns in laymen sample median</td>
<td>52.73%</td>
<td>77.73%</td>
<td>61.11%</td>
<td>68.33%</td>
<td>33.33%</td>
<td>52.73%</td>
</tr>
<tr>
<td></td>
<td>Percentage of professionals with too narrow intervals</td>
<td>72.00%</td>
<td>80.40%</td>
<td>77.80%</td>
<td>64.80%</td>
<td>74.10%</td>
<td>57.40%</td>
</tr>
<tr>
<td></td>
<td>Percentage of laymen with too narrow intervals</td>
<td>85.00%</td>
<td>85.00%</td>
<td>79.10%</td>
<td>64.30%</td>
<td>66.70%</td>
<td>56.70%</td>
</tr>
<tr>
<td></td>
<td>Ratio of professionals’ intervals divided by historical intervals</td>
<td>0.58</td>
<td>0.69</td>
<td>0.70</td>
<td>0.82</td>
<td>0.70</td>
<td>0.78^*</td>
</tr>
<tr>
<td></td>
<td>Ratio of laymen’s intervals divided by historical intervals</td>
<td>0.54</td>
<td>0.69</td>
<td>0.56</td>
<td>0.56</td>
<td>0.59</td>
<td>0.65^*</td>
</tr>
</tbody>
</table>

* significant difference between professional and laymen sample at 10% level  
** significant difference between professional and laymen sample at 5% level  
*** significant difference between professional and laymen sample at 1% level  
^^ significantly different from historical returns at 10% level  
^** significantly different from historical returns at 5% level  
^*** significantly different from historical returns at 1% level
Table 2. 90% confidence intervals for forecasts in the professional and laymen sample

Rows 1 to 3 contain the boundaries of the confidence intervals, the intervals themselves and the corresponding implied volatilities according to Pearson and Tukey (1955) in the professional sample. Rows 4 to 6 show the same numbers for the laymen sample and row 7 the historical volatility of annual returns. Rows 8 and 9 contain the percentage of annual returns the median interval includes for the professionals and the laymen.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Asset class</th>
<th>Swiss equities in general</th>
<th>Pension plan</th>
<th>CHF bonds in general</th>
<th>Pension plan</th>
<th>CHF bonds</th>
<th>Own pension plan</th>
<th>Average pension plan</th>
</tr>
</thead>
<tbody>
<tr>
<td>Professional</td>
<td>interval</td>
<td>0.00% - 10.00%</td>
<td>2.00% - 9.00%</td>
<td>1.25% - 3.00%</td>
<td>1.50% - 3.00%</td>
<td>2.00% - 6.00%</td>
<td>0.75% - 6.00%</td>
<td></td>
</tr>
<tr>
<td>Professional</td>
<td>interval</td>
<td>10.00% - 10.00%</td>
<td>7.00% - 7.00%</td>
<td>3.75% - 3.75%</td>
<td>3.00% - 3.00%</td>
<td>5.00% - 5.00%</td>
<td>5.00% - 5.00%</td>
<td></td>
</tr>
<tr>
<td>Professional</td>
<td>implied volatility</td>
<td>3.08% - 3.08%</td>
<td>2.15% - 2.15%</td>
<td>1.15% - 1.15%</td>
<td>0.92% - 0.92%</td>
<td>1.54% - 1.54%</td>
<td>1.54% - 1.54%</td>
<td></td>
</tr>
<tr>
<td>Laymen</td>
<td>interval</td>
<td>4.00% - 10.00%</td>
<td>3.00% - 8.00%</td>
<td>2.00% - 4.00%</td>
<td>2.00% - 4.00%</td>
<td>4.00% - 8.00%</td>
<td>3.00% - 3.00%</td>
<td></td>
</tr>
<tr>
<td>Laymen</td>
<td>interval</td>
<td>5.00% - 5.00%</td>
<td>5.00% - 5.00%</td>
<td>2.00% - 2.00%</td>
<td>2.00% - 2.00%</td>
<td>4.00% - 4.00%</td>
<td>3.00% - 3.00%</td>
<td></td>
</tr>
<tr>
<td>Laymen</td>
<td>implied volatility</td>
<td>1.64% - 1.64%</td>
<td>1.64% - 1.64%</td>
<td>0.62% - 0.62%</td>
<td>0.62% - 0.62%</td>
<td>1.23% - 1.23%</td>
<td>0.92% - 0.92%</td>
<td></td>
</tr>
<tr>
<td>Historical</td>
<td>volatility of annual</td>
<td>returns</td>
<td>25.65%</td>
<td>na</td>
<td>5.38%</td>
<td>na</td>
<td>na</td>
<td>na</td>
</tr>
<tr>
<td>Percentage</td>
<td>of included annual</td>
<td>returns in prof. sample</td>
<td>median</td>
<td>na</td>
<td>18.44%</td>
<td>na</td>
<td>na</td>
<td>na</td>
</tr>
<tr>
<td>Percentage</td>
<td>of included annual</td>
<td>returns in laymen sample</td>
<td>median</td>
<td>16.67%</td>
<td>na</td>
<td>13.83%</td>
<td>na</td>
<td>na</td>
</tr>
</tbody>
</table>

