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Determinants of Herding Behavior among Financial Analysts: A Study of French Listed Firms

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Abstract

Using a sample of 262 French firms over the period 1996-2000, we show that analysts who tend to move away from consensus and issue bold forecasts are more experienced, work for large brokerage houses, follow more firms. Bold analysts provide more precise forecasts than those who tend to herd. Thus, investors should use bold forecasts since they are more accurate and reflect more relevant information than herding forecasts.

Keywords: Earnings forecast, Herding behavior, Bold forecast, Financial analyst, Experience, Brokerage house

1. Introduction

The main role of the analysts is to provide earnings forecasts. Several professionals as the bankers, the financial advisers as well as the individual investors rely on these forecasts to establish their decisions. To really accomplish this role the analysts' earnings forecasts must be unbiased and accurate. Studies presented in the financial and accountant literature analyze such forecasts. Indeed, the results of some works of research showed that the analysts' forecasts are more exact than time- series forecasts [Brown, Griffin, Hagerman, and Zmijewski (1987a) and (1987b)].

Notwithstanding, in 1980's, the analysts' ability to anticipate future earnings has been in doubt calling on the question of whether analysts' forecasts are biased. Many studies showed that analysts are optimistic and consequently, their forecasts are biased [Fried and Givoly (1982), Brown, Foster, and Noreen (1985), O'Brien (1988), Stickel (1990), Abarbanell (1991), Ali, Klein, and Rosenfield (1992), Brown (1997 and 1998), Lim (1998), Richardson, Teoh, and Wysocki (1999), and Easterwood and Nutt (1999), Matsumoto, (1998)].

Analysts are blamed for the recent financial scandals. The press accuse them of, not to be sufficiently independent of the financial establishments which employ them, and not to have anticipated the deterioration of the financial situation of the big international groups as Enron Vivendi Universal, Worldcom..., to have followed some leaders blindly and therefore not to have been rational enough in an euphoric context, to issue biased forecasts based on management's (private) guidance to please managers. It is in this sense that some studies concluded that analysts don't contribute to improve the efficiency of the market, on the contrary, they provoke informational imperfections or anomalies.

Several factors have been advanced by several researches to explain bias in analyst's forecasts. For our part, we think that the interaction between analysts put them on the bad way and can increase errors forecasts. The interaction leads to a mimetic behaviour among some analysts who abandon their own forecasts to adopt those of their peers: to herd. Scharfstein and Stein (1990), Trueman (1994), Hong, Kubik and Solomon (2000) examine the relationship between herd behaviour among analysts and reputation, career concern and self-assessed ability. They find that experienced analysts are more likely to avoid herding behaviour, and provide bold forecasts than inexperienced analysts. These authors explain this result by the fact that inexperienced analysts are more likely to lose their job after providing inaccurate or bold forecast. Clement and Tse (2005) show that bold forecasts are more accurate than herding forecasts. Also, Clement and Tse (2005) report evidence suggesting that analysts who issue bold forecasts are more general experienced, employed by large brokerage houses, frequent forecaster and historically accurate analysts. These results are consistent with those in Hong et al. (2000). Both papers find that more experienced analysts are less likely to herd.

Krishnan, Lim and Zhou (2005), find herding increases with general experience, forecast horizon and decreases with brokerage size and forecasting frequency. Thus, the results confirm Clement and Tse's (2005) finding that forecast boldness is associated with brokerage size prior accuracy and brokerage size. However, in contrast with Clement and Tse's findings, Krishnan, Lim and Zhou (2005) show that herding behavior increases with forecast horizon and forecasts issued by analysts with more general experience are more likely to be herding forecasts.

In the context of the French marketplace, reasons of the herding behaviour among the financial analysts remain unexplored and the questions remain still arisen: Why do some analysts abandon their own information to copy the ideas of others? Are herding forecasts more accurate than bold forecasts? The purpose of this paper fits in this setting and aim to identify, in the French context, the determinants of analysts herding behavior.

First we classify forecasts as bold if they are above both the analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast, or else below both. We classify all other forecasts (i.e., those that move away from the analyst's own prior forecast and toward the consensus) as herding forecasts (Clement and Tse, 2005, Gleason and Lee, 2003) (Note 1). Then we identify the characteristics of analysts who tend to herd, therefore judge what is the more accurate: Bold or herding forecast. To our knowledge, our study is the first to investigate factors that could affect analysts' behavior.

