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Do German security analysts herd?

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Abstract We employ an innovative methodology suggested by Bernhardt et al. (J. Financ. Econ. 80:657–675, 2006) to examine the herding (or anti-herding) behavior of German analysts regarding earnings forecasts. This methodology avoids well-known shortcomings often encountered in related studies, such as correlated information signals, unexpected common shocks to earnings, systematic optimism or pessimism, or forecast target mismeasurement. Our findings suggest that German analysts anti-herd, that is, they systematically issue earnings forecasts that are further away from the consensus forecast than their private information indicates. Furthermore, we analyze the association between herding behavior and different characteristics, including the size of the brokerage, general or firm-specific experience, and the coverage of firms on the *Neuer Markt*. We mainly confirm findings for the United States, for example, that anti-herding is more severe in cases of higher competition among analysts. Contrary to anecdotal evidence, we also find anti-herding behavior in earnings forecasts for *Neuer Markt* firms during the "new economy" bubble.

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1 Introduction

Security analysts play an important intermediary role in financial markets. They evaluate public information, such as annual reports, or semi-public information and issue their analysis outcomes as recommendations and earnings forecasts to the market. In this way, they help market participants assess firm value. In an ideal world, analysts would issue unbiased forecasts representing their best estimate of future earnings. These unbiased forecasts could then be efficiently processed into security prices, which would guarantee a high level of informational efficiency of capital markets. However, it is doubtful whether analysts in the real world actually do issue unbiased earnings forecasts.

Indeed, security analysts are often accused of issuing biased forecasts that do not fully reflect their best estimate and thus reduce the information conveyed to market participants. On the one hand, analysts are accused of acting in a herd-like manner. In this paper, "herding" is to be understood as issuing a forecast that is biased toward the extant consensus forecast. On the other hand, analysts could show the reverse bias and anti-herd. For example, if analysts wanted to stand out from the crowd, they could bias their best estimate away from the consensus and overemphasize their private information. In both cases—herding and anti-herding—earnings forecasts would not be accurate representations of analyst knowledge about future earnings and could thus lead to "*poorer information aggregation*" (Welch 2000). This situation could drive security prices away from their intrinsic values, reduce the degree of capital market efficiency, and contribute to a higher level of security price volatility.[1] To assess the functionality of capital markets it is thus important to empirically investigate whether analysts engage in herding or anti-herding behavior.

In this study, we examine the herding behavior of German analysts using a new methodology suggested by Bernhardt et al. (2006). Although other studies have analyzed herding behavior in the German context, most notably Löffler (1998), their findings are potentially plagued by well-known problems, such as correlated information signals, unexpected common shocks to earnings, systematic optimism or pessimism, or forecast target mismeasurement. The new methodology employed in this paper is robust to these problems. In addition, we shed light on the question of whether German analysts act similarly to US analysts and on whether the tendency of German analysts to herd is associated with certain analyst, brokerage, or firm characteristics. Finally, our study offers evidence across a longer and more recent sample period than do existing studies, which do not examine the last 10 years of forecast data for this important capital market.

[1] See, e.g., Walter and Weber (2006), Bikhchandani and Sharma (2001), De Bondt and Forbes (1999), and Scharfstein and Stein (1990) for possible consequences of herding behavior.

Our evidence suggests that in the sample period, 1994–2005, German analysts released earnings forecasts that were on average biased *away* from the consensus. Approximately 60% of forecasts were either above or below both the consensus and realized earnings. It thus seems that analysts *do not* have a tendency to underweight their private information by herding on the extant consensus forecast but, instead, *do* overweight their private information to differentiate themselves from other analysts, thus engaging in anti-herding behavior. Our conclusions remain valid when we analyze subsamples based on time period, analyst or firm characteristics, or forecast revisions (instead of revisions and reiterations). As a result, our findings corroborate those of Bernhardt et al. (2006), Chen and Jiang (2006), and Zitzewitz (2001) on US analysts. However, as all other studies, except Bernhardt et al. (2006), could be affected by the above-described problems, a direct comparison with them might be inappropriate.

We find that the tendency to issue anti-herding forecasts increases with the number of analysts following a firm, but does not depend on the order in which forecasts are issued or the time remaining until the earnings announcement. Interestingly, the data suggests that earnings optimism decreases over time, which lends support to the "earnings-guidance game" proposed by Richardson et al. (2004). In case of analyst characteristics, we do not observe an association between brokerage size or analyst experience and herding behavior. In contrast, the more firms or industries covered by an analyst, the more likely the analyst is to engage in herding behavior. Our analysis of firm characteristics brings to light that size is positively associated with analysts' tendency to anti-herd, which could potentially be driven by the fact that more analysts follow large companies. The price-to-book ratio appears unrelated to herding behavior. Anti-herding behavior is much less pronounced for firm-years with negative earnings. We report significant anti-herding behavior for *Neuer Markt* firms during the "new economy" bubble, which contradicts popular opinion that analysts simply herded on the extant consensus in this time period and thereby aggravated the crisis. Finally, our findings indicate that earnings forecasts are biased, which could have serious consequences for stock market efficiency.

We structure our paper as follows. In Sect. 2, we briefly review the existing literature. Section 3 outlines the methodology of Bernhardt et al. (2006). A description of the data, the sample selection criteria, and descriptive statistics can be found in Sect. 4. In Sect. 5, we present our empirical results. We conclude in Sect. 6.

2 Prior literature

A great deal of research addresses the tendency of economic agents to exhibit herding behavior, some of which is devoted to the herding behavior of security analysts.[2] Starting with the theoretical literature, Bikhchandani et al. (1992) and Banerjee (1992) show that when agents observe other agents' decisions but not their information signals, mimicking the forerunner's decision might be rational, even if private

[2]For detailed reviews of the general herding literature, see, e.g., Spiwoks (2004), Hirshleifer and Teoh (2003), Bikhchandani and Sharma (2001), Oehler (1998), and Devenow and Welch (1996).

information suggests a different action. As private information is thus not completely reflected in agents' decisions, herding behavior imposes the social cost of a less efficient information environment. Scharfstein and Stein (1990), Trueman (1994), and Prendergast and Stole (1996) believe that herding behavior is related to career concerns. In these models, agents herd to signal ability. More specifically, Trueman (1994) shows that analysts may release earnings forecasts that are closer to the consensus than their private information suggests so as to give the impression of high forecasting ability. Trueman (1994) also asserts that analysts' herding propensity relates negatively to the ability to forecast earnings. In contrast, the theoretical findings of Prendergast and Stole (1996) suggest that junior managers, who lack reputation, exaggerate their private information and thus anti-herd in an effort to appear talented. Once junior managers have built up reputation, however, they become reluctant to overweight their own information and instead start to herd on the existing consensus opinion.

The empirical literature on security analyst herding can be split into two groups, with the first group focusing on stock recommendations. Welch (2000) reports that recommendation revisions are positively associated with the consensus and the recommendation revisions of the two subsequent analysts. In addition, Jegadeesh and Kim (2007) find that recommendation revisions are to a certain extent influenced "*by analysts' desire to herd with the crowd.*" Literature in the second group analyzes herding behavior in quarterly or annual earnings forecasts. Zitzewitz (2001) uses a regression-based approach to study the herding behavior of US analysts in the period 1993–1999. Similarly to Chen and Jiang (2006), his evidence suggests that US analysts exaggerate their private information and thus exhibit anti-herding behavior.

Empirical studies of European markets are rare.[3] De Bondt and Forbes (1999) examine UK analysts' earnings forecasts between 1986 and 1997 and find strong evidence of herding behavior. To the best of our knowledge, the herding behavior of German analysts has to date been analyzed only by Löffler (1998), who finds no herding behavior between 1988 and 1993. As Clement et al. (2003) argue, differences in conclusions about herding across countries could stem from differences in culture and corporate governance.