* significant difference between professional and laymen sample at 10% level
** significant difference between professional and laymen sample at 5% level
*** significant difference between professional and laymen sample at 1% level

* significantly different from historical volatility at 10% level
** significantly different from historical volatility at 5% level
*** significantly different from historical volatility at 1% level
Table 3 - Linear regression models on confidence intervals

The dependent variable is the log value of the participants 90% confidence intervals for forecasts and historical annual returns. The first 3 predictors are mutually exclusive dummy variables for the different types of education in our model. Participants with both practical and university education were considered as people with university degree to mitigate double counting. The predictors in rows 4 and 5 can take values from 1 (no experience) to 7 (more than 52 years of experience) and reflect a participant's experience in either finance or pension plans. The predictor in row 6 also takes values from 1 (below 25) to 7 (above 65) and reflects the range of a participant's age. The last two rows contain the R² of the regression model for each asset class as well as its F-value.

Panel A - Regression model on confidence intervals for historical returns in the professional sample

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Dependent variables</th>
<th>Swiss equities</th>
<th>World equities</th>
<th>CHF bonds</th>
<th>Gold</th>
<th>Oil</th>
<th>USD-CHF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-finance education from uni</td>
<td>0.387***</td>
<td>0.438***</td>
<td>0.266*</td>
<td>0.371**</td>
<td>0.322**</td>
<td>0.351***</td>
<td></td>
</tr>
<tr>
<td>Practical finance education</td>
<td>0.627*</td>
<td>0.571</td>
<td>0.524</td>
<td>0.212</td>
<td>0.810</td>
<td>0.241</td>
<td></td>
</tr>
<tr>
<td>Finance education from uni</td>
<td>0.938***</td>
<td>0.697</td>
<td>0.649</td>
<td>0.335</td>
<td>0.653</td>
<td>0.130</td>
<td></td>
</tr>
<tr>
<td>Experience in finance</td>
<td>0.194</td>
<td>0.156</td>
<td>0.424***</td>
<td>0.138</td>
<td>-0.100</td>
<td>0.292**</td>
<td></td>
</tr>
<tr>
<td>Experience in pension plans</td>
<td>0.261*</td>
<td>0.131</td>
<td>-0.245</td>
<td>-0.008</td>
<td>0.117</td>
<td>0.120</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.365***</td>
<td>-0.322**</td>
<td>-0.280**</td>
<td>-0.241*</td>
<td>-0.160</td>
<td>-0.407***</td>
<td></td>
</tr>
<tr>
<td>R-square</td>
<td>0.387</td>
<td>0.324</td>
<td>0.293</td>
<td>0.165</td>
<td>0.140</td>
<td>0.415</td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>5.15***</td>
<td>3.907***</td>
<td>3.244***</td>
<td>1.557</td>
<td>1.279</td>
<td>5.51***</td>
<td></td>
</tr>
</tbody>
</table>

Panel B - Regression model on confidence intervals for historical returns in the laymen sample

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Dependent variables</th>
<th>Swiss equities</th>
<th>World equities</th>
<th>CHF bonds</th>
<th>Gold</th>
<th>Oil</th>
<th>USD-CHF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-finance education from uni</td>
<td>0.005</td>
<td>-0.102</td>
<td>-0.101</td>
<td>0.284*</td>
<td>0.252</td>
<td>0.152</td>
<td></td>
</tr>
<tr>
<td>Practical finance education</td>
<td>0.054</td>
<td>-0.120</td>
<td>0.024</td>
<td>-0.165</td>
<td>-0.305*</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td>Finance education from uni</td>
<td>0.245</td>
<td>0.033</td>
<td>0.030</td>
<td>0.115</td>
<td>-0.021</td>
<td>0.136</td>
<td></td>
</tr>
<tr>
<td>Experience in finance</td>
<td>0.071</td>
<td>0.274</td>
<td>0.013</td>
<td>0.422**</td>
<td>0.329*</td>
<td>0.136</td>
<td></td>
</tr>
<tr>
<td>Experience in pension plans</td>
<td>-0.134</td>
<td>-0.068</td>
<td>-0.238</td>
<td>-0.051</td>
<td>0.159</td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.075</td>
<td>-0.121</td>
<td>0.074</td>
<td>-0.239*</td>
<td>0.372*</td>
<td>-0.092</td>
<td></td>
</tr>
<tr>
<td>R-square</td>
<td>0.077</td>
<td>0.100</td>
<td>0.048</td>
<td>0.250</td>
<td>0.193</td>
<td>0.092</td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>0.591</td>
<td>0.668</td>
<td>0.301</td>
<td>1.949*</td>
<td>1.358</td>
<td>0.323</td>
<td></td>
</tr>
</tbody>
</table>