2. Prior research

2.1 Definition

The theories of herding, one of which was the basic models in Scharfstein and Stein (1990), Bikhchandani, Hirshleifer and Welch (1992), Banerjee (1992), Zwiebel (1995), and Prendergast and Stole (1996) assume that individual is a communicator: he issues and receives informative signals. Hirshleifer (1995) notes that the transmission of information between individuals can take different shapes: individuals can observe either all information detained by others, either the result of their private calculations, either solely the actions achieved by another having already been confronted by the same choice. The individual tends to herd if he bases exclusively on the positions taken by others. For Bikchandani and Sharma (2000), an individual can be said to herd if she would have made an investment without knowing other investors' decisions, but does not make that investment when she finds that others have decided not to do so. Hirshleifer and Teoh (2001) assign by "herd behavior" the convergence of behaviors and by "informational cascades" the situations where the individual chooses his action based on the observation of other regardless of his own informational signal. According to Artus (1995), herding behaviour is rational, this means that the market organization and the information transmission imply that is rational for some analysts to copy others while forgetting their private information. In this case, the individuals abandon their own beliefs and base their decisions on the collective actions even though doing this contradicts their own predictions. Jondeau (2001) supposes that herding behavior is intentional when investors imitate the behavior of their peers deliberately. In summary, if herding behavior can be explained by different reasons and that if for certain it results from irrational and irresponsible behavior, for others herding is rational.

2.2 Herding behaviours among financial analysts

Scharfstein and Stein (1990) and Trueman (1994) were the first to investigate the herding behaviour among analysts. The authors stipulate that, in some cases, the analyst A prefers to copy the forecasts issue by the analyst B that he judges "superior" (Note 2) even when this is not justified by his own information. Since the article of Trueman (1994), the financial literature includes some attempts to model the influence that analysts exert reciprocally while they are producing their recommendations (Note 3) and forecasts.

Thus, several studies in accounting investigate the effect of experience on herding behavior. Scharfstein and Stein (1990), argue that the manager tends to herd if he is less confident about her competence. Trueman (1994) predicts that the initiative of herding among managers decreases with the manager's perceived competence. Trueman (1994) finds that the analyst tends to copy the behavior of the more strong to avoid revealing her lack of expertise.

Using a sample of 8,421 security analysts producing earnings forecasts between 1983 and 1996, Hong et al. (2000) investigate whether herding behaviour is influenced by career concerns. They assume that forecasts behaviour (herd or bold) differs between inexperienced (young) and experienced (older) security analysts. Since more experienced analysts have been more confident, they probably issue bold forecast. Hong et al. (2000) find that inexperienced analysts are more likely to exhibit herding behaviour than more experienced. They show also that, inexperienced analysts who issue inaccurate or bold forecasts are more likely to leave profession than experienced analysts. Additionally, older analysts are also more likely to issue timely forecasts and to revise their earnings forecasts less than younger analyst.

Clement and Tse’s (2005) study, extends Hong et al. (2000) by examining the importance of experience as well as other characteristics that proxy for analyst’s self-assessed ability such as the analyst’s prior accuracy, brokerage size, forecast frequency, and the number of companies and industries followed by analyst, for explaining forecast boldness. First, Clement and Tse (2005) classify each analyst’s last earnings forecast for a given firm-year as either herding or bold. They classify forecasts as bold if forecasts are either above or below both an analyst’s own prior forecast and a prevailing consensus. All other forecasts are classified as herding forecasts. First, they find that bold forecast are more past accurate forecaster, employed by larger brokerage houses, issue forecasts more frequently and enjoy more general experience. In contrast, bold forecast are issued by analysts who follow a large number of industries. Second, they find that bold forecasts are more accurate than herding forecasts, this suggests that bold forecasts reflect more relevant and private information than herding forecasts.

Using IBES forecasts data from 1989-2004, Krishnan et al. (2005) find that 85% of analysts tend to herd while 5% prefer to stand out of crowd (anti herding). Krishnan et al. (2005) identify some empirical determinants of herding behavior among analysts. They find that herding is increasing with prior forecast inaccuracy, forecast horizon, general experience and the number of industries followed, and is decreasing with brokerage size and forecasting frequency. With the exception of the effect of experience and forecast horizon, Krishnan et al.’s (2005) results seem to be consistent with those in Clement and Tse (2005).

