Stockholm School of Economics
Bachelor Thesis in Finance, May 2018

Herding Behavior in Forecasting of European Companies: Optimism and the Impact of the MiFID

A Study of the Causes and Consequences of Herding Behavior between 1996 - 2017 and the Impact of the Markets in Financial Instruments Directive (MiFID)

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Abstract

This thesis examines analysts' earnings per share forecast revisions for European companies and classifies them as either *herding* or *bold.* We further classify *bold* forecasts as *optimistic* or *pessimistic.* We find (i) optimistic boldness to be negatively associated with firm-specific characteristics such as leverage and stock return volatility, (ii) herding forecasts to be less accurate compared to bold (non-herding) forecasts, (iii) optimistic bold forecasts to be more accurate than pessimistic bold forecasts, and (iv) that optimistic bold forecasts have become less accurate relative to pessimistic bold forecasts following the implementation of MiFID. This study examines the firm-specific dimension of herding behavior and suggests that (optimistic) bold forecasts incorporate a higher degree of relevant private information, thus providing evidence that evaluating the impairment on analyst signaling due to herding behavior is relevant to consider for European investors. Lastly, this study assesses the impact of heightened regulation on analyst behavior in EU member states.

Keywords: Herding, Earnings per share forecasts, Optimism, Regulation, MiFID

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Acknowledgements: We would like to express our gratitude for the insightful comments and support from our tutor Jungsuk Han during the entirety of this process.

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Introduction

Equity research analysts serve an important role within the financial markets, as the earnings forecasts they issue are gauged by investors during the course of the fiscal year and used to guide financial decision-making. The consensus forecast for a company, frequently proxied by the mean or median of all individual forecasts, is representative of the market expectations for the future earnings of that company. Yet while analysts' forecast revisions function as valuable signals for investors, the tendency among analysts to herd, or to revise their previous forecasts in order to align more with the consensus, may have implications for the usefulness of the consensus forecast.

The purpose of this thesis is to add to the discussion of the causes and consequences of herding behavior by sell-side analysts, and thus to provide useful evidence to help financial decision-makers asses the information in analysts' forecast revisions. In particular, we examine the coverage of European companies and focus on optimism among bold forecast, as well as the implications of the regulatory framework MiFID. We examine last-forecast revisions for European companies over the time-period 1996 – 2017, utilizing data from I/B/E/S and Compustat Global.

The first research question examines the association of firm-specific characteristics with boldness (in relation to herding), as well as with optimistic boldness (in relation to pessimistic boldness). Prior studies, such as Clement and Tse (2005) find that bold forecasts are more likely to be issued by (i) historically accurate analysts, (ii) analysts employed by larger brokerage houses, (iii) frequent forecasters, and (iv) more experienced analysts. We seek to add to the discussion of the causes of herding behavior by examining the importance of a chosen set of firm-specific characteristics, specifically *Debt-to-Equity*, *Volatility*, and the *Information Environment* (the number of analysts covering a firm). The selection of these characteristics is motivated by associations rooted in existing theory. Graham (1999) and Trueman (1994) analytically predict that the incentives of analysts to issue herding forecasts will be higher when a firm's earnings uncertainty is low. We seek to examine this potential association, but focus on the uncertainty of the stock price of the covered company, measured by the standard deviation of daily returns (*Volatility)*. Additionally, Mansi et. al (2011) find that analyst forecasts have especially crucial economic impact when firms have high idiosyncratic risk, and affect debt-financing decisions to a high extent. We seek to further examine the relationship between capital structure and analyst behavior, by determining the association between forecast boldness and leverage (*Debt-to-Equity).* Lastly, Clement and Tse (2005) find that analysts tend to issue more bold forecasts for companies where revisions are frequently updated. We test if their findings can be further distilled and examine if boldness is associated with the number of analysts covering a company (*Information Environment).* In essence, we seek to assess if analyst behavior is systematically different based on the nature of the covered company, while controlling for other factors.