The above-mentioned studies have been criticized as their regression-based research designs cannot control for well-known problems that could affect conclusions. In particular, if analysts obtain similar, that is, correlated, information signals, then earnings forecasts would not be independent and should by construction cluster around a specific earnings value. In the same vein, if earnings are influenced by a common shock shortly before their announcement, this would also explain why they all either exceed or fall short of target. Finally, systematic optimism and forecast mismeasurement—that is, differences in the definition of earnings between analysts and firms—could also lead to the appearance of herding behavior. As we discuss later, the test statistic of Bernhardt et al. (2006) controls for these problems. Using

[3]Most empirical studies of European markets focus on whether analysts show a tendency to issue optimistic or pessimistic earnings forecasts. For example, Bessler and Stanzel (2007), Henze (2004), and Capstaff et al. (1998) report that German analysts' earnings forecasts show an optimism bias, but they do not directly examine herding.

their test statistic on US analysts' earnings forecasts between 1989 and 2001, Bernhardt et al. (2006) confirm the findings of Zitzewitz (2001), that is, they also find strong anti-herding behavior. Surprisingly, however, the new methodology has not yet been used to analyze herding behavior in non-US markets. Our study is a first step in this direction.

A fairly recent strand of literature attempts to explain why certain analysts show herding behavior and others exhibit anti-herding behavior. Hong et al. (2000) obtain evidence indicating that less experienced analysts are more severely penalized for poor and bold forecasts, leading them to herd more than experienced analysts.[4] Clement and Tse (2005) report that analysts' propensity to anti-herd increases with general experience, prior accuracy, forecast frequency, forecast horizon, and brokerage house size. In contrast, the propensity to anti-herd decreases with the number of industries an analyst covers and with the number of days elapsed since the prior forecast. Unfortunately, the definition of herding behavior applied in these studies could suffer from problems similar to those criticized in the above described studies.

3 Methodology

In this study, we employ the simple, yet persuasive, methodology of Bernhardt et al. (2006) to analyze the herding behavior of German analysts. This methodology does not suffer from correlated information signals, unexpected common shocks to earnings, systematic optimism or pessimism, or forecast target mismeasurement, problems that render it impossible to distinguish true (intentional) from spurious (unintentional) herding. For example, in the case of correlated information signals, a finding of herding could be spurious as analysts draw similar conclusions based on similar information and thus arrive at the same forecast, but have not actually engaged in herding to do so.

The idea behind the test statistic is as follows. Analysts observe public and private information signals that they use when making their forecasts. Combining all relevant information, analysts form probability distributions over earnings.[5] The crucial part in designing the herding test is the question of whether analysts issue unbiased forecasts. Following Bernhardt et al. (2006), a "*forecast is unbiased, if it corresponds to the analyst's best estimate of earnings given all available information.*" An analyst's best estimate is equal to the mean or median of her probability distribution over earnings. The unbiased forecast serves as a benchmark against which all forecasts are compared and it separates herding forecasts from anti-herding forecasts. A forecast

[4] Anti-herding forecasts are sometimes called "bold" forecasts. Clement and Tse (2005) define a bold forecast as a forecast that is either above or below both the analyst's prior forecast and the extant consensus. Their definition of a bold forecast differs from the definition of an anti-herding forecast in Bernhardt et al. (2006).

[5] In their study, Bernhardt et al. (2006) use the term "analysts' posterior distributions over earnings." As one of our referees correctly pointed out, this term could be misleading, as it might suggest that analysts use Bayesian techniques to update their prior beliefs, which is not required for the S statistic to produce valid outcomes. In fact, analysts can form their expectations in any conceivable way. As a result, we avoid the above term.

will be considered a herding forecast if the analyst decides to bias her forecast away from her best estimate in the direction of the extant consensus, in which case, the analyst understates her private information. In contrast, if an analyst decides to bias her forecast farther away from the outstanding consensus than suggested by her private information, her forecast will be considered an anti-herding forecast. In this case, the analyst overemphasizes her private information and tries to distinguish herself from the consensus.

We test the null of unbiased forecasts (no herding) against the alternative of two possible biases (herding or anti-herding). An unbiased forecast should be equally likely to overshoot as to undershoot actual earnings, which must be true conditional on anything in an analyst's information set, e.g., the outstanding consensus forecast. It follows:

$$\begin{aligned} &\Pr(F_\tau > A_\tau | F_\tau > \bar{F}_\tau; F_\tau \neq A_\tau) = 0.5 \quad \text{and} \\ &\Pr(F_\tau < A_\tau | F_\tau < \bar{F}_\tau; F_\tau \neq A_\tau) = 0.5 \end{aligned} \tag{1}$$

where F_τ is the earnings forecast during a given firm-forecasting period τ, $\bar{F}_\tau$ is the consensus forecast one day before the analyst publishes her forecast, and A_τ is actual earnings announced at the end of the firm-forecasting period τ.[6] If an analyst herds, the conditional probabilities become

$$\begin{aligned} &\Pr(F_\tau > A_\tau | F_\tau > \bar{F}_\tau; F_\tau \neq A_\tau) < 0.5 \quad \text{and} \\ &\Pr(F_\tau < A_\tau | F_\tau < \bar{F}_\tau; F_\tau \neq A_\tau) < 0.5. \end{aligned} \tag{2}$$

An analyst who herds, moves away from her best forecast toward the consensus. If the consensus is smaller than the analyst's forecast, this implies that the chance of overshooting earnings will be strictly smaller than 0.5. A similar logic applies to the case where the consensus is larger than the analyst's forecast.

In case of anti-herding, the following inequalities apply:

$$\begin{aligned} &\Pr(F_\tau > A_\tau | F_\tau > \bar{F}_\tau; F_\tau \neq A_\tau) > 0.5 \quad \text{and} \\ &\Pr(F_\tau < A_\tau | F_\tau < \bar{F}_\tau; F_\tau \neq A_\tau) > 0.5. \end{aligned} \tag{3}$$

The conditional probabilities are independent of analysts' decision mechanisms, which is a nice feature, as we cannot observe decision mechanisms. Instead, the conditional probabilities exploit the statistical properties of analysts' best forecasts, which should be equal to the conditional expectation of the variable to forecast plus an optimal bias, which is nonzero, if the variable to forecast is non-normally distributed and agents' loss function is non-quadratic (see Patton and Timmermann 2007).

[6] It should be noted that the equations shown under (1) are not dependent on a specific (symmetric) probability distribution. These results hold even under skewed distributions and non-normal preferences. Differences between the optimal forecast and the median of the distribution can be treated as common shocks, which—as we shall see—are canceled out through averaging. Consequently, in contrast to Gu and Wu (2003) or Lim (2001), we do not have to specify a loss function, which would only restrict the generality of our outcomes.

However, as we discuss in footnote 6, the optimal bias is eliminated through averaging and thus is of no consequence.

The test statistic S is the average of the sample estimates of the two conditional probabilities shown in (1), (2), or (3). The estimate of the first conditional probability is the number of earnings forecasts exceeding realized earnings conditional on the earnings forecast exceeding the consensus over the total number of earnings forecasts exceeding the consensus. The estimate of the second conditional probability is defined accordingly. For the remainder of this paper, these two conditional probabilities are called the conditional overshooting and undershooting probability, respectively. Obviously, if analysts use all information efficiently, then $S = 0.5$. If analysts herd, $S < 0.5$. If analysts anti-herd, $S > 0.5$. Note that the test statistic can be interpreted as the degree of herding among security analysts.