3. Hypotheses and empirical design

3.1 Hypotheses

3.1.1 Forecast accuracy

Welch (2000) shows that analyst could issue forecasts closer to consensus he was wrong yet. This suggests that imitate consensus reveals less precise and informative forecasts. Similary, Zitzewitz (2001) and Ottaviani and Sorensen (2003) explain the imitation by the fact that some analysts are abandoning their own sources of information for blindly following the behavior of others, while the distinction from the consensus reveals a self-confidence, charisma and possession of better information. In the same way, Galanti (2004) conjectures that a distinct forecast from consensus is more accurate than imitated since the analyst has spent all his time studying the company followed, therefore information obtained by his work has a good quality and may even be better than the average forecast (consensus).

Recently, Clement and Tse (2005) conclude that bold forecasts reveal information beyond that obtained from herding forecasts. Clement and Tse (2005) add that bold forecast is more accurate than herding forecast because it reflects private information that other analyst doesn’t have. In agreement with prior research we assume that bold forecasters are likely to use a variety of information sources when developing their earnings forecasts, this can explain the superiority of bold forecast in term of accuracy. This leads to our first hypothesis:

H1: Bold forecasts are more accurate than herding forecasts

3.1.2 Effect of experience on herding behaviour

In this study we retain only one measure of experience: general experience (Note 4). Analyst must be polyvalent and not specialist because he works for a brokerage house and he must follow a lot of firms and industries.

Consistent with Hong et al. (2000), Clement and Tse (2005) report that the association between general experience and forecast boldness is significantly positive. In contrast, Krishnan et al. (2005) find that more general experienced analysts tend to herd. We contribute towards this debate, by examining the relation between experience and herding forecasts in French context.

To formulate our hypothesis we build on prior researches that investigate the effect of experience on forecast accuracy [see, for example, Hutton and McEwen (1997), Mikhail, Walther, and Willis (1997), Clement (1999), Jacob et al. (1999), and Mikhail, Walther, and Willis (2003), Drake and Myers (2008)] (Note 5). These studies suggest that individual analyst forecast accuracy improves as analysts gain experience. Financial analysts’ forecasting skills should improve with repetition and feedback, as suggested by the learning by doing model (Arrow, 1962). We think these studies support the positive relation between experience and forecast boldness. If experienced analysts issue accurate forecasts, we predict they have not incentive to herd. In other words, inexperienced analysts who issue inaccurate forecasts tend to herd to hide their bad performance. This leads to our second hypothesis:

H2: inexperienced analysts are more likely to herd toward consensus than experienced analysts.

3.1.3 Effects of brokerage house’s size on herding behaviour

Krishnan et al. (2005) suggest that analyst tends to herd if she works for smaller brokerage house. This result is consistent to those reported in Clement and Tse (2005) who find that analyst who works for smaller brokerage house is more likely to act by herding behavior.

We think that herding behavior decreases with brokerage size. First large brokerage houses help their analysts by providing them different sources of information such as databases, forecasting tools, forecasts technology. Jacob et al. (1999) expect that analysts working for larger brokerage houses will have easier access to relevant information, increasing the likelihood that they will incorporate this information into their forecasts. Second larger brokerage houses attract also efficient analysts. Then, if larger brokers make available to their analysts several sources of information, therefore analysts will publish forecasts that reflect their own information without the others' decisions have an effect on their behavior. Thus we expect that analysts who work for larger brokerage houses have less incentive to herd. This leads to our third hypothesis:

H3: analysts employed by larger brokerage houses are less mimetic than those working for medium -and small- sized houses

3.1.4 Effects of portfolio on herding behavior (Note 6)

According to Clement (1999), it is difficult for analysts who follow several companies, to perform effectively their obligations and produce accurate forecasts. Thus, Clement (1999) shows that the more the analyst follows a large number of firms, the less he focuses on thoroughly each firm and therefore provides less accurate predictions. In agreement to this paper, we conjecture that herding behavior is rather associated to analysts who follow a large number of firms we propose to test the following hypothesis:

H4: Analysts working on a large number of firms are more mimetic than others.

3.1.5 Effects of forecast horizon on herding behavior

Forecast horizon is the difference between the forecast date and the earnings announcement date. At least three reasons favor the positive relation between forecast horizon and herding behavior.