In line with the methodology used by Gleason and Lee (2003), we classify forecast revisions as *bold* if they exceed both the analyst's previous forecast as well as the consensus, or else is lower than both. All other forecasts, which thus move closer to the consensus are classified as *herding*. We examine the associations between our chosen firm-specific characteristics on both bold forecasts in general, as well as with specifically optimistic bold forecasts.

We find optimistic boldness to be significantly associated with *Debt-to-Equity* at a 1% level, and with *Volatility* at a 10% level. These results indicate that while controlling for other analyst- and forecast-specific characteristics, the same analyst will on average issue more optimistic relative to pessimistic bold forecasts for (i) more highly leveraged companies and (ii) companies with more volatile stock returns. Additionally, our results suggest a possible association between boldness and information environment, albeit significant at an ambiguous 11% level.

The second research question is whether a consensus restricted to include solely bold forecasts will signal more valuable information to investors. Clement and Tse (2005) find that bold forecasts are on average more accurate than herding forecasts, while controlling for characteristics that prior studies such as Hong et al. (2000) & Hong and Kubik (2003) have found to affect forecast accuracy. We seek to explore the globality of herding behavior in forecasting and expect to reaffirm the findings of Clement and Tse (2005) for forecasts issued on European companies. We find that bold forecasts are on average more accurate than herding forecasts, meaning that the results of Clement and Tse (2005) hold for European companies over a more recent period (1996 – 2017), after controlling for firm-, forecast-, and analyst-specific characteristics. This suggests that bold forecasts are based on relevant private information that is not incorporated in herding forecasts, and that a consensus based solely on bold forecast revisions may be more useful than the general one.[3]

The third research question explores the differences in forecast accuracy between optimistic and pessimistic bold forecasts, where a forecast revision is classified as optimistic if it exceeds both the analyst's previous forecast as well as the consensus prior to the announcement. Prior studies by Ke and Yu (2006) find that equity research analysts whose forecast revisions follow an optimistic-pessimistic pattern during the course of the fiscal year are on average more accurate than their professional peers. On the other hand, Chen and Jiang (2006) find evidence that sell-side equity analysts have a tendency to place an overweight on their private information, and that this tendency is especially prevalent for optimistic forecasts. The study of forecast boldness in relation to optimism is fairly unexplored by prior literature. Brun and Nyh (2014) find that optimistic bold forecasts are more accurate on average than pessimistic bold forecasts. We conduct our own study based on European data and find that among bold forecasts, optimistic forecasts are

[3] Private information refers to an analyst's individual interpretation of the available data and must not necessarily contain information that is not publicly obtainable.

on average more accurate than pessimistic forecasts. The findings might suggest that the access to private information from corporate managers enjoyed by optimistic analysts outweighs the suboptimal weighting of that information (Chen and Jiang (2006) and Ke and Yu (2006)).

The fourth research question assesses the impact of the Markets in Financial Instruments Directive (MiFID) on the association between forecast accuracy and optimistic forecast boldness, by dividing the sample into two time-periods based on its implementation date in EU member states: 1996 – 2007 and 2008 – 2017.[4] MiFID is a result of European regulators aim to increase the quality of analysts' signals and to further protect investors within the EU. It followed The Market Abuse Directive, or MAD (Directive 2003/125/EC) which was enacted by the European Commission in 2003 and adopted by member states between 2004 and 2006. The legislature "intended to guarantee the integrity of European financial markets and increase investor confidence … to create a level playing field for all economic operators in the Member States as part of the effort to combat market abuse". One of the key aspects of MAD was the requirement of financial analysts to disclose all material assumptions forming the basis for their recommendations as well as prohibiting managers from disclosing private information without making it public. Following MAD, the Markets in Financial Instruments Directive or MiFID (Directive 2004/39/EC) came into effect in November of 2007. Among other things, MiFID required financial services firms to separate investment research from activities that may impair analysts' objectivity and implement internal controls that ensure analyst independence. We choose to focus specifically on MiFID since it addresses many of the same issues as MAD, but introduces a significantly stricter set of rules regarding the internal governance structure of financial actors.