The test statistic S is robust to the five previously discussed problems that can undermine inferences. Under no herding or no anti-herding, systematic biases in either direction do not occur because, if they did, the analyst could improve on her best estimate by adjusting for the systematic bias. As a consequence, the test is robust to information signal correlation. Similarly, the test is robust to the arrival of new information within a forecasting cycle. Analysts who engage later in the forecasting cycle may exploit more recent information. In addition, S is robust to cross-sectional correlation of error terms under the null of unbiased forecasts. Cross-sectional correlation occurs due to unexpected shocks that affect all firms, systematic optimism or pessimism, and "*forecast target mismeasurement.*" In these cases, the cross-sectional correlation leads to a systematic upward or downward bias in the two conditional probabilities. However, the biases in the two conditional probabilities are always in opposite directions and of equal magnitude and thus cancel each other out. Moreover, S is robust to the analyst's probability distribution being different from the distribution of observed earnings.[7]

As Bernhardt et al. (2006) show, the test statistic S is conservative in detecting herding or anti-herding behavior, for two reasons. First, the mean of S is biased upward (downward) to the null of unbiased forecasts under the alternative of herding (anti-herding) behavior, which makes it harder to reject forecast unbiasedness.[8] Sec-

[7] Bernhardt et al. (2006) show that the S statistic may be biased if reported earnings are influenced by analysts' forecasts and are thus no longer exogenously determined. The S statistic could also be biased if analysts' forecasts are more reflective of the present than of the future—a phenomenon that Andres and Spiwoks (1999) call topically-orientated trend adjustment. Assume, e.g., that analysts' forecasts are always equal to the last reported earnings plus a creeping adjustment toward the conditional mean. In this case, the S statistic would suggest that analysts herd, even though, in reality, the problem is that analysts issue naïve forecasts. We test for a topically-orientated trend adjustment through the TOTA coefficient. The TOTA coefficient is computed as the R^2 from an OLS regression of the realized value of the variable to forecast at the end of the forecast horizon on the forecast over the R^2 of an OLS regression of the realized value of the variable to forecast at the time the forecast is made on the forecast. A TOTA coefficient below unity suggests a topically-orientated trend adjustment. As EPS are normally not available at the time the forecast is made, we use the last reported EPS. For the whole sample, we find a TOTA coefficient that is above unity. For subsamples based on firms or analysts, we find that the majority of TOTA coefficients are above unity.

[8] Since systematic pessimism among analysts is identical to a positive exogenous shock to all firms' earnings, we shall hereafter refer to this bias in the mean of S under the alternative of anti-herding as the "pessimism bias."

ond, the theoretically derived variance of the test statistic S depends on the cross-sectional correlation in error terms and obtains its maximum when the cross-sectional correlation equals zero, which is the value we assume when we compute the variance.[9]

4 Data, sample selection, and consensus construction

4.1 Data and sample selection

Analyst data are taken from the Institutional Brokers Estimate System's (I/B/E/S) Detail History Database. These data should be free of survivorship bias, since earnings forecasts from companies that either ceased to exist or are no longer covered by any analyst can still be found in the database. Each observation in the database includes the earnings forecast on an EPS basis, the company ticker, the individual analyst code, and the broker code. Additionally, it contains the date on which the forecast was entered into I/B/E/S, the fiscal year-end of the company for which the forecast is provided, and the actual reporting date, i.e., the earnings announcement date. The accuracy of the earnings forecasts can be evaluated using actual reported EPS, which are also provided in I/B/E/S. For the purpose of the later analysis, note that we cannot differentiate between individual analysts and analyst teams. We obtain share prices from DataStream. Both DataStream and I/B/E/S data are adjusted for capital actions. DataStream and I/B/E/S data are also adjusted for the Euro conversion using the irrevocably fixed exchange rates as of December 31, 1998.

Early I/B/E/S data suffer from the problem of systematic time lags between the actual publication date of an analyst's earnings forecast and its entry in the I/B/E/S database. As Cooper et al. (2001) argue, Thomson Financial cannot exactly specify the date on which forecasts were entered into I/B/E/S in 1993. We avoid this problem by starting our sample period in 1994. Consequently, we consider the date on which the forecast was entered into I/B/E/S as the date on which the forecast was made publicly accessible. This guarantees that only those forecasts that an analyst was able to observe with a one-day lag are included in the extant consensus, as suggested by Zitzewitz (2001). Finally, our sample does not contain forecasts made for firm-forecasting periods later than 2005, since a subset of firms had not yet reported their 2006 fiscal year earnings when the data were collected.

Our initial sample has 265,534 observations for the period from 1994 to 2005. We include forecasts for all firm-forecasting periods if (1) they are made during the corresponding fiscal year or (2) they are issued after the fiscal year-end but before the earnings announcement date. The firm-forecasting period can thus have a maximum length of two years, depending on the earnings announcement date. We delete earnings forecasts that are not made for the next fiscal year-end, thus dropping 128,943 observations. To facilitate cross-sectional comparison, we eliminate firms whose fiscal-year end is not December, which results in a further reduction of the

[9] For more details on the properties of S and the calculation of variance, see Bernhardt et al. (2006).

sample to 20,754. We also remove a small number of forecasts that are quoted in currencies other than Euros or Deutschmarks. We remove likely data entry errors from the sample, e.g., we classify as likely errors observations whose forecast dates are after the announcement dates (total of 14,450 observations). Some observations are deleted from the sample because the same analyst issued two *different* forecasts for the same firm-forecasting period on the same day.

In line with the prior literature (e.g., Bernhardt et al. 2006; Clement and Tse 2005; Henze 2004; Zitzewitz 2001), all EPS forecasts and actual earnings are normalized by the respective firm's security price two days before the estimation date so as to achieve better cross-sectional comparability. Since we analyze annual instead of quarterly forecasts, we follow Clement and Tse (2005) in using the security price two days before the estimate date for normalization rather than Bernhardt et al. (2006), who apply the security price prevailing at the end of the previous quarter. In line with Clement and Tse (2005), we drop observations with an absolute normalized forecast exceeding 0.10 and those exhibiting an absolute normalized forecast error of more than 0.40. This reduces the sample by another 15,450 observations.

During the 1990s, I/B/E/S assigned an identical analyst identifier code to all analysts who covered the same market or industry segment. As proposed by prior studies (Henze 2004; Löffler 1998), this problem can be circumvented by combining the analyst code with the broker code, a combination that should result in a unique identification code. We also discard forecasts made by analysts having an identifier code of zero, indicating that the analyst vetoed an individual identification in I/B/E/S. During the 1994–2005 time period, 14,370 forecasts were made by analysts with identifier code zero. Following Löffler (1998), we also exclude forecasts made by the analyst with the identifier code 2288 because she issued 3,272 forecasts between 1994 and 2003, an average of 327 forecasts per year. The analyst with the next highest number of forecasts made less than 90 forecasts per year on average and thus Analyst 2288 appears to be an extreme outlier. Finally, the test requires each observation to exhibit a consensus forecast, a normalized actual earnings value, and a normalized forecast, requirements that decrease the sample by another 4,917 forecasts. Our final sample consists of 77,279 forecasts over firm-forecasting periods from 1994 to 2005. A table showing the selection criteria and their effect on sample size is available upon request.

4.2 Construction of consensus forecast

To construct the consensus forecast, we order forecasts for a specific firm-forecasting period by their release date. Prior forecasts by the analyst under consideration are excluded from the respective consensus calculation, as the consensus should reflect only other analysts' views of the EPS. In addition, only the most recent forecast of each analyst is considered, since it is this forecast that may contain valuable information other analysts might want to incorporate into their subsequent forecasts. It seems unlikely that an analyst observes and incorporates other analysts' forecasts into her own forecast without any time lag and we thus discard other analysts' forecasts made on the same day. Although this choice is consistent with Zitzewitz (2001), it contrasts with Clement and Tse (2005), who use a three-day lag. In line with Clement and Tse (2005), forecasts are included in the consensus calculation only if they were published at most 90 days before the analyst under consideration issues her forecast.