First, analysts are considered as specialists and information researchers. They have to know regularly the private and public information. They anticipate the value of benefits and revise their expectations as they are in possession of new information. Analysts incorporate in their forecasts recent information as they became closer to announcement date. We expect that forecast closer to the announcement date reflects certainly all available information and therefore it's a bold forecast.

Second Brown et al. (1987), Brown, Richardson, and Schwager (1987), and Kross, Ro, and Schroeder (1990) document that analyst forecast accuracy improves as the forecast date is closer to the earnings announcement date. As a consequence, when earnings announcement dates are approaching, analysts have less incentive to herd since they have had more information and have been more accurate.

Third, Krishnan et al. (2005) find that herding forecast is significantly positively associated with forecast horizon. Nevertheless, there are some reasons to believe that herding behavior may not increase with forecast horizon.

First, closer to the announcement date, analyst can observe forecasts of his peers and thus may abandon its own forecast to imitate those of others. Second, Clement and Tse (2005) find that bold forecasts are significantly positively associated with forecast horizon. This result suggests, in contrast to Krishnan et al.'s (2005) findings, that forecasts that have larger forecast horizons (Note 7) are more likely to be bold.

As shown above, the relationship between herding behavior and forecast horizon is subject to controversial results. We should highlight the effect of forecast horizon on herding behavior in the French context. We propose to test the following hypothesis:

H5: Herding behavior increases with forecast horizon.

3.2 Sample selection

Our sample begins with all French listed firms with December 31st fiscal year ends, appearing in the Worldscope database over the 1996-2000 five-year period. We exclude all financial establishments (SIC codes 6000–6999) because of the specificity of their rules accountants. Institutional Broker Estimate System (I/B/E/S) detail file provides individual analysts' earnings forecasts. We use the last annual forecast made by each analyst within 120 days before year t-1 earnings announcement date. We use also the earnings per share (EPS) provided by I/B/E/S Actual file (Note 8). Earnings announcement dates are obtained from two sources: press release and I/B/E/S Actual file. We require non-missing information for (1) the value of the forecast, (2) the corresponding actual earnings, (3) date of the forecast, (4) earnings announcement date. We exclude firms followed by fewer than three analysts. We require each analyst to issue at least two forecasts for firm j in year t. The final sample consists of 262 companies and 9997 firm-year observations spanning 5 years (1996-2000).

3.3 Measurement of variables and empirical model

Following prior research we describe our variables:

$HERD_{ijt}$ is an indicator variable for herding of analyst *i*'s forecast for firm *j* in year *t*. It is equal to 1 if analyst *i*'s forecast moves away from the analyst *i*'s own prior forecast and toward the consensus. It is set to 0 otherwise (Clement and Tse, 2005). Figure 1 explains more this variable by providing a bold or herding forecast's classification.

$PMAFE_{ijt} = AFE_{ijt} - \overline{AFE_{jt}} / \overline{AFE_{jt}}$, is the proportional mean absolute forecast error calculated as the analyst *i*'s absolute forecast error of firm *j* for year *t* (AFE_{ijt}) minus $\overline{AFE_{jt}}$: the mean absolute forecast error for firm *j* for firm *t* (Note 9) scaled (Note 10) by the mean absolute forecast error for firm *j* for firm (Note 11). Forecast error is defined as the difference between I/B/E/S actual annual earnings and the last forecast made by the analyst within 120 days before year *t-1* earnings announcement.

$DGEXP_{ijt}$, is a measure of analyst *i*'s experience, calculated by the number of years that analyst appears in the data set minus the average number of years analysts following firm *j* at time *t* appeared in the data set.

$DBZISE_{ijt}$ is a measure of the analyst *i*'s brokerage size, calculated as the number of analysts employed by the brokerage employing analyst *i* following firm *j* in year *t* minus the mean value of this variable for all analysts following the firm *j* in year *t*.

$DAPFE_{ijt}$ (analyst's portfolio) is a measure of the number of firms analyst *i* follows calculated as the number of firms followed by analyst *i* following firm *j* in year *t* minus the mean value of this variable for all analysts following the firm *j* in year *t*.

$DAGE_{ijt}$ (forecast age or horizon) is a measure of time from the forecast date to the year *t-1* earnings announcement date, calculated as the forecast horizon (the number of days between the forecast date and the earnings announcement date) for analyst *i* following firm *j* in year *t* minus the mean value of this variable for all analysts following the firm *j* in year *t*.