We examine the consequences of the regulatory framework by analyzing the incremental effect on forecast accuracy of optimistic forecasts, looking at specifically bold forecasts issued before and after MiFID. We find that among bold forecasts, optimistic forecasts have become less accurate relative to their pessimistic counterparts following the implementation of MiFID. The results may be explained as the regulation resulting in a net-loss of available private information to optimistic analysts, outweighing the reduction in the amount of low-information optimistic forecasts being made with career incentives in mind; and consequently, an overall decrease in forecast accuracy.

This thesis contributes to the discussion environment of the causes and consequences of herding behavior. We direct some of the focus onto the companies being covered, which to the extent of our knowledge are characteristics not explored by prior studies, and our results suggest a possible association between the information environment of a company and forecast boldness. Furthermore, we extend the findings of Clement and Tse (2005) and Hong et. al (2000) by examining the causes of specifically

[4] MiFID was implemented in Austria the 1st of January 2007.

optimistic bold forecasts and find significant associations with leverage and volatility. We also find that more experienced analysts will, on average, issue more optimistic than pessimistic bold forecasts.

Furthermore, this study contributes to the existing literature of herding behavior, by affirming the results of Clement and Tse (2005) for European-wide data. Our results thereby indicate that herding behavior is not a tendency exclusive to the coverage of US companies, and that the evaluation of analyst signaling arising from herding behavior is relevant over a more recent period. Moreover, we find evidence that a consensus based solely on bold optimistic forecasts may be more useful than one based of solely bold forecasts, although this association was stronger before the implementation of MiFID.

Lastly, this study contributes to the general debate of the effect of regulation on the behavior of financial decision-makers, by providing evidence that optimistic bold forecasts have become less accurate following the implementation of MiFID in November of 2007. Our results thereby convey information of the extent of the private information gathered and utilized by analysts, before and after MiFID.

The rest of the study has the following outline. Section II discusses prior literature and introduces eventual hypotheses related to the research questions. Section III describes the process of obtaining and selecting the data sample. Section IV goes through the methodology and describes the regression models used. The results are presented in Section V and finally, conclusions and implications are discussed in Section VI.

II. Prior Literature

Herding Behavior in Forecasting

Herding behavior in relation to a financial context was first explored by Scharfstein and Stein (1990). They find that financial decision-makers, such as managers and analysts, may exhibit herding behavior, i.e. mimicking the decisions of their professional peers, in a rational attempt to enhance their reputation. This is since they are shielded from reputational loss in the event of having made poor forecast recommendations as the blame is then shared among analysts, unlike for the bold, or non-herding, analysts who must bear the whole brunt of the failure by themselves.

The primary theoretical basis for this study is provided by Clement and Tse (2005) who analyzed the differences between accuracy of forecasted earnings per share for herding and bold (non-herding) forecasts. Through applying the method developed by Gleason and Lee (2003), their study classifies analyst last-forecast revisions as *bold* if they are either above the consensus forecast as well as the analyst's prior forecast, or else below both. All other forecast revisions, which thus move farther from the earlier forecast towards the consensus, are classified as *herding*. Their study examines data for United States companies over the time-period 1989 – 1998 and provides empirical evidence that forecast boldness is positively associated with analyst characteristics such as general and firm-specific experience, confirming the findings of Hong, Kubik, and Solomon (2000). Their study contributes to the discussion of causes of herding behavior, by presenting empirical evidence which suggests an inverse relationship between herding and analyst characteristics such as prior accuracy, brokerage size, and forecast frequency. They also find that bold forecasts are more accurate than herding forecasts, when controlling for factors that previous studies have shown affect forecast accuracy. This "[…] suggests that bold forecasts impound more private information about upcoming earnings than do herding forecasts, and, therefore, consensus earnings forecasts that are based on bold forecasts may be more accurate than consensus estimates based on all forecasts, whether bold or herding."