5 Empirical results

5.1 Descriptive statistics

In Table 1, we see that an average of 14 German analysts cover a firm during a specific forecasting-year. This contrasts with an average of 10 US analysts during a specific forecasting-quarter, as shown in Bernhardt et al. (2006).[10] However, US brokerage houses (≈37 analysts) are on average much larger than their German counterparts (≈13 analysts) when measured as the number of analysts employed during a specific quarter or year, respectively. The higher average of analysts per firm for Germany could be explained by the much smaller number of firms to be covered in Germany (378) than in the United States (4,456).

The experience of German analysts, measured as the number of years an analyst is included in the I/B/E/S database (≈2.7 years), is less than the experience of their US peers (≈5.9 years), even though the German figures might be slightly understated due to our definition of an individual analyst. As individual analysts are defined through the combination of analyst identifier and brokerage code, an analyst who moves from

Table 1 Final sample descriptive statistics

	Mean	Std. Dev.	p25	Median	p75	Min	Max
Number of analysts per firm (by year)	13.9	13.9	3.0	9.0	21.0	1.0	65.0
Size of brokerage house (by number of analysts)	12.6	10.6	3.0	10.0	19.0	1.0	68.0
General experience (in years)	2.7	1.9	1.0	2.0	4.0	1.0	15.0
Firm-specific experience (in years)	2.3	1.6	1.0	2.0	3.0	1.0	14.0
Consensus error (in % of stock price)	0.90	4.41	−0.64	0.16	1.44	−38.50	50.22
Forecast error (in % of stock price)	0.77	4.38	−0.69	0.03	1.39	−36.61	39.97

The final sample includes 77,279 forecasts made for firm-years from 1994 to 2005. The number of analysts per firm is calculated for each year. The size of the brokerage house is measured as the number of different analysts employed by the brokerage house in a particular year. General experience and firm-specific experience are both calculated starting in 1987 up to the year of the forecast date and signify the number of years that an analyst has been in the database or provided at least one forecast for a specific firm, respectively. The consensus error and the forecast error are expressed as a percentage of the stock price prevailing two days before the forecast date. Unlike the forecast error, the consensus error is not truncated at 0.40 and −0.40, respectively

[10] All US figures in this section are obtained from Bernhardt et al. (2006).

one broker to another effectively becomes a new analyst in our data set. German analysts' firm-specific experience, measured as the number of years that analysts forecast a specific firm's earnings, is smaller than the corresponding general experience.

The consensus errors (0.90%) and the individual forecast errors (0.77%) of German analysts are higher than those of US analysts (0.40% and −0.20%).[11] However, one should be cautious about concluding that German analysts perform worse than their US counterparts, as Bernhardt et al. (2006) investigate quarterly earnings forecasts, whereas our data involve yearly forecasts. A shorter forecasting period should lead to less uncertainty, which in turn should translate into a lower rate of forecast errors (see, e.g., O'Brien 1990). Overall, however, our findings corroborate those of Clement et al. (2003), who report that German analysts' forecasting accuracy is relatively poor compared to that of analysts from other countries. The positive sign of the mean forecast error indicates that German analysts are on average too optimistic, consistent with the empirical outcomes of Easterwood and Nutt (1999), De Bondt and Forbes (1999), and De Bondt and Thaler (1990).

5.2 Herding behavior and forecast characteristics

Table 2 shows that German analysts exhibit significant anti-herding behavior. In particular, the herding parameter equals 0.583, which implies that 58.3% of the time analysts release earnings forecasts that are biased away from the extant consensus. The fact that analysts overemphasize private information in the direction away from the consensus implies a higher volatility of earnings forecasts in the cross section compared to unbiased forecasts. The point estimate is significantly different from 0.5 at the 99% confidence level. Our outcomes align with those reported by Bernhardt et al. (2006) on US analysts, but are contrary to those of De Bondt and Forbes (1999) on UK analysts. However, we again emphasize that the methodology of De Bondt and Forbes (1999) is not robust and that their outcomes could thus be misleading. We find further evidence of anti-herding behavior when investigating subsamples based on forecasting periods. The test statistic S ranges from a minimum of 0.523 in 1998 to a maximum of 0.599 in 2004 and never drops below 0.5. Again, all point estimates are significantly different from 0.5 at the 99% confidence level. Also, the reported 95% confidence intervals are relatively narrow, which lends further support to our conclusions.

Figure 1 more intuitively illustrates why the S test statistic suggests that analysts anti-herd. In this figure, we show the average forecast error, i.e., realized earnings minus forecast, over all individual analysts' forecasts in a forecast production period of five days in relation to the earnings announcement date (event date zero). Average forecast errors are conditional on the forecasts being either above or below the extant consensus. If an analyst's best estimate is above the consensus, then an anti-herder will issue a forecast above her best estimate so as to move away from the consensus. As the anti-herder's forecast is thus too high, she generates negative forecast errors on average. Figure 1 shows that this is always the case. In contrast, if her best estimate is

[11] The forecast error is calculated as the difference between a given analyst's forecast and actual earnings over the stock price for the forecasting period under consideration.

Table 2 Herding behavior and forecast characteristics (Part I)

Sample	N	Overshooting probability	Cond. overshooting probability	Cond. undershooting probability	S	Lower CI (95%)	Upper CI (95%)	t-statistic
Total sample	77,279	0.510	0.617	0.549	0.583	0.579	0.586	45.74
By forecasting period τ								
1994	3,753	0.409	0.489	0.596	0.542	0.526	0.558	5.18
1995	4,736	0.570	0.654	0.445	0.550	0.535	0.564	6.77
1996	5,349	0.467	0.595	0.562	0.578	0.564	0.592	11.10
1997	5,060	0.397	0.511	0.678	0.595	0.580	0.609	13.16
1998	5,250	0.827	0.860	0.185	0.523	0.509	0.536	3.29
1999	6,119	0.522	0.614	0.546	0.580	0.568	0.593	12.53
2000	5,364	0.518	0.617	0.540	0.579	0.565	0.592	11.46
2001	7,851	0.688	0.785	0.357	0.571	0.560	0.582	12.55
2002	7,820	0.590	0.691	0.504	0.597	0.586	0.608	17.21
2003	7,537	0.454	0.586	0.611	0.598	0.587	0.610	16.60
2004	7,969	0.348	0.471	0.728	0.599	0.588	0.611	17.68
2005	10,471	0.398	0.519	0.670	0.594	0.585	0.604	19.10

The test statistic S as defined by Bernhardt et al. (2006) is calculated for the final sample and for different subsamples according to the forecasting period τ. The null of unbiased forecasts (no herding) translates into $S = 0.5$. N stands for the number of observations for each sample. Unconditional overshooting probabilities show the frequency with which analysts' forecasts exceed actual earnings; both the conditional overshooting probability and the conditional undershooting probability represent the frequency with which analysts' forecasts overshoot actual earnings in the same direction as they overshoot consensus forecasts. 95% confidence intervals are also reported