Panel C - Regression model on confidence intervals for forecast returns in the professional sample

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Dependent variables</th>
<th>Swiss equities</th>
<th>Pension plan</th>
<th>CHF bonds</th>
<th>Own pension plan</th>
<th>Average pension plan</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-finance education from uni</td>
<td>0.147</td>
<td>0.227**</td>
<td>0.314***</td>
<td>0.170</td>
<td>0.091*</td>
<td>0.119</td>
</tr>
<tr>
<td>Practical finance education</td>
<td>0.367*</td>
<td>0.269</td>
<td>0.303</td>
<td>0.171</td>
<td>0.243*</td>
<td>0.276</td>
</tr>
<tr>
<td>Finance education from uni</td>
<td>0.555**</td>
<td>0.456*</td>
<td>0.538**</td>
<td>0.379</td>
<td>0.435*</td>
<td>0.368</td>
</tr>
<tr>
<td>Experience in finance</td>
<td>0.084</td>
<td>0.220*</td>
<td>0.102</td>
<td>0.154</td>
<td>0.128*</td>
<td>0.218*</td>
</tr>
<tr>
<td>Experience in pension plans</td>
<td>0.243**</td>
<td>0.151</td>
<td>0.060</td>
<td>0.029</td>
<td>0.123*</td>
<td>0.117</td>
</tr>
<tr>
<td>Age</td>
<td>-0.214**</td>
<td>-0.230**</td>
<td>-0.175*</td>
<td>-0.137</td>
<td>-0.140</td>
<td>-0.183*</td>
</tr>
<tr>
<td>R-square</td>
<td>0.190</td>
<td>0.219</td>
<td>0.164</td>
<td>0.112</td>
<td>0.122*</td>
<td>0.144</td>
</tr>
<tr>
<td>F</td>
<td>3.487***</td>
<td>3.336***</td>
<td>2.852**</td>
<td>1.638</td>
<td>2.036*</td>
<td>2.330**</td>
</tr>
</tbody>
</table>

Panel D - Regression model on confidence intervals for forecast returns in the laymen sample

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Dependent variables</th>
<th>Swiss equities</th>
<th>Pension plan</th>
<th>CHF bonds</th>
<th>Own pension plan</th>
<th>Average pension plan</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-finance education from uni</td>
<td>0.267***</td>
<td>0.296***</td>
<td>0.097</td>
<td>0.155</td>
<td>0.347***</td>
<td>0.321***</td>
</tr>
<tr>
<td>Practical finance education</td>
<td>0.044</td>
<td>0.150</td>
<td>0.132</td>
<td>-0.047</td>
<td>0.030</td>
<td>0.101</td>
</tr>
<tr>
<td>Finance education from uni</td>
<td>0.202**</td>
<td>0.293**</td>
<td>0.153</td>
<td>0.142</td>
<td>0.069</td>
<td>0.136</td>
</tr>
<tr>
<td>Experience in finance</td>
<td>0.072</td>
<td>-0.002</td>
<td>0.022</td>
<td>-0.022</td>
<td>-0.039</td>
<td>-0.047</td>
</tr>
<tr>
<td>Experience in pension plans</td>
<td>0.104</td>
<td>0.272**</td>
<td>0.025</td>
<td>0.122</td>
<td>0.212*</td>
<td>0.227**</td>
</tr>
<tr>
<td>Age</td>
<td>-0.358***</td>
<td>-0.397***</td>
<td>-0.293**</td>
<td>-0.267**</td>
<td>-0.279**</td>
<td>-0.391***</td>
</tr>
<tr>
<td>R-square</td>
<td>0.194</td>
<td>0.254</td>
<td>0.122</td>
<td>0.106</td>
<td>0.161</td>
<td>0.169</td>
</tr>
<tr>
<td>F</td>
<td>3.859***</td>
<td>5.45***</td>
<td>2.229**</td>
<td>1.881*</td>
<td>3.034***</td>
<td>3.229***</td>
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</tbody>
</table>

* significant at 10% level
** significant at 5% level
*** significant at 1% level