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Financial professionals' overconfidence: Is it experience, job, or attitude?

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Abstract

This paper examines financial professionals' overconfidence in their forecasting performance. We are the first to compare *individual financial professionals*' self-ratings with their true forecasting performance. Data spans several years at monthly frequency. The forecasters in our sample do not provide feasible self-ratings compared to their true performance but show overconfidence on average. In analyzing this, we find an easing relation to experience. Job characteristics are also related to less overconfidence, such as being a fund manager and using fundamental analysis. The same effect is found for the attitude to herd, whereas recent forecasting success comes along with more overconfidence.

JEL-Classification: G 1, D 84, F 31
Keywords: overconfidence, self-rating, forecasting, foreign exchange, better-than-average, experience, performance

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Financial professionals' overconfidence: Is it experience, job, or attitude?

1 Introduction

We know from a series of by now "classical" studies that most people are overconfident regarding their own abilities, such as their driving performance (Svenson, 1981). Subsequent research has shown that overconfidence is not an invariant characteristic but depends on circumstances (Klayman et al., 1999). Important in this respect is the feedback that people receive which seems helpful to adjust one's own perception (Fischhoff et al., 1977). It is therefore surprising that overconfidence extends to behavior in financial markets where participants can get frequent and precise feedback. This overconfident behavior seems even more surprising as it has demonstrated to be costly in financial terms: overconfidence reduces investor performance (Barber and Odean, 2000). A decisive counterargument against this strand of research is, however, that it is mostly derived from experiments with students or laymen (Koehler et al., 2002). These subjects are less relevant for the outcome of financial markets than financial professionals who are the important marginal actors on these markets. Thus it is highly warranted to know about potential overconfidence of financial professionals; but it is exactly this evidence that is scarce.

We contribute two new aspects to this research on financial professionals' overconfidence: First, we measure overconfidence of this target group in a precise way as it has not been done before. It seems important that overconfidence really captures the difference between self-rating and the same person's true performance. This precise measure is usually not available. Second, we make use of the comprehensive data set by employing forecasters' demographic, job and forecasting characteristics in analyzing overconfidence.

In order to conduct these analyses we use a sample of 105 professional forecasters who are regularly contributing to the ZEW financial market survey. From this survey we gather the monthly forecasts on the US-Dollar exchange rate (versus the Euro, respectively Deutsche Mark) over several years so that we can calculate a meaningful forecasting performance. We complement this performance information by data from additional surveys being conducted at the same time as the regular surveys. These supplementary surveys reveal the professionals' self-rating and detailed characteristics about them.

The financial professionals in this study are experienced, educated and hold senior positions in the financial industry so that the sample seems to be relevant for our purpose. These professionals regard themselves mostly better in their self-rating than their fellow

forecasters and thus clearly show some overconfidence (which is of course a precondition for further analyses). As a side-aspect we confirm former findings that different measures of overconfidence which are often presumed to be related are actually not. This underlines the reliability of our study and also motivates our approach to use a straight forward criterion for overconfidence.

Further analyses reveal the following aspects of financial professionals' overconfidence: first, the better-than-average self-rating of financial professionals is not significantly related to the same person's (true) performance. As overconfidence is just the difference between self-rating (being better than the average) and performance, our finding implies that forecasters with tentatively lower performance are overconfident. As this effect applies equally to good and bad forecasters, we do not only find overconfidence, but interestingly also find a large degree of underconfidence. Second, in analyzing correlates of overconfidence, there is an easing effect from experience. The same applies for some job related criteria, such as being a fund manager and relying on fundamental analysis. Recent forecasting successes seem to generate a too optimistic attitude which induces immoderately good self-evaluations. By contrast, the attitude to herd goes in hand with lower levels of overconfidence.

This paper is structured as follows: Section 2 reviews the previous literature showing that our approach is original, Section 3 introduces the data used, Section 4 shows relations between self-rating and performance as well as overconfidence and performance. Section 5 provides several robustness checks and Section 6 concludes.

2 Literature

The aim of this study is to analyze overconfidence of professionals in financial markets. Financial professionals are hardly considered in this literature and if so, there is lack of data to analyze overconfidence in the precise and comprehensive way we are able to do.

The amount of literature covering overconfidence is vast. First studies develop different dimensions of overconfidence, such as Greenwald (1980) for the better-than-average effect, Fischhoff et al. (1977) for the miscalibration bias, or Langer (1975) for the illusion-of-control. Subsequent studies find overconfidence in different areas, e.g. Svenson (1981) for driving abilities, and for other professions (e.g. Barber and Odean, 2001). There are four particular outcomes of previous research, which are important for the motivation of our study: first, there are different dimensions of overconfidence which do not necessarily measure the same kind of behavior (Glaser et al., 2005; Cesarini et al., 2006), second, overconfidence is domain

specific (Klayman et al., 1999), and, third, overconfidence is reduced when tasks are highly predictable and involve frequent feedback (Fischhoff et al., 1977).

The last issue, frequent feedback, is of high relevance here. Exactly this fact characterizes financial markets: its participants get frequent and precise feedback about their decisions. Consequently, one should expect a lower degree of overconfidence here than elsewhere. However, there may be differences between various groups on financial markets: particularly professionals might use and be able to interpret the feedback they get. On contrast, non-professional participants, such as individual investors, may have lower incentives to use feedback and may have less ability to interpret this.

Available studies do support the notion that there is overconfidence also on financial markets but this evidence refers mainly to non-professionals or to financial markets in general, where non-professionals are included. In detail, there are three kinds of studies: (1) one stream of literature relies on the theoretically derived finding that overconfidence of financial market participants can be detected by their increased trading activity (Odean, 1998). There is ample evidence about "too much trading volume" in *financial markets in general* (Statman et al., 2006; Griffin et al., 2007). (2) Other studies use information about *individual investors* which is collected from their trading accounts (examples are among others Odean, 1999; Barber and Odean, 2000; Grinblatt and Keloharju, 2006; Glaser and Weber, 2007). (3) Finally, overconfidence is shown in *experiments* simulating financial markets; these experiments are mostly conducted with students (e.g.: Biais et al., 2005; Deaves et al., 2009; Hales, 2009). Thus, we know from these various perspectives that overconfident behavior appears on financial markets but we do not know whether financial market professional also show this overconfident behavior.