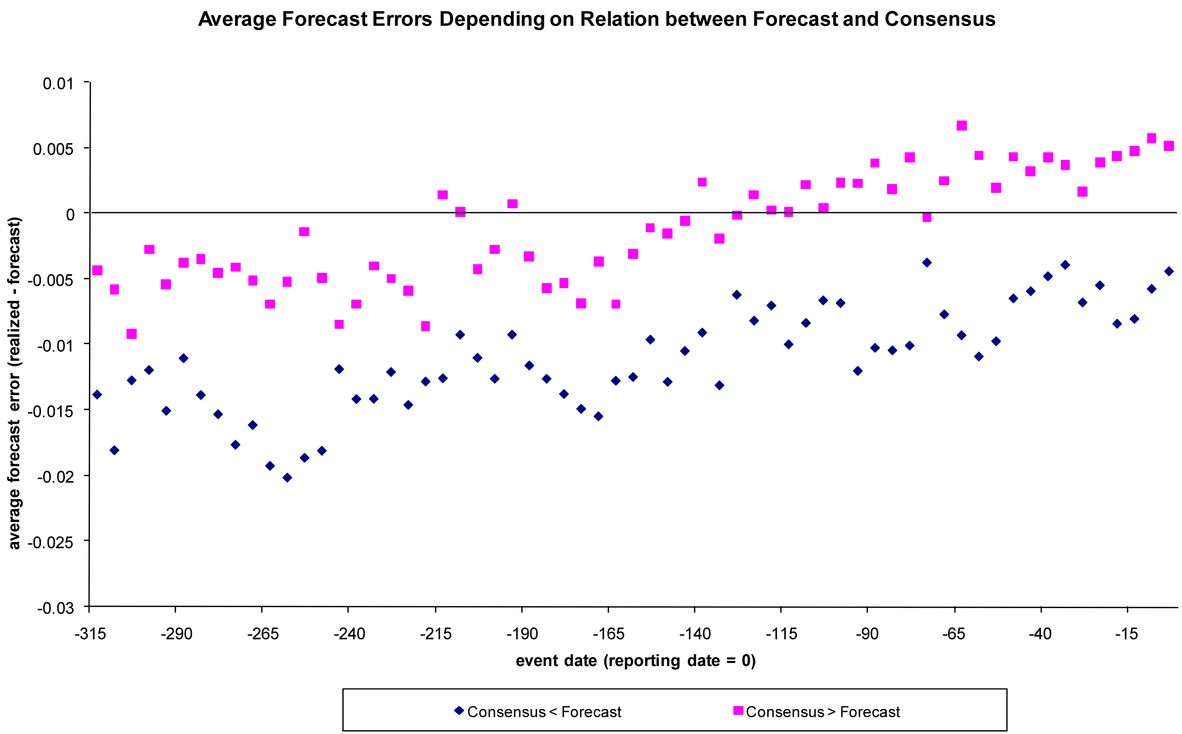

Fig. 1 Graphical representation of forecast errors. In this figure, we show the evolution of average forecast errors prior to the earnings announcement date conditional on the forecast being above or below the extant consensus forecast. We define the earnings announcement date as event time 0. Other dates are defined relative to the earnings announcement date, with, e.g., a date 20 days before the earnings announcement date being classified as event date −20. The forecast error is defined as realized earnings minus the forecast, where both realized earnings and forecast are scaled by the stock price. Individual analysts' forecast errors are averaged by event date, and then again over a consecutive period of five days

below the consensus, the anti-herder will make her forecast too low. As a result, she generates positive forecast errors on average. This also holds, at least in the period closer to the announcement date. The S test statistic counts how often these conjectures hold, e.g., conditional on the forecast being above (below) the consensus, what percentage of forecast errors are negative (positive), and then takes a simple average of the two percentages.

The figure also reveals how the S test statistic corrects for systematic biases. For example, if anti-herders also exhibit an optimism bias, this will decrease the tendency to create positive forecast errors when the best estimate is below the consensus. However, overoptimism will also more strongly emphasize the tendency to produce negative forecast errors when the best estimate is above the consensus. On average, a systematic bias should thus cancel out. The patterns in Fig. 1 are consistent with forecasters being overoptimistic the farther away they are from the earnings announcement date.

In a next step, we test for an association between analysts' herding behavior and the number of analysts following a firm. As can be seen in Table 3, our findings suggest a positive relation between the number of analysts following a firm and the propensity to anti-herd. This implies that analysts try to stand out from the crowd when the crowd is big. These findings contrast with those of Bernhardt et al. (2006), who report a negative association. If we reason that only a few analysts cover small firms for which only limited information is available, then our findings could support the informational cascades models of, e.g., Bikhchandani et al. (1992), in which agents herd because of relatively little information. However, analysts covering the least heavily followed firms do not herd as these models would imply, but instead simply show a lower propensity to anti-herd.

We also examine the order of the forecast in the forecasting period. While the second and the third analysts exaggerate their private information away from the consensus in almost 56% of the cases, the degree of anti-herding behavior drops to 54% and 52% for the second-to-last and the last analyst, respectively. The last analyst is a special case, since in her case we cannot reject unbiasedness at the 99% confidence level.[12] However, the numbers corresponding to the last two analysts are biased toward the null, as the unconditional probabilities (also shown in Table 3) suggest that optimism decreases over the forecasting period, as the overshooting probability decreases. As a result, we cannot necessarily conclude that herding behavior relates to the order of the forecast. Still, this analysis reveals that analysts who do not report at the beginning or end of the forecasting cycle must exhibit higher anti-herding behavior as, otherwise, the outcomes in Table 3 would not align with those for the whole sample. These findings are consistent with those of Bernhardt et al. (2006).

When we condition on the number of days to the next earnings announcement, we find that analysts in the middle of the forecasting cycle do, indeed, show the strongest anti-herding behavior. Interestingly, analysts reporting more than nine months before the earnings announcement are slightly less prone to exaggerate their private information than are analysts reporting at least three months and at most nine month be-

[12] Unreported tests omitting the outlier elimination of Sect. 4.1 show that, in this case, S is also significantly different from the null at the 1% significance level for the last analyst in a forecasting period ($S = 0.536$).

Table 3 Herding behavior and forecast characteristics (Part II)

Sample	N	Overshooting probability	Cond. overshooting probability	Cond. undershooting probability	S	Lower CI (95%)	Upper CI (95%)	t-statistic
By number of analysts following a given firm								
cover ≤ 20	20,024	0.548	0.641	0.487	0.564	0.557	0.571	18.03
$20 <$ cover ≤ 34	19,790	0.503	0.590	0.539	0.564	0.557	0.571	18.03
$34 <$ cover ≤ 45	18,891	0.449	0.566	0.627	0.596	0.589	0.603	26.36
cover > 45	18,574	0.540	0.674	0.546	0.610	0.602	0.617	29.67
By order of forecast release in forecasting period τ								
order = 2nd	1,819	0.608	0.678	0.435	0.556	0.533	0.579	4.79
order = 3rd	1,661	0.589	0.656	0.457	0.557	0.533	0.581	4.61
order = 2nd-to-last	1,661	0.449	0.554	0.516	0.535	0.511	0.559	2.83
order = last	1,819	0.433	0.540	0.508	0.524	0.501	0.547	2.03
By number of days to earnings announcement								
to ann ≤ 92	12,991	0.413	0.570	0.598	0.584	0.575	0.593	18.82
$92 <$ to arm ≤ 275	30,061	0.512	0.620	0.561	0.591	0.585	0.596	31.26
to arm > 275	34,227	0.546	0.630	0.517	0.573	0.568	0.579	27.06

The test statistic S as defined by Bernhardt et al. (2006) is calculated according to the number of analysts covering a given firm (cover), the order in which forecasts are released during a given forecasting period (order), and the remaining number of days to a given earnings announcement date (to_ann). The null of unbiased forecasts (no herding) translates into $S = 0.5$. N stands for the number of observations for each sample. Unconditional overshooting probabilities show the frequency with which analysts' forecasts exceed actual earnings; both the conditional overshooting probability and the conditional undershooting probability represent the frequency with which analysts' forecasts overshoot actual earnings in the same direction as they overshoot consensus forecasts. 95% confidence intervals are also reported fore the earnings announcement. This contradicts any hypotheses predicting that anti-herding relates positively and monotonically to time to the next earnings announcement. In contrast, we could speculate that the greater uncertainty at the beginning of the forecasting cycle leads analysts to exhibit weaker anti-herding behavior. In line with Richardson et al. (2004) and Chan et al. (2003), we also report that analysts are more optimistic at the beginning of the cycle. Be that as it may, we show that analysts issue anti-herding forecasts irrespective of the time to the announcement or the order of the forecast.