We use the analyst- and forecast-specific characteristics used by Clement and Tse (2005) and seek to further contribute to the discussion of factors associated with boldness through examining the firm-specific dimension (research question 1). We expect to confirm the predicted association of Trueman (1994) and Graham (1999), that boldness will be more prevalent for companies with higher degree of uncertainty. We thus expect to find a positive association between forecast boldness and *Volatility* and *Debt-to-Equity*. We also expect the results to suggest a positive association between forecast boldness and *Information*

Environment, in line with the findings of Clement and Tse (2005) that analysts issue more bold forecasts for more intensively covered companies.[5]

In addition, we seek to re-affirm their findings of a positive association between forecast boldness and accuracy, for last-forecast revisions of European companies over a more recent time-period (research question 2).

Systematic Optimism Amongst Equity Research Analysts

The potential conflict of interest in equity research, arising from analysts issuing recommendations and earnings forecasts for companies which their employer might have current or prospective investment banking ties to, has been the focus of several previous studies. Prior studies which have examined the issue have found that affiliated analysts, defined as "[…analysts who issues earnings forecasts on a firm for which his or her employer has acted as an underwriter]" tend to issue more optimistic forecasts than non-affiliated analysts (Michaely & Womack, 1999). Their findings are consistent with those of Easterwood and Nutt (1999), who find that "[…] analysts underreact to negative information, but overreact to positive information", further adding to the evidence of systematic optimism.

Hong and Kubik (2003) examine the association between optimism and career concerns and find that brokerage houses reward analysts who issue optimistic forecasts relative to the consensus. Furthermore, for analysts covering stocks underwritten by their brokerages, the favorability of an analyst's job separation is more dependent on optimism than the accuracy of their earnings forecasts. A later study by Ke and Yu (2006) present evidence that analysts tend to follow a pattern of issuing optimistic forecasts early during the fiscal year and revising them to be more pessimistic closer to the earnings announcement. They find their results to be "consistent with the hypothesis that analysts use biased earnings forecasts to gain support from firm management in order to obtain better access to management's private information." According to their findings, analysts who follow the pattern are characterized by producing consistently more accurate earnings forecasts compared to their peers, indicating that they do obtain relevant information.

Chen and Jiang (2006) find a tendency among sell-side analysts to place larger than efficient weights on their private information when they forecast corporate earnings. Furthermore, they find that "[…] analysts overweight more when issuing forecasts more favorable than the consensus, and overweight less, and may even underweight, private information when issuing forecasts less favorable than the consensus." The deviation from efficient weighting results in optimistic forecasts being associated with a higher forecast error. Chen and Jiang find that incentives play a larger role in suboptimal weighting than their behavioral biases.

[5] Clement and Tse (2005) find that forecast boldness is negatively associated with the number of days elapsed since the issuance of the last forecast, by any analyst for a particular firm.

We explore the differences in forecast accuracy between optimistic and pessimistic bold forecasts, by examining the association between optimistic boldness and forecast accuracy (research question 3). Although the findings of Ke and Yu (2006) might indicate a positive association between forecast accuracy and optimism, we theorize that since we are retaining solely last-revision forecasts, these will naturally be issued later on during the fiscal year, closer to the earnings announcement date. The analysts following the optimistic/pessimistic pattern described by Ke and Yu (2006) may therefore have revised their forecasts lower relative to the consensus, thereby registering as either herding or pessimistic-bold. However, the median forecast horizon for all bold observations is 164 days, indicating that a significant portion of last-revision forecasts are made earlier on during the year. Additionally, the findings of Chen and Jiang (2006) suggest that optimistic forecasts in general will be characterized by a higher forecast error. Consequently, existing theory does not provide a clear indication of the association between forecast accuracy and optimistic boldness, and thus we do not form a definitive hypothesis.

Financial Regulation in Europe

The MiFID could potentially alter the association between forecast accuracy and optimistic boldness in different ways. On the one hand the regulatory framework seeks to restrict the unwanted flow of private information from corporate managers to systematically optimistic analysts, which should have a negative effect on their forecast accuracy. However, when examining U.S. data, Mohanram and Sunder (2006) find that regulation aimed at reducing the disclosure of private information by managers may have unclear net-effects, as analysts compensate for the loss of private information by "[…] investing more effort in idiosyncratic information discovery."