As professionals trade the largest volumes and have the best information among financial market participants, evidence on their behavior is of particular interest. Empirical examinations, however, lack data. The few studies on financial professionals' overconfidence mostly rely on the overconfidence measure of miscalibration but not on the measure of better-than-average (Thomson et al., 2003; Deaves et al., 2005; Menkhoff et al., 2006; Ben-David et al., 2007).[1] One reason for this is data availability as miscalibration requires just information about the professional's assessment, such as e.g. an estimation of a fact (length of a well-known river etc.). Another popular way of eliciting miscalibration is assessing a professional's forecast about an interval of a future asset price level, such as the 90%

[1] Other studies of professionals' overconfidence use approximations, such as late option execution (Malmendier and Tate, 2005a), press related criteria (Malmendier and Tate, 2005b), investor size (Ekholm and Pasternack, 2007), overweighting of private information (Friesen and Weller, 2006), and turnover ratio (Pütz and Ruenzi, 2008).

probability interval for the Dow Jones index in one month. Interestingly, there are methodological concerns against the interval estimation approach, even more as different ways of eliciting miscalibration can lead to conflicting results (Cesarini et al., 2006). If, however, the overconfidence measure of better-than-average is applied, the researcher needs two kinds of information, i.e. a measure of performance and the self-perception of the same professionals about their performance. This information is missing so far. Closest to this measurement come Oberlechner and Osler (2008) who approximate performance by ratings of superiors and colleagues; this endangers the results to be inflated by judgment errors from other subjects.

Overall, studies are rare on financial professionals' overconfidence and existing studies still lack a direct comparison of individual financial professionals' self-rating with the same person's true performance.

3 Data

The study builds on a unique data set which consists of individual exchange rate forecasts over several years plus extensions covering demographic, job and forecasting characteristics of the sample's 105 financial professionals.

3.1 The ZEW data set

The basis for our research is the individual survey data of the Financial Market Survey (Finanzmarkttest) being conducted by the ZEW, Mannheim. Aggregate statistics are derived from the individual data and are published in financial media like Reuters or Bloomberg. Like comparable datasets, e.g. Consensus Economics London, the majority of the participants are employed in the banking sector (75%). Others work in the insurance sector (15%) or in large industry enterprises (10%). Overall there are 350 financial experts asked to participate monthly in the survey of which on average about 300 answers are received each month.

The financial professionals give individual forecasts for the 6-month ahead exchange rate of the USD/EUR, or of the USD/DEM exchange rate before December 1998 respectively. The observations range from December 1991 to October 2008. This provides us with a maximum of almost 17 years of monthly data on individual expectations. The forecasts are qualitative and indicate whether the exchange rate is expected to appreciate, depreciate or stay unchanged. From these regular forecasts we retrieve average hit rates which approximate the true skill level of the forecasters (for the exact procedure see Section 4). To obtain a reliable and valid criterion for the true skill level we solely use observations from forecasters who

participated in the survey for at least 36 times, i.e. for minimum of three years if they participate every single month.

In addition to this, several special surveys were conducted contemporaneously with the regular monthly surveys. Therewith we observe demographic and job characteristics which we describe in the following Section 3.2. Since we use personal characteristics and individual forecasts in our analysis we want to make sure that each observation corresponds to one person. We follow all changes in the contact persons and employers and use solely data which refers to the very same person. This provides us with a highly consistent micro data set. The drawback is that we end up with a sample of 105 professional forecasters for which we have complete observations, i.e. enough forecasts as well as information about their self-rating as forecasters, demographic and job information. Reassuringly, this sample does not show any significantly different attributes regarding professionals' characteristics than those professionals who are not considered here.

3.2 Measures of overconfidence

Since the measurement of overconfidence is somewhat arbitrary it is important for us to show that our forecasters exhibit the same behavioral biases as other people. We demonstrate this in two exercises. On the one hand, we observe the same better-than-average effect in the self-rating as other studies do. On the other hand, the three often suggested dimensions of overconfidence are not closely related.

Our observation for the better-than-average rating is quite general and similar to the one of other studies. Professionals' rank themselves compared to the average forecaster on a range from 1 to 21. When we asked participants to rate their forecasting performance in relation to the other participants of the ZEW survey, our result as well as the experience from related studies shows that there is a tendency to overrate one's own performance. This is usually interpreted as overconfidence of the total group (Larrick et al., 2007). Indeed, we find this behavior in our sample as well, as Figure 1 shows. The mean answer of 11.9 is above the value of 11. This indicates a relatively well-calibrated sample as the degree of overconfidence lies in between former studies. For instance the distribution of answers of currency traders is more negatively skewed than ours (Oberlechner and Osler, 2008), whereas private investors give less skewed answers (Glaser and Weber, 2007). We view this result as a cue in two directions. First, we obtain answers which indicate that some forecasters believe themselves as being below average. The forecasters in our sample do not seem to have an incentive to exaggerate self-rating due to social pressure in the sense that they are afraid of getting

dropped from the survey etc. Second, the direct monthly feedback of the public release of the forecasts might give the forecasters generally a good idea how well they perform.

In order to learn about behavior of professionals in our sample, we also collect data for the two other measures of overconfidence introduced in the literature section, i.e. miscalibration and illusion-of-control. In the survey of October 2008 participants were asked with respect to miscalibration for a 90% confidence interval for the 6-month ahead USD/EUR exchange rate. Data for the illusion-of-control was extracted from the following question, which has been used for this purpose before (Menkhoff et al., 2006): "Most of the published business news does not surprise me at all." Respondents answered on a scale ranging from 1 to 20. As Table 1 shows these criteria are rather loosely related. This is a standard finding in the literature (e.g. Klayman et al., 1999; Glaser et al., 2005; Moore and Cain, 2007) and implicitly demonstrates that our sample behaves "well". The coefficients of correlation in Table 1 show in particular that the miscalibration measure is unrelated to the two other measures of overconfidence which is in line with Cesarini et al. (2006).

3.3 Professionals' characteristics

In aiming for an analysis of overconfidence the ZEW standard individual forecasting data has to be extended by detailed information about the financial professionals. We do this in three directions, addressing professionals' demographic, job and forecasting characteristics.

Regarding demographic characteristics the average professional is male, holds a university degree, is in his mid age and has been working for almost 18 years in the financial industry. The descriptive statistics for the sample of 105 financial professionals are shown in the upper panel of Table 2.

Regarding job characteristics the average professional holds a senior position, i.e. with operative and personnel responsibilities. It is most likely that he works as a fund manager (30%), another 23% work as researchers, 18% as advisors and the remaining 29% as others, such as in treasury departments. Forecasts are mainly the results of fundamental analyses with a share of 55%, whereas technical analysis and reliance on flow analysis make up for the rest. Details are given in the middle panel of Table 2.