In Table 4, we exclusively consider earnings forecasts that are revisions. Because we examine annual instead of quarterly earnings forecasts, our sample contains more revisions than that of Bernhardt et al. (2006). Nonetheless, the properties of German analysts' forecast revisions are similar to those of their US counterparts insofar as two of three revisions are downgrades. In line with Richardson et al. (2004) and Chan et al. (2003), German analysts issue more optimistic forecasts at the start of the forecasting cycle and, subsequently, lower these to levels which can more easily be beaten (exceeded) by a company's earnings. We obtain virtually the same S statistic for earnings forecast revisions and the whole sample. However, analysts exhibit somewhat stronger anti-herding behavior in the case of upward revisions than for downward revisions. They also exhibit stronger anti-herding behavior in the case of revisions moving farther away from the extant consensus than when revisions move closer to the extant consensus, a finding that contradicts Bernhardt et al. (2006), who find the less intuitive inverse relation.

5.3 Herding behavior and analyst characteristics

Several existing studies (e.g., Bernhardt et al. 2006; Clement and Tse 2005) hypothesize that analysts' herding behavior is related to certain analyst characteristics. For example, it is possible that the propensity to anti-herd increases with brokerage size, as analysts in large brokerages might face especially fierce competition and might thus try to differentiate themselves through *unusual* forecasts. While Clement and Tse (2005) find the hypothesized association, Table 5 shows that, in line with Bernhardt et al. (2006), we do not. Neither do we observe a pattern between analysts' general experience and anti-herding, i.e., more (less) experienced analysts release forecasts that overshoot both the consensus and actual earnings in the same direction in 57.8% (59.3%) of all cases. Since the more experienced analysts are on average more pessimistic, this figure is subject to the pessimism bias. In addition to the characteristics studied by Bernhardt et al. (2006), we also examine firm-specific experience. Analysts who have covered a specific firm for a longer time period might have accumulated firm-specific knowledge and thus might have lower incentives to herd. However, Table 5 shows that this hypothesis is not supported by the data.

We also predict that analysts who follow more firms or industries might exhibit a higher propensity to herd, since they should have less time for their analysis of a specific firm or industry. The outcomes in Table 6 indicate that the frequency of overshooting earnings in the direction away from the consensus diminishes with the number of different firms followed by an analyst. While this is consistent with our hypothesis, it does not align with the findings of Clement and Tse (2005), who fail

Table 4 Herding behavior and forecast revisions

Sample	N	Overshooting probability	Cond. overshooting probability	Cond. undershooting probability	S	Lower CI (95%)	Upper CI (95%)	t-statistic
All forecast revisions	48,773	0.494	0.606	0.562	0.584	0.579	0.588	36.80
By the direction of the revision								
Upward revised	16,480	0.452	0.568	0.654	0.611	0.603	0.619	28.35
Downward revised	32,293	0.515	0.633	0.528	0.580	0.574	0.586	28.03
By the distance to the consensus								
Closer to consensus	24,535	0.461	0.593	0.556	0.575	0.568	0.582	20.74
Further away from consensus	24,238	0.527	0.611	0.574	0.592	0.586	0.599	28.02

The test statistic S as defined by Bernhardt et al. (2006) is calculated for all forecast revisions. Furthermore, we report results for whether the revised forecast is above or below the stale forecast. The null of unbiased forecasts (no herding) translates into $S = 0.5$. N stands for the number of observations for each sample. Unconditional overshooting probabilities show the frequency with which analysts' forecasts exceed actual earnings; both the conditional overshooting probability and the conditional undershooting probability represent the frequency with which analysts' forecasts overshoot actual earnings in the same direction as they overshoot consensus forecasts. 95% confidence intervals are also reported

Table 5 Herding behavior and analyst characteristics (Part I)

Sample	N	Overshooting probability	Cond. overshooting probability	Cond. undershooting probability	S	Lower CI (95%)	Upper CI (95%)	t-statistic
By size of broker								
1st quartile (small broker)	2,059	0.494	0.601	0.553	0.577	0.555	0.599	6.92
2nd quartile	11,660	0.509	0.613	0.550	0.581	0.572	0.590	17.45
3rd quartile	25,818	0.509	0.618	0.549	0.583	0.577	0.590	26.70
4th quartile (large broker)	37,742	0.513	0.618	0.548	0.583	0.578	0.588	32.04
By years of general experience								
genexp ≤ 1	13,795	0.536	0.646	0.539	0.593	0.584	0.601	21.70
$1 <$ genexp ≤ 4	47,852	0.516	0.622	0.541	0.581	0.577	0.586	35.25
genexp > 4	15,632	0.471	0.575	0.581	0.578	0.570	0.586	19.45
By years of firm-specific experience								
firmexp ≤ 1	24,784	0.533	0.639	0.531	0.585	0.579	0.591	26.63
$1 <$ firmexp ≤ 3	37,921	0.510	0.617	0.545	0.581	0.576	0.586	31.39
firmexp > 3	14,574	0.473	0.578	0.588	0.583	0.575	0.591	20.00

The test statistic S as defined by Bernhardt et al. (2006) is calculated according to the number of years of general experience and of firm-specific experience, respectively. The null of unbiased forecasts (no herding) translates into $S = 0.5$. Years of experience are calculated as the number of years for which a given analyst has at least issued one forecast (general experience) or for the respective firm (firm-specific experience). Both figures are calculated starting in 1987. N stands for the number of observations for each sample. Unconditional overshooting probabilities show the frequency with which analysts' forecasts exceed actual earnings; both the conditional overshooting probability and the conditional undershooting probability represent the frequency with which analysts' forecasts overshoot actual earnings in the same direction as they overshoot consensus forecasts. 95% confidence intervals are also reported

Table 6 Herding behavior and analyst characteristics (Part II)

Sample	N	Overshooting probability	Cond. overshooting probability	Cond. undershooting probability	S	Lower CI (95%)	Upper CI (95%)	t-statistic
By number of firms covered								
1st quartile (small number)	10,887	0.493	0.616	0.590	0.603	0.594	0.612	22.43
2nd quartile	9,541	0.485	0.597	0.586	0.592	0.581	0.602	18.03
3rd quartile	18,857	0.522	0.632	0.542	0.587	0.580	0.594	24.36
4th quartile (large number)	37,994	0.516	0.614	0.531	0.573	0.568	0.578	28.62
By number of industries covered								
1st quartile (small number)	9,225	0.497	0.606	0.569	0.588	0.578	0.598	17.25
2nd quartile	14,856	0.510	0.632	0.564	0.598	0.590	0.606	24.01
3rd quartile	17,706	0.512	0.625	0.559	0.592	0.584	0.599	25.76
4th quartile (large number)	35,492	0.513	0.609	0.532	0.571	0.565	0.576	27.83

The test statistic S as defined by Bernhardt et al. (2006) is calculated according to the number of different firms followed by a given analyst in a given year as well as according to the number of different industries followed by a given analyst in a given year. The null of unbiased forecasts (no herding) translates into $S = 0.5$. Different industries are defined according to the two-digit SIC numbers. N stands for the number of observations for each sample. Unconditional overshooting probabilities show the frequency with which analysts' forecasts exceed actual earnings; both the conditional overshooting probability and the conditional undershooting probability represent the frequency with which analysts' forecasts overshoot actual earnings in the same direction as they overshoot consensus forecasts. 95% confidence intervals are also reported to find a significant association. To analyze the impact of the number of industries covered by an analyst on anti-herding behavior, we obtain the number of industries followed by an analyst using two-digit SIC industry classifications. When we condition on the number of industries, we observe that German analysts who cover more industries are less likely to issue anti-herding forecasts, even though the hypothesized relation appears nonlinear. These findings are consistent with Clement and Tse (2005).