Variables are defined, and we have to describe the model adopted to test our hypothesis. Thus, we follow Clement and Tse (2005) using our annual data by estimating the following Logit model:

$$HERD_{ijt} = \alpha_0 + \alpha_1 PMAFE_{ijt} + \alpha_2 DGEXP_{ijt} + \alpha_3 DBZISE_{ijt} + \alpha_4 DAPFE_{ijt} + \alpha_5 DAGE_{ijt} + \varepsilon_{ijt;}$$

4. Empirical results

4.1 Descriptive statistics and correlations

Table 1 presents descriptive statistics of the variables used in our survey. Consistent with prior studies, we find that analysts' one-year-ahead earnings forecasts are optimistic on average; the mean forecast error is -1.6137. However the median is -0.1593, this is consistent with several studies that document that analysts become less optimistic when earnings announcement dates are approaching (e.g, O'Brien, 1988). Average experience is 4.0992, Analyst follows on average 11 French firms and brokerage houses employ approximately 20 analysts on average. Average forecast horizon is around 44 days, analysts seem to wait for the earnings announcement date to issue their forecasts.

In order to avoid problems of autocorrelation between our independent variables, a survey of correlation matrix has been done: table 2 presents the Pearson correlations for independent variables adopted in our model. In terms of Pearson correlation coefficients, we find that general experience is positively and significantly correlated with analyst's portfolio. Therefore, more experienced analysts tend to follow a larger number of firms. To avoid all problems of auto-correlation in a linear regression, we are going to treat the variable experience and analyst's portfolio in two separated models. Finally we test our hypothesis using the two following equations:

$$HERD_{ijt} = \alpha_0 + \alpha_1 PMAFE_{ijt} + \alpha_2 DGEXP_{ijt} + \alpha_3 DBZISE_{ijt} + \alpha_4 DAGE_{ijt} + \varepsilon_{ijt} \quad (1)$$

$$HERD_{ijt} = \beta_0 + \beta_1 PMAFE_{ijt} + \beta_2 DBZISE_{ijt} + \beta_3 DAPFE_{ijt} + \beta_4 DAGE_{ijt} + \varepsilon'_{ijt} \quad (2)$$

4.2 Analysts' characteristics and herding behavior

We reports in Table 3 the results from the estimation of equations (1) and (2) determining the effect of forecast accuracy, general experience, brokerage size, portfolio, forecast horizon on herding behavior among financial analysts. In our sample, we find that forecast error is significantly and positively associated with herding behaviour (however, the t-student does not exceed 1.71 in both cases). Analyst fails when he reconsiders his own information to copy the consensus. Analyst who uses his own information and therefore doesn't adopt a herding behavior issues more accurate forecast. This result confirms our first hypothesis, then bolder analysts who tend to move away from the consensus produce more accurate forecast. May be they have information that other analysts don't have or they maintain good relationship with managers. This result is consistent with Clement and Tse (2005).

Concerning the variable general experience, it is negatively and significantly related with herding behaviour. The coefficient on general experience is -0.1026, this result is significant at the 1% level. This suggests the fact that analysts have some information and they could publish perfect forecasts based on information available to them, others' decisions have no effect on their behavior. On the other side, the inexperienced analysts have a minimum level of knowledge, they are more likely to care about their career and they are aware that a more important error than those of their peers, can put on risk their reputation and their career, they have no other choice only distort their forecasts in response to specific interests. Therefore, they are more likely to move away from their own prior forecast and toward the consensus to meet their own interests.

Regarding analyst's portfolio, the p-value indicates that analysts tend to herd if they follow less number of firms. This result is consistent with this in Krishnan et al. (2005). However, Clement and Tse (2005) report different result for this coefficient, it seems that analyst's portfolio does not have effect on herding behavior. In our study we find that analysts who follow a larger number of firms are less likely to herd. This result is reasonable since we have found that more experienced analysts, who are bolder, follow more firms.

The results also allow us to see that the brokerage size appears to be significant in explaining the herding behaviour. The coefficient relating to this variable is negative and significant at the 1% level. This confirms our fourth hypothesis and joined the results of various studies (Clement and Tse, 2005; Krishnan et al., 2005) that have concluded that analysts employed by large firms are less likely to herd and provide forecasts that reflect their own private information.

The forecast horizon's coefficient is positive but insignificant for both equations. Forecast horizon doesn't seem pertinent to explain analyst's behavior. This finding indicates that neither herding behavior increases with forecast horizon (Krishnan et al. (2005), nor bold forecast increases with forecast horizon (Clement and Tse, 2005).