Regarding forecasting characteristics, we first report the average hit rate which can vary between a lower bound of zero and an upper bound of two. Its exact calculation will be discussed in Section 4.1 below. Beyond that we are interested in two possible behavioral effects: first, do recent forecasting successes lead to an optimistic attitude which may affect behavior, such as self-assessment? Second, is the professional influenced by the attitude to herd in his forecasts?

We investigate the impact from recent forecasting performance by two variables. (1) In order to obtain a measure of the forecasters' recent performance we construct two dummy variables which are one in case of a significant – positive or negative – trend in the hit rates over the last three years.[2] Results remain qualitatively the same for variations in the time horizon. On average, professionals do not realize positive or negative trends indicating the reliability of the sample over time. (2) As another proxy of most recent performance we derive individual hit rates of their 6-month forecasts for a 1-month period. Therefore, we compare the 6-month forecast with the factual development of the exchange rate within the first 1 month. For this procedure we adjust the no change category according to the square root formula (Diebold et al., 1998), i.e. the 6-month boundary of 3% corresponds to a 1-month boundary of 1.22%. We repeat this exercise five more times so that we generate the average success over the last 6 months, which is in line with Statman et al. (2006). Reassuringly, our results are robust for other time periods such as 5 or 7 months. The level of recent success as shown in the lower panel of Table 2 is not significantly different from the general performance.

As a last variable in this section we consider the possible importance of herding behavior among forecasters (see e.g. Lux, 1998). We implement a herding measure as a simple percentage share of one's monthly forecast in which the professionals agrees with the market's opinion of the month before. Due to forecasts' persistence, taking the contemporaneous month yields the same result. To ensure a robust estimate of the market opinion the minimum participation rate is 30. The individual minimum participation for which we calculated the herding measure is 12. The bottom line of Table 2 shows that most of the time professionals stay in line with the market expectation.

4 Descriptive analysis

4.1 Self-rating and performance

Our measure of individual overconfidence is the difference between the self-rating and the effective performance. We receive the information about self-rating from the survey, but we have to calculate the measure of performance which requires some decisions to make.

(1) We consider all forecasts of one person. (2) We exactly calculate whether the forecast was right or wrong. In this respect, the survey participants have a time window of about two weeks to submit their forecasts. To achieve a maximum of accuracy and

[2] We used a 10% significance level for Spearman's rank correlation. Kendall's tau provides nearly identical results, since we use just the directional trend information.

consistency we use individual forecasting windows, i.e. we compare the forecasted change of the exchange rate to the realized exchange rate in exactly six months for each individual separately. This provides us with a precise measure of how often the individual forecast hits the actual exchange rate movement. (3) Due to the trivariate nature of forecasts (up, down, unchanged) we need to make a decision as to how much of change is compatible with an "unchanged" exchange rate. Fortunately, we can use information directly from the forecasters themselves. In a special survey in 2006 they state that on average a 3% change of the exchange rate over 6-months is considered to be stable. (4) Since the expectations are qualitative forecasts usual error measures on an individual basis, e.g. RMSE, are not computable. Instead we apply the measure of hit rates. For this purpose we convert the continuous exchange rate process into a discrete process which corresponds with the forecast categories of appreciation, depreciation and no change. (5) To incorporate that the experts can choose between three options, a hit rate is coded in three categories: large deviation, small deviation and no deviation of forecast from the true process. Large deviations are predictions which indicate the opposite direction of the actual movement, whereas small deviations are expectations which are neither a correct forecast nor a large deviation. The code values are 0-1-2 in a way that a higher hit rate is better. This performance measure has been used for ZEW exchange rate forecasts and reveals that forecasts are on average close to random forecasts (MacDonald et al., 2009) and heterogeneous on the individual level (Menkhoff et al., 2009).[3]

In Figure 2 we plot the 105 forecasters' self-rating against their true performance which is again measured via hit rates. A relation between self-rating and performance cannot be recognized, neither from graphical analysis nor from the correlation coefficient (-0.0084). This is quite surprising since overconfidence leads to excessive trading and significant lower profits (for example Odean, 1998; Barber and Odean, 2001; Biais et al., 2005). Such independence has been shown in publications such as Ackerman et al. (2001) and for an overview Moore (2007). Glaser and Weber (2007) argue that inexperienced private investors do not know their past portfolio performance and therefore cannot give an appropriate evaluation of their skills. For professionals the result remains surprising. Professionals in the financial sector do receive frequent feedback either from the market or the customer and moreover their salary is based on their performance in many cases. Hence, one might expect that professionals are better in assessing their own relative performance. However, we find that even professionals are unable to correctly assess their relative forecasting performance.

[3] A similar approach to distinguish between the three categories of forecasting performance was chosen by Nolte et al. (2008) for the same panel but with different forecasts.

4.2 Overconfidence and performance

As forecasters cannot correctly asses their relative performance, overconfidence, which is measured as the difference between self-rating and effective performance, is driven by performance.

Since we measure overconfidence as the difference between self-rating and hit rate, we rescale hit rate to the same scale as self-rating.[4] As a result, observed values range from -13 to 14, which means that on an individual basis professionals exhibit both, overconfidence as well as underconfidence. The good forecasters are rather underconfident, whereas the relatively overconfident forecasters tend to be in effect worse than the average.

In a sense, this may be what one expects in efficient markets. Under efficiency, the universe of forecasters will not be able to produce clearly valuable forecast. This is true here. Moreover, as it is difficult to systematically outperform the market, it will be difficult to assess any systematic component in one's own forecasting performance and thus self-ratings will be biased and largely accidental. This applies here as well.

5 Determinants of overconfidence and underconfidence

5.1 Methodology

We have shown that the professional forecasters are overconfident as well as underconfident, which we aim to explain in the following by a set of demographic, job, and forecasting characteristics. We estimate an ordinal regression model for over- and underconfidence (Greene, 2008). Therefore we define the level of over-/underconfidence as a piecewise-defined function of the difference between self-rating and hit rate:

$$OVC_i = \begin{cases} 1 \; if \; SR_i - HR_i > 0 \\ 0 \; if \; SR_i - HR_i = 0 \\ -1 \; if \; SR_i - HR_i < 0 \end{cases} \tag{1}$$

with SR_i as self-rating and HR_i representing hit-rate, each for forecaster i. So, the criterion distinguishes overconfident and underconfident forecasters as well as forecasters who are

[4] Hit rate is initially a continuous variable ranging from 0 to 2. We split the initial range into 21 equal parts. We do not use 0 and 2 as hit rate boundary since these values are possible but unlikely. We choose symmetric boundaries which are four times around the mean, which is 0.548 (1.727). According to Chebychev's inequality this corresponds to 94% of the distribution at minimum. The actual sample ranges from 0.577 to 1.510. Therefore all observations are included in the transformed hit rate measure.

neither. We observe 51% overconfident, 36% underconfident and 12% "balanced" professionals.