5.4 Herding behavior and firm characteristics

We further extend the analysis of Bernhardt et al. (2006) by studying firm characteristics, including market capitalization and the book-to-market ratio. Market capitalization and the book-to-market ratio are obtained from DataStream. Analysts might exhibit stronger herding behavior in the case of small and high book-to-market firms, as there is usually only limited public information available for these firms (Bikhchandani and Sharma 2001; Wermers 1999). To put it differently, analysts might be more tempted to anti-herd in the case of big or low book-to-market firms, as the large quantity of public information available for these firms might make it necessary to provide more *unusual* forecasts to attract attention. Our outcomes in Table 7 partially confirm these hypotheses in that they reveal that anti-herding decreases with size. However, we find no association between analyst herding and the book-to-market ratio.

Clement and Tse (2005) and Henze (2004) argue that it could be more difficult for analysts to predict negative earnings and that they thus might exhibit lower anti-herding behavior in such cases. As can be seen in Table 8, our data confirm this hypothesis. Although analysts exhibit anti-herding behavior for both positive and negative earnings, the degree of anti-herding behavior varies substantially from 53% for firm-forecasting periods with negative earnings to 59% for firm-forecasting periods with positive earnings. The unconditional overshooting rates are revealing. In 90% of all cases, analysts are too optimistic regarding firms reporting negative earnings compared to 47% for firms reporting positive earnings. In addition, almost 95% of the forecasts that are above the consensus overshoot the actual earnings of firms reporting negative earnings.

Even though the conjecture finds little support in the academic literature, business commentators and the media often assert that analysts issued overly optimistic earnings forecasts during the "new economy" bubble at the end of the 1990s, especially for firms traded on the *Neuer Markt* (Wallmeier 2005a, 2005b; Bessler and Stanzel 2007). We thus find it interesting to examine whether analysts showed strong herding behavior regarding these firms during the "new economy" boom. To this end, we examine *Neuer Markt* earnings forecasts between 1998 and 2003. We discard forecasts for the 1997 fiscal year, since there were only 14 forecasts released. The analyzed subsample consists of all firms that have been quoted at least once on the *Neuer Markt* segment during this period and are thus included in the DataStream *Neuer Markt* constituent list (XXEURONM1001). We delete cross-listings and consider only those firms with I/B/E/S codes that were at least once covered by an analyst.

Our findings on the *Neuer Markt* segment confirm prior conclusions of consistent anti-herding behavior. As Table 9 indicates, forecasts were either above or below both

Table 7 Herding behavior and firm characteristics (Part I)

Sample	N	Overshooting probability	Cond. overshooting probability	Cond. undershooting probability	S	Lower CI (95%)	Upper CI (95%)	t-statistic
By market capitalization								
1st quartile (small m_cap)	3,787	0.717	0.781	0.288	0.534	0.518	0.550	4.21
2nd quartile	9,012	0.604	0.675	0.420	0.548	0.537	0.558	9.02
3rd quartile	18,846	0.512	0.605	0.526	0.566	0.558	0.573	17.95
4th quartile (large m_cap)	45,609	0.474	0.597	0.604	0.600	0.596	0.605	42.62
By price-to-book ratio								
1st quartile (small ptbv)	14,326	0.575	0.682	0.502	0.592	0.583	0.600	21.86
2nd quartile	21,731	0.557	0.659	0.497	0.578	0.572	0.585	22.95
3rd quartile	21,570	0.443	0.556	0.622	0.589	0.583	0.596	26.10
4th quartile (large ptbv)	19,043	0.480	0.583	0.564	0.574	0.566	0.581	20.10

The test statistic S as defined by Bernhardt et al. (2006) is calculated according to the size of a company represented by its market capitalization at the end of the previous firm-year and the price-to-book ratio as a proxy for value vs. growth firms. The null of unbiased forecasts (no herding) translates into $S = 0.5$. N stands for the number of observations for each sample. Deviations from the final sample size of 77,279 forecasts are due to missing values for market capitalization or price-to-book values, respectively. Unconditional overshooting probabilities show the frequency with which analysts' forecasts exceed actual earnings; both the conditional overshooting probability and the conditional undershooting probability represent the frequency with which analysts' forecasts overshoot actual earnings in the same direction as they overshoot consensus forecasts. 95% confidence intervals are also reported

Table 8 Herding behavior and firm characteristics (Part II)

Sample	N	Overshooting probability	Cond. overshooting probability	Cond. undershooting probability	S	Lower CI (95%)	Upper CI (95%)	t-statistic
Positive earnings	69,346	0.466	0.584	0.604	0.594	0.590	0.597	49.16
Negative earnings	7,904	0.900	0.947	0.112	0.529	0.518	0.541	5.13

The test statistic S as defined by Bernhardt et al. (2006) is calculated for firms reporting positive earnings and for firms reporting negative earnings. Twenty-nine forecasts are not included in the sample since they refer to firms reporting actual earnings of zero. The null of unbiased forecasts (no herding) translates into $S = 0.5$. N stands for the number of observations for each sample. Unconditional overshooting probabilities show the frequency with which analysts' forecasts exceed actual earnings; both the conditional overshooting probability and the conditional undershooting probability represent the frequency with which analysts' forecasts overshoot actual earnings in the same direction as they overshoot consensus forecasts. 95% confidence intervals are also reported

Table 9 Herding behavior and *Neuer Markt* firms

Sample	N	Overshooting probability	Cond. overshooting probability	Cond. undershooting probability	S	Lower CI (95%)	Upper CI (95%)	t-statistic
Total Neuer Markt sample	6,265	0.635	0.697	0.382	0.540	0.527	0.552	6.25
By forecasting period τ								
1998	184	0.522	0.613	0.529	0.571	0.498	0.644	1.90
1999	431	0.378	0.472	0.645	0.559	0.511	0.606	2.43
2000	1,023	0.655	0.686	0.344	0.515	0.484	0.546	0.96
2001	1,984	0.747	0.787	0.241	0.514	0.492	0.536	1.23
2002	1,520	0.685	0.744	0.356	0.550	0.525	0.575	3.90
2003	1,123	0.467	0.548	0.542	0.545	0.515	0.575	2.92

The test statistic S as defined by Bernhardt et al. (2006) is calculated for earnings forecasts of *Neuer Markt* firms during 1998 and 2003, both for the whole *Neuer Markt* sample and for each forecasting period. The null of unbiased forecasts (no herding) translates into $S = 0.5$. N stands for the number of observations for each sample. Unconditional overshooting probabilities show the frequency with which analysts' forecasts exceed actual earnings; both the conditional overshooting probability and the conditional undershooting probability represent the frequency with which analysts' forecasts overshoot actual earnings in the same direction as they overshoot consensus forecasts. 95% confidence intervals are also reported the consensus and actual earnings in 54% of all cases. Still, the degree of anti-herding is somewhat lower compared to the total sample. When we separately examine the forecasting periods, we find slightly different outcomes. While the test statistic S is above 0.5 for all forecasting periods, the degree of anti-herding behavior fluctuates from a low of 0.514 in 2001 to a high of 0.571 in 1998. However, the high value of the S statistic in 1998 might be due to the scarcity of observations in this forecasting period. We cannot reject the null of unbiased forecasts at the 5% significance level for the forecasting periods 2000 and 2001.[13]

6 Conclusion

In this study, we show that German analysts do not herd but, instead, anti-herd. More specifically, we find that German analysts bias their earnings forecasts away from the prevailing consensus in almost 60% of all cases. Thus, it seems that German analysts overemphasize their private information on average. This implies a higher volatility in the cross section of earnings forecasts than would be justified by analysts' private information. In addition, anti-herding behavior resulting in biased earnings forecasts may dilute information quality of stock prices and thus harm the functionality of the stock market in general. Our findings align with those obtained by a related study on US analysts' earnings forecasts (Bernhardt et al. 2006), yet they are not necessarily similar to those on analysts' stock recommendations. The findings on herding behavior in stock recommendations could, however, be driven by the fact that the studies showing these outcomes cannot control for well-known problems such as correlated information signals, common shocks, and related issues. Our methodology, which we adapt from Bernhardt et al. (2006), is robust to these shortcomings.