5. Conclusion

In this study we focused on identifying factors that could explain herding behavior among financial analysts in a French context. The results show that analysts who move away consensus and issue bold forecasts based on their own information are more efficient in terms of accuracy. Similarly, they are more experienced and work for larger brokerage houses. We also find that analysts issuing herding behavior tend to cover fewer firms, this finding contrasts with Clement and Tse (2005). Finally, contrary to previous studies, in our sample, forecast horizon has no effect on herding behavior. To our knowledge, these results are new to the literature. The coefficient relating to forecast horizon is positive suggested that closer to earnings announcement dates, information will be more available, and analysts are more likely to issue bolder forecasts reflecting their own information, however this result is insignificant. When information is more provided, analysts could not look after their peers' signals. The effect of information's quality and herding behavior calls for future research.

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Notes

Note 1. Gleason and Lee (2003) call the bold forecasts as high innovation and the herding forecasts as low- innovation forecasts.

Note 2. The analyst A judges that the Analyst B is more efficient (superior) in terms of forecasts accuracy.

Note 3. Graham (1999) shows that newsletters classified to have both high reputation and low ability, follow Value line in their market-making decision. Using the Zacks'Historical Recommendations Database (1989-1994) Welch (2000) finds that the prevailing consensus and the two most recent revisions have a positive significant influence on the next analyst's recommendation.

Note 4. Prior research identifies two measures of experience: firm specific experience and general experience.

Note 5. These studies investigate the association between analyst characteristics (e.g., general experience, firm-specific experience, and/or broker size) and forecasting performance.

Note 6. Analyst's portfolio designs the number of companies followed by that analyst.

Note 7. Large forecast horizon means many days elapsed between the forecast date and the earnings announcement date.

Note 8. IBES adjusts EPS to be in the same basis as analysts' forecasts.

Note 9. Clement (1998) controls for firm-year effects by subtracting from all variables their related firm-year means.

Note 10. Clement (1998) shows that deflating $AFE_{ijt} - \overline{AFE_{jt}}$ by $\overline{AFE_{jt}}$ reduces heteroscedasticity.

Note 11. For example, if three analysts follow firm j in a given year t and their absolute forecast error are 0.15, 0.2 and 0,1 respectively, the mean absolute forecast error for firm j in that year $\overline{AFE_{jt}}$ would be *0.15* (i.e, (0.15 + 0.2 + 0,1)/3). The proportional mean absolute forecast error $PMAFE$ of firm j in that year would be *0* (i.e, (0.2 – 0.15)/0.15), *0.33* (i.e, (0.15 – 0.15)/0.15) and *-0.33* (i.e, (0.1 – 0.15)/0.15) respectively for analyst 1, 2 and 3.

Table 1. Descriptive statistics

Variables	Observations	Mean	Sdt.dev	Median
FE	9997	-1.6137	10.31832	-0.1593
EXP	9997	4.0992	2.5076	3
APF	9997	11.0346	19.7729	6
BZISE	9997	20.1442	8.8043	19
AGE	9997	43.6382	34.2403	37

FE is the difference between I/B/E/S actual annual earnings and the last analyst *i*'s forecast made by the analyst within 120 days before year *t-1* earnings announcement. EXP is the number of years that analyst appears in the data set. APF is number of firms followed by analyst *i* following firm *j* in year *t.* BZISE is the number of analysts employed by the brokerage employing analyst *i* following firm *j* in year *t*. AGE is the number of days between the forecast dates and the earnings announcement dates.

Table 2. Correlation matrix

Variables	PMAFE	DGEXP	DAPFE	DBZISE	DAGE
PMAFE	-				
DGEXP	0.017	-			
DAPFE	0.014	0.686***	-		
DBZISE	-0.026**	-0.049***	-0.11***	-	
DAGE	0.050***	0.015	-0.036***	-0.057***	-