Using this estimation procedure provides us with several advantages compared to a normal ordinary least square analysis. First, as argued above, it is important to address overconfidence properly, i.e. consider both, the own self-rating as well as the true skill level. We take this into account by deriving the overconfidence measure from the difference between self-rating and true performance. Second, just using the directional information of the difference puts less restrictive assumptions on the data than using a cardinal criterion. Third and most importantly, estimating the difference by linear estimation procedures does not distinguish between the effect on over- and underconfidence of the regressors which could be asymmetric, i.e. nonlinear. In order to account for this possible asymmetry we use the non-linear ordered logit approach. To control for heteroscedasticity we use robust variance estimators for all estimations.

5.2 Results

We estimate the level of over- / underconfidence conditional on a large number of control variables which we derive from personal, job, and forecasting characteristics. We find that experience, job, and attitude are significantly related to the level of overconfidence.

(1) Demographic characteristics

Estimation results are shown in Table 3. Column (1) provides the benchmark specification where all demographic, job and forecasting characteristics are considered. We use the results of the restricted regression for interpretation which uses exclusively the significant regressors, see column (2) and Table 4 for marginal effects. We discuss them in the following one after the other, starting with the demographic characteristics. Chevalier and Ellison (1999) have shown that these characteristics can influence financial professionals' behavior. We find indeed that *experience* has a significant effect, which is negative for overconfidence. The direction of this effect is not as obvious as it may look on the first sight. While becoming more and more experienced one would assume misalignments to decrease. Starting one's career as a forecaster, one might not know one's true forecasting abilities. But during one's career a forecaster gains experience about successes and failures. Using this information allows one to form rational expectation about one's own forecasting performance even when the true skill was unknown in the beginning. Being one of the first, Brehmer (1980) puts this positive effect of experience into question and discusses the reasons which might prevent us from learning, like confirmatory evidence and causality assumptions and

negligence of negative information. Supporting this hypothesis, Deaves et al. (2005) find that experience increases overconfidence. On the other hand, Gervais and Odean (2001) argue that experience might lead to lower overconfidence. In the short run self-attribution bias leads to a larger degree of overconfidence with increasing experience. In the long run it depends on the level of self-attribution bias whether experience decreases overconfidence or remains on an equilibrium level or even explodes for longer time horizons. The empirical evidence in our work shows that forecasters seem to hold reasonable levels of self-attribution. Working experience in the financial sector decreases overconfidence on the 5 % significance level. This result is independent from controlling for age, so the experience effect does not stem from just getting older. In our reference situation of an average forecaster, eight more years (one standard deviation) of experience lead to a 12% lower probability to be overconfident and to a 10% higher probability to be underconfident (see Table 4).

Another often discussed *gender* related finding in the literature is the fact that women are less affected by the better-than-average bias than men (Barber and Odean, 2001). To cut the evidence short: women seem to be equally confident as men in general, but men match the stereotype whenever the tasks are typical masculine (Beyer and Bowden, 1998; Barber and Odean, 2001). Even though financial markets could be said to be masculine domains (for example remember that our sample encompasses 8% women only) some studies find also for the financial market domain no difference in overconfidence for gender: in an experimental financial market Deaves et al. (2009) cannot report any significant effect of gender – neither on trading volume nor on overconfidence. Oberlechner and Osler (2008) survey US traders but also do not report gender differences. We join these studies by finding no significant difference between the behavior of women and men, neither for the group of overconfident nor the group of underconfident professionals. But due to the large fraction of men in our sample we abstain from relying too much on these results.

(2) Job characteristics

Besides the information about demographic attributes we analyze the influence of job related characteristics by including dummies for advisor, researcher and fund manager in the benchmark regression. Researchers tend to be more overconfident, but not for every estimation specification. For fund managers we find robust evidence for lower overconfidence. Fund managers are more (less) likely to be underconfident (overconfident) by 32% than the average forecaster who is not a fund manager. We explain this result by the direct feedback, which fund managers receive. For the observed groups fund managers are the financial market participants with the clearest and the most direct feedback. Since their salary

is usually linked to their performance they are supposed to evaluate their performance correctly.

Besides the position dummy for fund managers we find a significant effect of the use of fundamental analysis. We interpret this variable as a measure for the extent to which one uses complex analysis methods rather than simple technical rules or relying just on good luck. Former research has shown that sophistication can decrease biases (Feng and Sesholes, 2005). Nevertheless the effect of the variable is not robust for all alternative regressions (specification 4). This result might stem from the effect that only the best informed benefit from their information (Huber et al., 2009). Others might just feel well informed and thus believe to be over performing but in fact they do not.

(3) Forecasting characteristics

The third domain of characteristics stems from professionals' own forecasting characteristics. We find that recent forecasting successes and herding matter for the level of overconfidence. We refer to this transmission channel as forecasters' attitude.

In the theoretical literature overconfidence is modeled as a process of learning due to biased self-attribution (e.g. Daniel et al., 1998; Gervais and Odean, 2001): recent successes take relatively too much weight for self-evaluation (e.g. Miller and Ross, 1975). We find evidence for self-attribution bias. We observe positive as well as negative *trends in the forecasting performance* of the recent past. If self-attribution bias is a reason for overconfidence the positive trend should be significant and the negative should not be significant. Indeed, this is the case. The dummy variable for a positive trend in the hit rate is continuously significant for all model specifications. The analysis for the reference case of an average forecaster shows that becoming a better forecaster results in a 27% higher chance to be overconfident and reduces the likeliness of being underconfident by 19%.

This finding also raises the stakes for the hypothesis that the most *recent successes* and failures are most important for a high self-evaluation. Using aggregate data Statman et al. (2006) find that returns up to 6 month matter for trading volume, which they interpret as overconfidence. We are able to provide further support for this relationship. We estimate an adjusted model which includes the mean hit rate of the last 6 months rather than the dummy variables for positive and negative trend in the hit rate (see specifications 3 and 4 in Table 3). The coefficient for the new variable of recent success is significantly positive, which supports the hypothesis. Present successes seem to generate an optimistic attitude which biases their self-evaluation positively.