The tendency of German analysts to anti-herd depends on several forecast, analyst, or firm characteristics. More specifically, we observe that anti-herding behavior is positively related to the number of analysts following a firm, market capitalization, and the sign of earnings, and negatively related to the number of firms or industries followed by an analyst. However, herding does not depend on the time remaining until the earnings announcement, the order of the forecasts, the size of the brokerage, general or firm-specific experience, or the book-to-market ratio. Remarkably, German analysts did not engage in significant herding behavior during the "new economy" bubble of the late 1990s, as is often claimed by the media.

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[13] It seems surprising that German analysts consistently exhibit significant anti-herding behavior in all studied subsamples except in case of the *Neuer Markt* firms in the years 2000–2001. In fact, in unreported tests we find that when we do not apply the strict outlier elimination strategy as outlined in Sect. 4.1, we can reject the null of unbiased forecasts for the forecasting period 2001 at the 1% significance level, but we still fail to reject the null for 2000 at the 5% significance level. This effect could also be—at least partially—due to the relatively small number of observations. Be that as it may, we clearly do not find any evidence of herding behavior for the earnings forecasts of *Neuer Markt* firms during the period 1998–2003.

References

Andres, P., Spiwoks, M.: Prognosequalitätsmatrix—Ein methodologischer Beitrag zur Beurteilung der Güte von Kapitalmarktprognosen. Jahrb. Natl. Stat. **219**, 513–542 (1999)
Banerjee, A.V.: A simple model of herd behavior. Q.J. Econ. **107**, 797–817 (1992)
Bernhardt, D., Campello, M., Kutsoati, E.: Who herds? J. Financ. Econ. **80**, 657–675 (2006)
Bessler, W., Stanzel, M.: Qualität und Effizienz der Gewinnprognosen von Analysten: Eine empirische Untersuchung für den deutschen Kapitalmarkt. Kredit Kap. **40**, 1–41 (2007)
Bikhchandani, S., Sharma, S.: Herd behavior in financial markets. IMF Staff Papers **47**, 279–310 (2001)
Bikhchandani, S., Hirshleifer, D., Welch, I.: A theory of fads, fashion, custom, and cultural change as informational cascades. J. Polit. Econ. **100**, 992–1026 (1992)
Capstaff, J., Paudyal, K., Rees, W.: Analysts' forecasts of German firms' earnings: A comparative analysis. J. Int. Financ. Manag. Account. **9**, 83–116 (1998)
Chan, L.K.C., Karceski, J., Lakonishok, J.: Analysts' conflict of interest and biases in earnings forecasts. NBER Working Paper 9544 (2003)
Chen, Q., Jiang, W.: Analysts' weighting of private and public information. Rev. Financ. Stud. **19**, 319–355 (2006)
Clement, M.B., Tse, S.Y.: Financial analyst characteristics and herding behavior in forecasting. J. Finance **60**, 307–341 (2005)
Clement, M.B., Rees, L., Swanson, E.P.: The influence of culture and corporate governance on the characteristics that distinguish superior analysts. J. Account. Audit. Finance **18**, 593–618 (2003)
Cooper, R.A., Day, T.E., Lewis, C.M.: Following the leader: a study of individual analysts' earnings forecasts. J. Financ. Econ. **61**, 383–416 (2001)
De Bondt, W.F.M., Forbes, W.P.: Herding in analyst earnings forecasts: Evidence from the United Kingdom. Eur. Financ. Manag. **5**, 143–163 (1999)
De Bondt, W.F.M., Thaler, R.M.: Do security analysts overreact? Am. Econ. Rev. **80**, 52–57 (1990)
Devenow, A., Welch, I.: Rational herding in financial economics. Eur. Econ. Rev. **40**, 603–615 (1996)
Easterwood, J.C., Nutt, S.R.: Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism? J. Finance **54**, 1777–1797 (1999)
Gu, Z., Wu, J.S.: Earnings skewness and analyst forecast bias. J. Account. Econ. **35**, 5–29 (2003)
Henze, J.: Was leisten Finanzanalysten? Eine empirische Analyse des deutschen Aktienmarktes. Eul, Lohmar (2004)
Hirshleifer, D., Teoh, S.H.: Herd behaviour and cascading in capital markets: A review and synthesis. Eur. Financ. Manag. **9**, 25–66 (2003)
Hong, H., Kubik, J.D., Solomon, A.: Security analysts' career concerns and herding of earnings forecasts. Rand J. Econ. **31**, 121–144 (2000)
Jegadeesh, N., Kim, W.: Do analysts herd? An analysis of recommendations and market reactions. NBER Working Paper 12866 (2007)
Lim, T.: Rationality and analyst's forecast bias. J. Finance **56**, 369–385 (2001)
Löffler, G.: Der Beitrag von Finanzanalysten zur Informationsverarbeitung: Eine empirische Untersuchung für den deutschen Aktienmarkt. Wiesbaden, Deutscher Universitätsverlag (1998)
O'Brien, P.C.: Forecast accuracy of individual analysts in nine industries. J. Account. Res. **28**, 286–304 (1990)
Oehler, A.: Do mutual funds specializing in German stocks herd? Financ. Mark. Portf. Manag. **12**, 452–465 (1998)
Patton, A.J., Timmermann, A.: Properties of optimal forecasts under asymmetric loss and nonlinearity. J. Econom. **140**, 884–918 (2007)
Prendergast, C., Stole, L.: Impetuous youngsters and jaded old-timers: Acquiring a reputation for learning. J. Polit. Econ. **104**, 1105–1134 (1996)
Richardson, S., Teoh, S.H., Wysocki, P.D.: The walk-down to beatable analyst forecasts: The role of equity issuance and insider trading incentives. Contemp. Account. Res. **21**, 885–924 (2004)
Scharfstein, D.S., Stein, J.C.: Herd behavior and investment. Am. Econ. Rev. **80**, 465–479 (1990)
Spiwoks, M.: External Triggered Herding bei Rentenmarkt-Analysten. Financ. Mark. Portf. Manag. **18**, 58–83 (2004)
Trueman, B.: Analyst forecasts and herding behavior. Rev. Financ. Stud. **7**, 97–124 (1994)
Wallmeier, M.: Analysts' earnings forecasts for DAX100 firms during the stock market boom of the 1990s. Financ. Mark. Portf. Manag. **19**, 131–151 (2005a)
Wallmeier, M.: Gewinnprognosen von Finanzanalysten: Ein europäischer Vergleich. Finanz Betrieb **11**, 744–750 (2005b)

Walter, A., Weber, F.M.: Herding in the German mutual fund industry. Eur. Financ. Manag. **12**, 375–406 (2006)
Welch, I.: Herding among security analysts. J. Financ. Econ. **58**, 369–396 (2000)
Wermers, R.: Mutual fund herding and the impact on stock prices. J. Finance **54**, 581–622 (1999)
Zitzewitz, E.: Measuring herding and exaggeration by equity analysts and other opinion sellers. Working Paper (2001)

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