Another noteworthy aspect of MiFID is the requirement on financial actors to implement stricter internal controls to ensure analyst independence. This will lead to a reduction of optimistic forecasts which are not based on relevant information. Prokop and Kammann (2018) find that MiFID has been successful in reducing both the short and long-term biases of affiliated analysts. They find that prior to the implementation of MiFID, affiliated analysts are more optimistic in a longer time frame, and less optimistic in the short term, consistent with the previous findings of Burgstahler & Eames (2006) that analysts downward manage their earnings forecasts to allow target firms to achieve zero or small earnings surprises. Their results suggest that since MiFID reduces the career incentives of affiliated analysts to issue systematically optimistic forecasts, the number of optimistic forecasts which are not based on relevant information should decrease. This would in turn suggest that optimistic bold forecasts will be more accurate, relative to all bold forecasts, after the implementation of MiFID. Due to the different plausible effects of MiFID described above, we do not hypothesize a definitive outcome on the change of optimistic bold forecast accuracy (research question 4).

III. Sample Selection

From the I/B/E/S (Institutional Brokers' Estimate System) International Detail History File, we gather data on forecasts for European companies' earnings per share issued by sell-side analysts. Additionally, for every forecast observation we collect data for: the date of the forecast announcement, identification codes for the analyst issuing the forecast and the brokerage firm which employs the analyst, a SEDOL code for each company, and the reported earnings per share for the relevant fiscal year. We collect data for 16 European countries over the period 1996 – 2017 which is deemed to be appropriate to yield a satisfactory amount of observations while being recent and thereby retaining relevance. [6]

From the Compustat Global Security Daily file, we acquire end-of-day prices of the listed common stocks for our chosen group of nations as well as four-digit SIC (Standard Industry Classification) codes. From the Compustat Global Fundamentals Annual file we collect the number of common shares outstanding and amount of interest-bearing liabilities for each firm-year. The three datasets are then merged, by basis of firm-specific SEDOL codes, and all the observations that cannot be matched are subsequently excluded.

In accordance with the approach used by Clement and Tse (2005), for each analyst and company we retain only the last forecast for the year (O'Brien (1990), Sinha, Brown, and Das (1997), Clement (1999)). Additionally, forecasts issued earlier than 1 year ahead of, or later than 30 days before the fiscal year end are excluded, as well as firm-years where only a single analyst provided forecasts. All analyst forecasts without prior year data on forecast accuracy are dropped. Forecast revisions and forecast errors are divided by the covered company's security price two days prior to the forecast revision date, which deflates the observations and allows for intra-company comparisons be made. Observations where the absolute price-deflated forecast revision or forecast error is above 0.10 and 0.40 respectively are deemed to be outliers and are dropped.

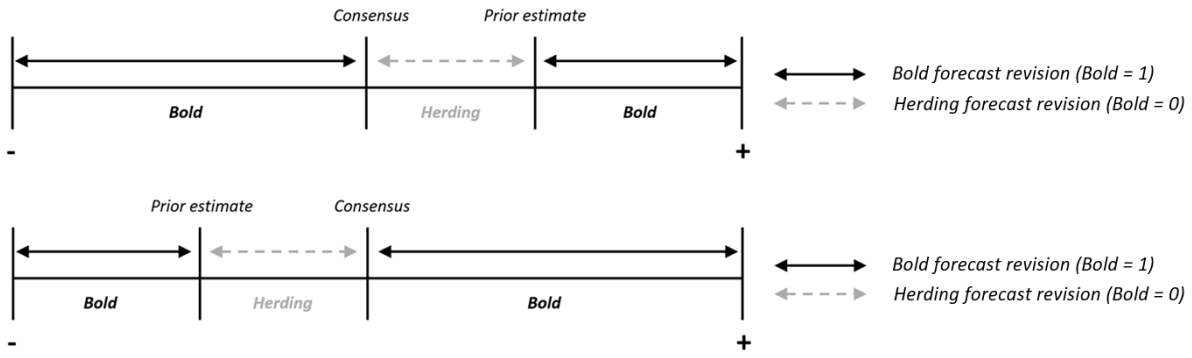
The raw I/B/E/S datafile initially contains 2,454,636 unique observations, out of which 1,056,971 are dropped during the merging-process with the firm-specific data from Compustat Global. 332,404 more observations are dropped due to falling outside of the timing restriction for forecast revisions. Another 307,750 observations are dropped due to fulfilling at least one of the previously mentioned outlier-conditions. Since the analysis is focusing on the last forecast-revision for each analyst-firm-year, a further 526,439 observations are excluded. Lastly, dropping observations with missing values resulting from the creation and scaling of new variables excludes 185,571 observations. Following these steps yields a final sample of 41,636 observations.