Another aspect which we relate to attitude is the tendency to *herd*. We measure how much each forecaster agrees in one's forecasts with the market and interpret this as herding behavior. We can observe that the more (less) the forecaster aligns one's forecast with the market the less (more) overconfident (underconfident) one is. A similar relationship is found by Rangvid et al. (2009) for stock market forecasters. We offer two explanations for this relationship. (1) Forecasters' risk attitude may influence both, herding and overconfidence. On the one hand, a herding forecaster tends to rate oneself quite conservatively due to risk aversion. Theoretical studies show that due to reputation effects lower risk taking and more intensive herding go hand-in-hand (Hirshleifer and Thakor, 1992). Empirical evidence for this relationship is vast, for example Graham (1999). On the other hand, overconfident traders underestimate the riskiness of projects, which is modeled by De Long et al. (1991) and empirically verified for CFOs by Ben-David et al. (2007). Therefore attitudes toward risk and herding may be the reason for forecasters to give a conservative self-evaluation. In the end, forecasters who herd are unlikely to give positive self-rating and to be overconfident. (2) Overconfident investors overweigh the accuracy of their own information relatively to the precision of the information of other investors (Odean, 1998). Zitzewitz (2001) shows that stock analysts who herd overweight their private information as do overconfident subjects. Thus, overconfident investors do not pay as much attention to the beliefs of others as to their own valuations and are unlikely to herd. We believe the first argument to be more convincing, because the second argument reverses the direction of the relationship. We use the market alignment of the past forecasts, which actually rules out any reverse causality. But since the forecasts are relatively persistent, we cannot ultimately stick to one of the arguments.

5.3 Robustness

We apply several variations on our estimates to check the robustness of our results. These turn out to be quite robust to any manipulation we apply. A consistent finding of our research is that experience, job, and mood have an impact on the level of overconfidence.

First, alternative assumptions for the error distribution yield similar results. For the estimation of the ordered response model we assume logistic distribution of the error terms. To examine the effects of a different assumption of the error distribution closer we try an ordered probit model (Greene, 2008). As the analysis of information criteria suggests the logistic assumption fits our data set quite well. Akaike Information Criterion and Bayes Information Criterion are both fairly smaller for the ordered logit model. But even when we use the normal error distribution assumption the significance levels of the parameter estimates remain the same.

Second, the estimates remain stable for different approximations of the hit rate which is part of the explained level of overconfidence. For our baseline estimations we use a hit rate which codes no forecasting failures as well as small and large failures. Since we receive the forecasts also in three different outcomes, this procedure seems quite reasonable. For robustness we estimate our baseline model again using a hit rate which distinguishes only between giving a correct and an incorrect forecast (see Appendix 1). Thereby we obviously discriminate forecasters who make just small mistakes, but get the direction right. Despite of this mistake our results remain generally the same. Forecasters still do not get their self rating right, which means that self-rating and performance are uncorrelated. On average forecasters are truly overconfident. The determinants of overconfidence also remain the same. Working experience as well as the approximations of mood remain significant and keep their effect. The effect of fund managers also remains stable whereas the effect of fundamental analysis vanishes. This underlines the low significance level of fundamental analysis in our baseline model and encourages us not to overestimate the effect of fundamental analysis.

Third, we test for the parallel regression assumption of the ordered logit model and use alternative models which relax this assumption. A likelihood ratio test with the null hypothesis of proportional odds shows no evidence for a violation of the assumption for our data set. Using the more exact test procedure of Brant (1990) allows us to tackle single variables and see whether the coefficients for a variable are the same for the different outcomes as it is assumed by the ordered logit model. The test suggests that a few variables violate the parallel regression assumption. Therefore we relax the parallel regression assumption and estimate a partially generalized ordered logit model (see Appendix 2). This method allows to lift the constraint for some variables and to restrict the rest (Boes and Winkelmann, 2006). For most of the variables the results remain the same. But the estimation suffers from a large proportion of negative predicted probabilities, which accounts for about two thirds for some specifications. Moreover the estimates are blurred due to the opaque impact of some variables, like the gender variable which makes only seven percent of the sample. Hence, we prefer the ordered logit model compared to the generalized ordered logit model. For further robustness checks we introduce a model which removes the assumptions of the ordinal features of the data and estimate a multinomial regression model (Appendix 3). Also for this estimation approach the results remain mainly the same. Since the multinomial estimation clearly violates the results of the likelihood ratio test and neglects the ordinal nature of the dependent variable, we stick to the ordered logit model as our preferred model.

We conclude that our result of the significant effects of experience, job and mood are quite robust to various manipulations and variations.

6 Conclusion

This study examines overconfidence (and underconfidence) among financial professionals. We contribute to the literature in that we combine “hard” performance information with self-rated performance and complement this with a comprehensive set of demographic, job and forecasting characteristics. There are not many studies with a comparable depth of information and with respect to the “true” better-than-average overconfidence measure among financial professionals this study is unique according to our knowledge.

We find indeed that financial professionals in our sample are overconfident on average, although the degree of overconfidence seems relatively small compared to many studies with individual investors. Moreover, we find that there is no relation between the self-rating and effective performance which is surprising for professionals. Consequently, overconfidence is driven by performance in that bad forecasters are on average rather overconfident and the reverse. Interestingly, there are also underconfident professionals who have been largely neglected in earlier research.

In an effort towards understanding financial professionals’ over- and underrating of their own performance, we examine correlates being suggested in the literature. We find that experience in the financial sector comes along with less overconfidence. In addition we show that some job related variables such as being a fund manager and the use of fundamental analysis are also related to less overconfidence. Finally, we provide evidence for a significant effect of attitude in that recent success and more courageous non-herding is observed among more overconfident financial professionals. Overall, these intuitively plausible correlates contribute to a rich picture of financial professionals’ behavior.