***: Correlation is significant at the 1% level (2-tailed)

**: Correlation is significant at the 5% level (2-tailed)

PMAFE is the individual analyst *i*'s absolute forecast error of firm *j* for year *t* minus the mean of all analysts' absolute forecast errors of firm *j* for year *t* scaled by the mean of all analysts' absolute forecast errors of firm *j* for year *t*. forecast errors is the difference between I/B/E/S actual annual earnings and analyst's forecast. DGEXP is the number of years that analyst appears in the data set minus the average number of years analysts following firm *j* at time *t* appeared in the data set. DAPFE is the number of firms analyst *i* follows calculated as the number of firms followed by analyst *i* following firm *j* in year *t* minus the mean value of this variable for all analysts following the firm *j* in year *t*. DBZISE is the number of analysts employed by the brokerage employing analyst *i* following firm *j* in year *t* minus the mean value of this variable for all analysts following the firm *j* in year *t*. DAGE is the forecast horizon (the number of days between the forecast date and the earnings announcement date) for analyst *i* following firm *j* in year *t* minus the mean value of this variable for all analysts following the firm *j* in year *t*.

Table 3. Main results from Logit Models estimates for individual analyst

$$HERD_{ijt} = \alpha_0 + \alpha_1 PMAFE_{ijt} + \alpha_2 DGEXP_{ijt} + \alpha_3 DBZISE_{ijt} + \alpha_4 DAGE_{ijt} + \varepsilon_{ijt}, \quad (1)$$

$$HERD_{ijt} = \beta_0 + \beta_1 PMAFE_{ijt} + \beta_2 DBZISE_{ijt} + \beta_3 DAPFE_{ijt} + \beta_4 DAGE_{ijt} + \varepsilon'_{ijt}. \quad (2)$$

	Coefficient	t-statistic	p-value
Model (1)			
Constante	-0.1381	-6.76***	0.000
PMAFE	0.0541	1.71*	0.087
DGEXP	-0.1026	-11.63***	0.000
DBZISE	0.0121	-4.65***	0.000
DAGE	0.0004	0.72	0.471
Model (2)			
Constante	-0.1370	-6.73***	0.000
PMAFE	0.0519	1.65*	0.099
DAPFE	-0.0090	-7.88***	0.000
DBZISE	-0.0131	-5.00***	0.000
DAGE	0.0001	0.22	0.823

***Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level

HERD is an indicator variable for herding of analyst *i*'s forecast for firm *j* in year *t*. It is equal to 1 if analyst *i*'s forecast moves away from the analyst's own prior forecast and toward the consensus. It is set to 0 otherwise. PMAFE is the individual analyst *i*'s absolute forecast error of firm *j* for year *t* minus the mean of all analysts' absolute forecast errors of firm *j* for year *t* scaled by the mean of all analysts' absolute forecast errors of firm *j* for year *t*. forecast errors is the difference between I/B/E/S actual annual earnings and analyst's forecast. DGEXP is the number of years that analyst appears in the data set minus the average number of years analysts following firm *j* at time *t* appeared in the data set. DBZISE is the number of analysts employed by the brokerage employing analyst *i* following firm *j* in year *t* minus the mean value of this variable for all analysts following the firm *j* in year *t*. DAPFE is the number of firms analyst *i* follows calculated as the number of firms followed by analyst *i* following firm *j* in year *t* minus the mean value of this variable for all analysts following the firm *j* in year *t*. DAGE is the forecast horizon (the number of days between the forecast date and the earnings announcement date) for analyst *i* following firm *j* in year *t* minus the mean value of this variable for all analysts following the firm *j* in year *t*.

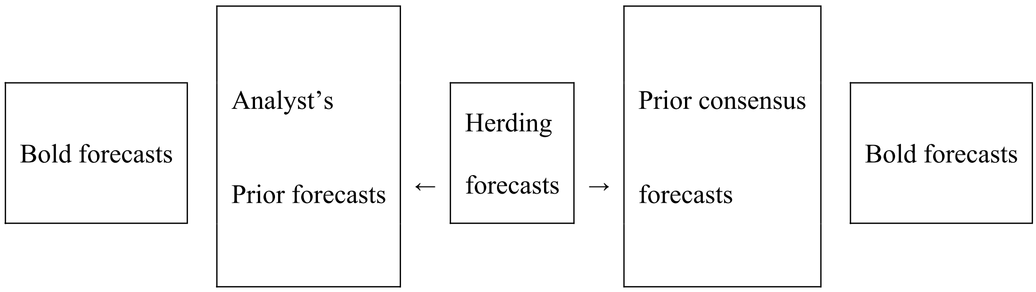

Figure 1. Bold and herding forecasts: Clement and Tse's (2005) classification.

Forecasts are classified as bold if they are above both the analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast. All other forecasts are classified as herding.