[6] The European countries included are: Austria, Belgium, Czech Republic, Denmark, Finland, France, Greece, Germany, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom. We originally also include data from Poland and Iceland, but they retain no observations in the final sample.

IV. Methodology

Boldness Measure

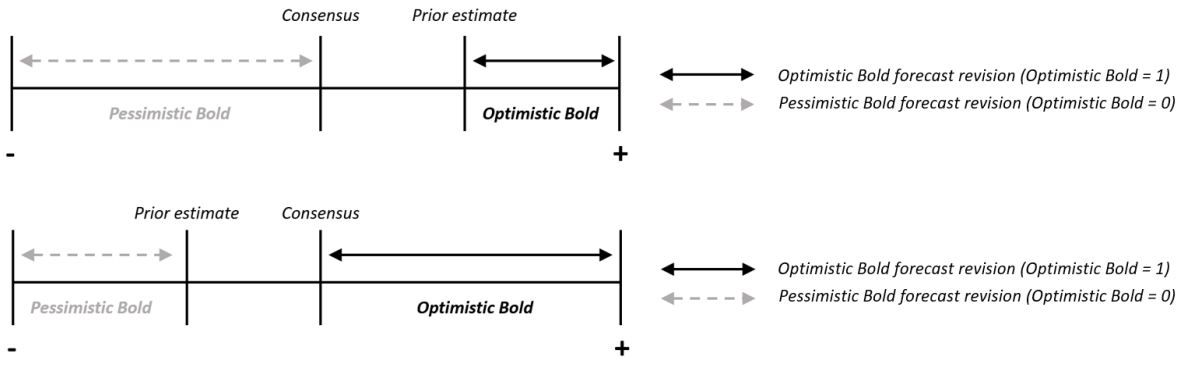
In order to study the causes of and effect of herding on analyst forecasts, a definition of boldness is required. We use the same boldness measure as Clement and Tse (2005), where boldness signifies the absence of herding and is statistically represented by the dummy variable *Bold*. As illustrated by Figure 1 below, a forecast revision that is closer to the consensus compared to the prior estimate yet does not pass the consensus is classified as herding.[7] The consensus is defined as the mean of all last-revision forecasts for the same firm, issued within 90 days of the forecast revision. It then follows that all other forecast revisions are classified as bold, i.e. forecast revisions that move further away from both the consensus and prior estimate, or cross to the opposite side of the consensus in relation to the prior estimate. For these analyst-firm-observations, the variable designed to capture boldness: *Bold,* assumes the value 1. Otherwise it is set to 0.



(Figure 1)

Additionally, *Optimistic Bold* is constructed as an indicator variable for optimistic bold forecast revisions, taking the value 1 if a forecast revision is bold and above the consensus immediately prior to the revision. Otherwise it takes the value 0. The classification of the variable is illustrated by Figure 2 below.

[7] Clement and Tse (2005) use the classification of Gleason and Lee (2003), where forecasts that are above both the analyst's prior consensus and the mean forecast, or else below both, are referred to as high-innovation forecasts, and the remaining forecasts are low-innovation forecasts. In line with Clement and Tse (2005), we refer to high-innovation and low-innovation forecasts as bold and herding forecasts, respectively.