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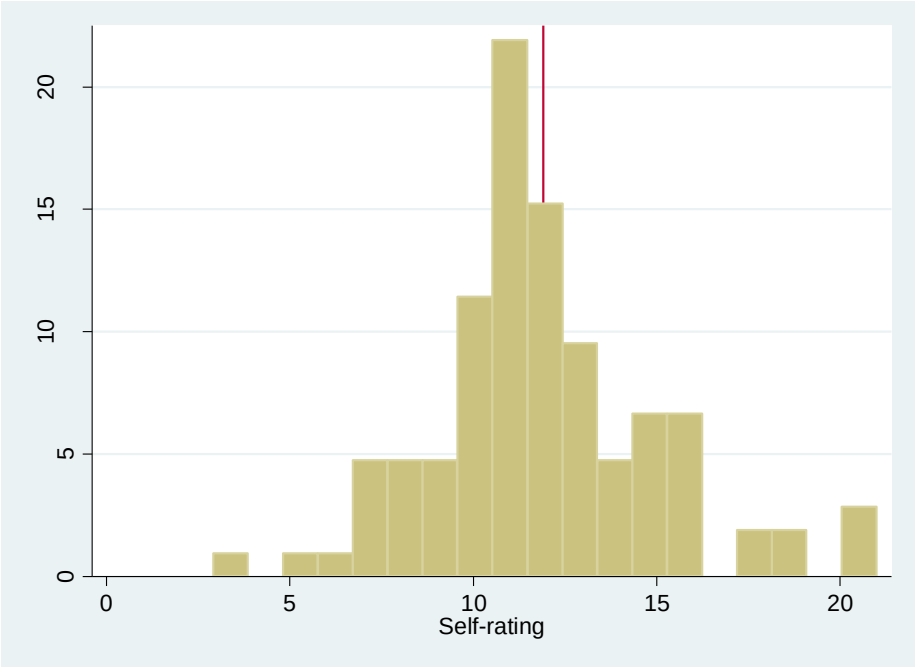
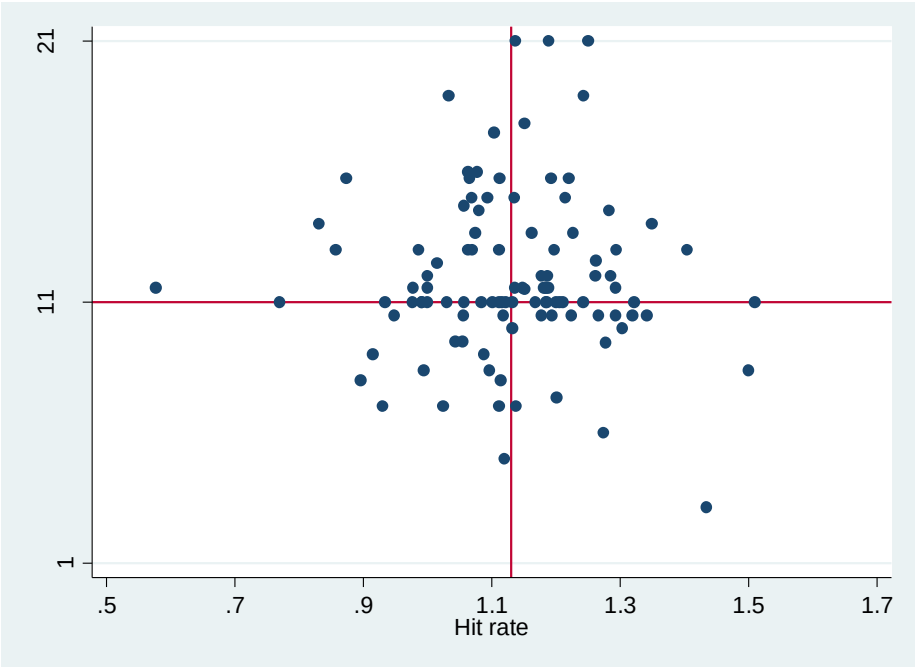
Figure 1: Distribution of self-rating



Note: We asked the financial experts in two surveys (April 2007 and October 2008) the following question: „How do you evaluate your USD/EUR-forecast compared to the average forecasting hit rate of all participants of the ZEW financial market survey?“. The scale ranges from 1 to 21. The mean answer is 11.9.

Figure 2: Scatter plot of self-rating and hit rate



Note: The self-rating is a survey item ranging from 1 to 21 and indicates whether someone believes to be above (21) or below (1) the average hit rate. Hit rate is the individual average of the survey forecasts. We code three categories, large deviation (0), small deviation (1) and no deviation (2) of forecast from the true process. Large deviations are predictions which indicate the opposite direction of the actual movement, whereas small deviations are expectations which are neither a correct forecast nor a large deviation.

Table 1: Descriptive statistics about overconfidence measures

						Correlation		
	Obs.	Mean	Std. Dev.	Min.	Max.	BTA	MISC	IOC
Better-than-average	105	11.91	3.15	3	21	1.0000		
Obs.						71		
p-value						.		
Miscalibration	74	0.14	0.07	0.04	0.33	-0.0444	1.0000	
Obs.						71	71	
p-value						(0.7131)	.	
Illusion-of-control	73	13.47	3.7	4	20	0.3124***	-0.1398	1.0000
Obs.						71	71	71
p-value						(0.008)	(0.245)	.

Note: Correlations are Spearman's rank correlation coefficients. Corresponding p-values are in parenthesis. The level of significance are denoted by *** p<0.01, ** p<0.05, * p<0.1.

[1] We asked the financial experts in two surveys (04/2007 and 10/2008) the following question: „How do you evaluate your USD/EUR-forecast compared to the average forecasting hit rate of all participants of the ZEW financial market survey?". The scale ranged from 1 to 21.

[2] The question for miscalibration was an item in the survey of October 2008. Respondents gave a 90-% confidence interval for the 6-month future USD/EUR exchange rate. Miscalibration is defined here as the relative confidence interval.

[3] Illusion-of-control was surveyed in October 2008. The information was extracted from the following question: "Most of the published business news does not surprise me at all." Respondents answered on a scale ranging from 1 to 20.

Table 2: Descriptive statistics of financial experts' characteristics

	Obs.	Mean	Std. Dev.	Min.	Max.
Demographic characteristics					
Male†	105	0.92	0.27	0	1
Academic education†	105	0.76	0.43	0	1
Age	105	44.56	8.11	29	65
Working experience in fin. sector	105	17.69	8.78	3	43
Job characteristics					
Personnel responsibilities†	105	0.50	0.50	0	1
Operative responsibilities†	105	0.78	0.42	0	1
Advisor†	105	0.18	0.39	0	1
Fund manager†	105	0.30	0.46	0	1
Researcher†	105	0.23	0.42	0	1
Fundamental analysis[4]	105	55.05	22.41	0	100
Forecasting characteristics					
Hit rate[1]	105	1.13	0.14	0.58	1.51
Positive trend in hit rate†,[2]	105	0.15	0.36	0	1
Negative trend in hit rate†,[2]	105	0.07	0.25	0	1
Recent success[3]	105	1.18	0.43	0	2
Herding[5]	105	51.42	18.54	1.02	92.08

Note: Dummy variables are denoted by "†".

[1] Hit rate measures the individual average hit rate over the observation period, where the individual hit rate at a time point codes the forecasting performance in no deviation (2), small deviation (1), and large deviation (0).

[2] Positive (negative) trend in hit rate is a dummy variable for a significant positive (negative) trend in the forecasting performance over the last three years.

[3] Recent success is the individual average hit rate of 1-month forecasts over the last 6 months.

[4] Fundamental analysis is the self-reported degree (in %) of how much fundamental analysis is used for creating the exchange rate expectation.

[5] Herding (in %) measures how often a forecaster expects the exchange rate to change in the same direction as the market expected the period before. We refer to market by using the mode of all participating forecasters.

Table 3: Ordered logit estimation results for over-/underconfidence

	(1)	(2)	(3)	(4)
Male	0.436		0.194	
	(0.668)		(0.847)	
Academic education	-0.249		-0.153	
	(0.682)		(0.787)	
Age	0.0389		0.0464	
	(0.494)		(0.391)	
Working exp. in fin. sector	**-0.0880***	**-0.0578****	**-0.0903***	**-0.0546****
	(0.100)	**(0.019)**	**(0.073)**	**(0.029)**
Personnel responsibility	-0.476		-0.438	
	(0.271)		(0.343)	
Operative responsibility	0.0546		-0.158	
	(0.940)		(0.829)	
Advisor	0.127		0.0999	
	(0.852)		(0.890)	
Fund manager	**-1.240****	**-1.384*****	**-1.156****	**-1.097*****
	(0.034)	**(0.002)**	**(0.033)**	**(0.008)**
Researcher	1.023		0.588	
	(0.167)		(0.468)	
Positive trend in hit rate	**1.318***	**1.352***		
	(0.097)	**(0.055)**		
Negative trend in hit rate	-0.763			
	(0.419)			
Fundamental analysis	**-0.0197***	**-0.0165***	**-0.0152***	
	(0.052)	**(0.096)**	**(0.080)**	
Herding	**-0.0394*****	**-0.0305****	**-0.0406*****	**-0.0314****
	(0.003)	**(0.018)**	**(0.004)**	**(0.013)**
Recent success			0.814	**0.874***
			(0.127)	**(0.052)**
Cut 1	**-3.611***	**-4.399*****	-2.667	**-2.554****
	(0.098)	**(0.000)**	(0.185)	**(0.013)**
Cut 2	-2.969	**-3.785*****	-2.035	**-1.950****
	(0.168)	**(0.001)**	(0.306)	**(0.049)**
Pseudo-R2	0.134	0.108	0.121	0.0935
Observations	105	105	105	105

Note: The level of significance are denoted by *** p<0.01, ** p<0.05, * p<0.1, robust p-values in parentheses. For description of the variables see annotations of Table 1.

Table 4: Effects of a marginal/discrete change in the ordered logit regression model

	UNC	NN	OVC
Working experience in fin. sector	0.1039	0.0197	-0.1236
Fund manager	0.3296†	-0.0085†	-0.3212†
Positive trend in hit rate	-0.1935†	-0.0723†	0.2658†
Fundamental analysis	0.0757	0.0145	-0.0901
Herding	0.1156	0.0219	-0.1374
P(y | x)	28.85	13.96	57.19
P(y)	36.19	12.38	51.43

Note: UNC (OVC) corresponds to forecasters who are underconfident (overconfident) and NN to forecasters who are neither nor. The marginal effects are calculated for a change of one standard deviation for the reference case of a forecaster who shows average working experience (18 years) and use of fundamental analysis (55 %) and herding (51 %) and who is neither a fund manager nor has a positive trend in the hit rate. The effect for the dummy variables is a discrete change from 0 to 1, denoted by "†".

Appendix 1: Ordered logit estimation results for overconfidence with alternative hit ate

	(1)	(2)	(3)	(4)
Male	-0.168		-0.648	
	(0.847)		(0.507)	
Academic education	0.403		0.468	
	(0.483)		(0.413)	
Age	0.0362		0.0676	
	(0.558)		(0.214)	
Working experience in financial sector	-0.0913	**-0.0657*** **	**-0.112** **	**-0.0650*** **
	(0.135)	**(0.006)**	**(0.045)**	**(0.006)**
Personnel responsibility	-0.645		-0.695	
	(0.179)		(0.114)	
Operative responsibility	0.631		0.473	
	(0.344)		(0.479)	
Advisor	0.893		0.634	
	(0.262)		(0.414)	
Fund manager	-0.344	-0.650	-0.566	**-0.774* **
	(0.565)	(0.149)	(0.307)	**(0.085)**
Researcher	**1.679** **		**1.217* **	
	(0.022)		**(0.077)**	
Positive trend in hit rate	**2.558** **	**2.497** **		
	(0.027)	**(0.022)**		
Negative trend in hit rate	1.032			
	(0.369)			
Fundamental analysis	-0.00400	-0.00257	-0.00382	-0.00258
	(0.717)	(0.797)	(0.720)	(0.795)
Herding	**-0.0493*** **	**-0.0364*** **	**-0.0583*** **	**-0.0444*** **
	(0.003)	**(0.009)**	**(0.000)**	**(0.001)**
Recent success			0.962	1.300*
			(0.274)	(0.0950)
Cut 1	-2.665	**-4.002*** **	-2.705	**-4.104*** **
	(0.212)	**(0.000)**	(0.158)	**(0.000)**
Cut 2	-1.998	**-3.395*** **	-2.070	**-3.515*** **
	(0.353)	**(0.001)**	(0.282)	**(0.000)**
Pseudo-R2	0.193	0.139	0.155	0.108
Observations	105	105	105	105

Note: Note: The level of significance are denoted by *** p<0.01, ** p<0.05, * p<0.1, robust p-values in parentheses. For description of the variables see annotations of Table 1. Variables referring to performance use a hit rate with alternative coding of right (1) / wrong (0) forecast.

Appendix 2: Generalized ordered logit estimation results for overconfidence

	(1)		(2)		(3)		(4)	
	UNC	NN	UNC	NN	UNC	NN	UNC	NN
Male	**17.32*** **	**-15.75*** **			**19.46*** **	**-17.62*** **		
	(0)	**(0)**			**(0)**	**(0)**		
Academic education	**5.556** **	**-2.541** **			-0.629	-0.629		
	(0.023)	**(0.023)**			(0.256)	(0.256)		
Age	-0.636**	0.136			0.0810	0.0810		
	(0.039)	(0.428)			(0.148)	(0.148)		
Working exp. in fin. sector	**0.598** **	-0.202	**-0.0474* **	**-0.0474* **	**-0.108** **	**-0.108** **	**-0.0447** **	**-0.0447** **
	(0.034)	(0.206)	**(0.077)**	**(0.077)**	**(0.039)**	**(0.039)**	**(0.044)**	**(0.044)**
Personnel responsibility	-0.493	-0.493			-0.558	-0.558		
	(0.405)	(0.405)			(0.206)	(0.206)		
Operative responsibility	**2.067* **	-1.142			0.464	0.464		
	(0.059)	(0.148)			(0.519)	(0.519)		
Advisor	**-2.330* **	1.328			-0.747	-0.747		
	(0.076)	(0.119)			(0.258)	(0.258)		
Fund manager	-0.977	-0.977	**-1.247*** **	**-1.247*** **	**-1.492** **	**-1.492** **	**-1.085** **	**-1.085** **
	(0.197)	(0.197)	**(0.008)**	**(0.008)**	**(0.010)**	**(0.010)**	**(0.011)**	**(0.011)**
Researcher	0.511	0.511			0.0162	0.0162		
	(0.454)	(0.454)			(0.983)	(0.983)		
Positive trend in hit rate	**-21.55*** **	**17.01*** **	**-16.49*** **	**16.33*** **				
	(0)	**(0)**	**(0)**	**(0)**				
Negative trend in hit rate	1.885	-1.245						
	(0.213)	(0.285)						
Fundamental analysis	**-0.0334** **	-0.000866	-0.0161	-0.0161	-0.00735	-0.00735	-0.00709	-0.00709
	(0.0188)	(0.952)	(0.123)	(0.123)	(0.457)	(0.457)	(0.427)	(0.427)
Herding	**-0.0387** **	**-0.0387** **	**-0.0333** **	**-0.0333** **	**-0.0345*** **	**-0.0345*** **	**-0.0234** **	**-0.0234** **
	(0.038)	**(0.038)**	**(0.016)**	**(0.016)**	**(0.004)**	**(0.004)**	**(0.048)**	**(0.048)**
Recent success					0.834	0.834	**0.841* **	**0.841* **
					(0.118)	(0.118)	**(0.062)**	**(0.062)**
Constant	-1.847	**18.93*** **	**4.339*** **	**3.653*** **	**-18.18*** **	**17.91*** **	**2.448** **	1.581
	(0.814)	**(0.000)**	**(0.001)**	**(0.003)**	**(0)**	**(0)**	**(0.019)**	(0.120)
Pseudo-R2	0.431	0.431	0.195	0.195	0.162	0.162	0.0748	0.0748
Observations	105	105	105	105	103	103	103	103

Note: Note: The level of significance are denoted by *** p<0.01, ** p<0.05, * p<0.1, robust p-values in parentheses. Coefficients give the between the impact between the respective category and the base outcome (overconfident). For description of the variables see annotations of Table 1.

Appendix 3: Multinomial logit estimation results for overconfidence

	(1)		(2)		(3)		(4)	
	UNC	OVC	UNC	OVC	UNC	OVC	UNC	OVC
Male	**-18.30*** **	**-17.56*** **			**-18.75*** **	**-18.40*** **		
	(0.000)	**(0.000)**			**(0)**	**(0)**		
Academic education	**-2.109** **	**-2.298** **			0.244	-0.416		
	(0.046)	**(0.046)**			(0.756)	(0.609)		
Age	0.160	0.190			0.0272	0.0637		
	(0.164)	(0.155)			(0.730)	(0.458)		
Working exp. in fin. sector	-0.148	**-0.221* **	0.0215	-0.0353	-0.0304	-0.114	-0.0105	**-0.0624** **
	(0.217)	**(0.097)**	(0.587)	(0.369)	(0.686)	(0.137)	(0.729)	**(0.035)**
Personnel responsibility	0.182	-0.334			0.0357	-0.268		
	(0.824)	(0.684)			(0.955)	(0.674)		
Operative responsibility	**-1.766* **	-1.551			-0.597	-0.131		
	(0.084)	(0.115)			(0.542)	(0.877)		
Advisor	1.067	1.190			0.137	-0.628		
	(0.419)	(0.339)			(0.878)	(0.486)		
Fund manager	1.090	-0.287	1.057	-0.502	0.995	-0.584	1.056	-0.243
	(0.242)	(0.764)	(0.152)	(0.495)	(0.221)	(0.459)	(0.107)	(0.716)
Researcher	**-2.224* **	-0.452			-1.550	-0.806		
	(0.071)	(0.649)			(0.164)	(0.365)		
Positive trend in hit rate	20.41	**21.50*** **	20.57	**21.76*** **				
	()	**(0)**	()	**(0)**				
Negative trend in hit rate	-0.643	-1.701						
	(0.603)	(0.227)						
Fundamental analysis	**0.0323* **	0.00720	0.0257	0.00719	0.0222	0.00827	0.0169	0.00688
	(0.083)	(0.671)	(0.107)	(0.631)	(0.121)	(0.491)	(0.177)	(0.553)
Herding	0.0171	-0.0280	0.0175	-0.0154	0.00907	-0.0237	0.00874	-0.0191
	(0.458)	(0.161)	(0.375)	(0.419)	(0.612)	(0.145)	(0.583)	(0.195)
Recent success					0.0688	0.945	-0.0181	0.942
					(0.925)	(0.183)	(0.978)	(0.183)
Constant	**15.25*** **	18.83	-2.113	2.319	**17.06*** **	19.11	-0.882	1.587
	(0)	()	(0.231)	(0.161)	**(0)**	()	(0.530)	(0.290)
Pseudo-R2	0.215	0.215	0.126	0.126	0.126	0.126	0.0870	0.0870
Observations	105	105	105	105	103	103	103	103

Note: The level of significance are denoted by *** p<0.01, ** p<0.05, * p<0.1, robust p-values in parentheses.
For description of the variables see annotations of Table 1.