(Figure 2)

The first research question relates to further exploring the causes of forecast boldness. More specifically we investigate the association between analyst-, forecast- and firm-specific characteristics with forecast boldness. The analyst- and forecast-specific characteristics used by Clement and Tse (2005) are included along with the three firm-specific characteristics. We expect our data sample to yield results suggesting the same associations between boldness and analyst- and forecast-specific characteristics as those found by Clement and Tse; positive associations between boldness and *Forecast Horizon, Lagged Accuracy, Broker Size, Forecast Frequency and General Experience*, while *Days Elapsed* and *Industries* will be negatively associated with boldness.

The negative association between *Days Elapsed* and forecast boldness suggested by Clement and Tse (2005) indicate that analysts tend to issue more bold forecasts for companies where revisions are frequently updated. This suggests that more intense coverage is related to higher boldness and leads us to hypothesize that *Information Environment* will be positively correlated with forecast boldness. We reason that companies being covered by a higher number of analysts are larger ones with more available information; which should lead to a higher proportion of bold forecasts.

Furthermore, we expect to find positive associations between forecast boldness and *Volatility* as well as *Debt-to-Equity*, in line with the predictions of Trueman (1994) and Graham (1999) that boldness will be more prevalent for companies with higher degrees of uncertainty. A contrary potential outcome rooted in economic intuition, is that the higher uncertainty proxied by *Volatility* and *Debt-to-Equity* instead leads to analysts resorting to a higher degree of conformity; thus, extracting more information from the consensus. The coefficients should then be negative.

Raw Characteristics

We apply a two-step method to arrive at the final variables used in the logit model. First, the following raw variables are derived from the dataset:

Absolute Forecast Error is the difference between forecasted and reported earnings per share in absolute terms, divided by the share price two days before the announcement date of the forecast.

Days Elapsed is the number of days elapsed since the last forecast by any analyst during the same firm-year.

Forecast Horizon is the number of days until the end of the fiscal year for each forecast.

Broker Size is the number of unique analysts employed by the same brokerage house, who have issued forecasts during a year.

Forecast Frequency is the number of forecasts for a particular company issued by an analyst during that year.

Firm Experience is calculated as the total number of years that an analyst has reported forecasts for a particular company.

General Experience is a measure of an analyst's overall experience, calculated as the total number of years an analyst has issued forecasts for any company.

Companies is the number of companies an analyst has issued forecasts for during a particular year.

Industries is the number of two-digit SIC industries an analyst has issued forecasts for during a particular year.

Year-To-Date Distance (YTD_Dist) is calculated as the absolute difference between the forecast revision and the prior consensus.

Fiscal Year End Distance (FYE_Dist) is calculated as the absolute difference between the forecast revision and the consensus at fiscal year-end.

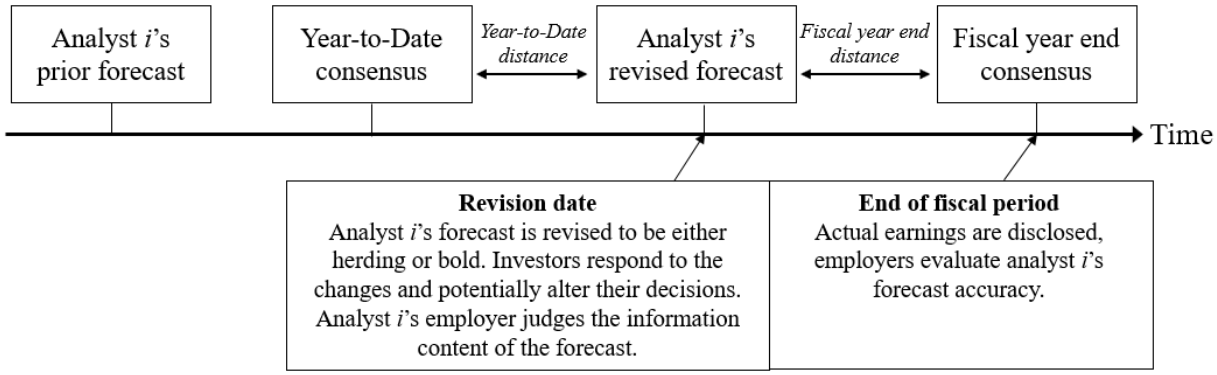
We also derive the following firm-specific characteristics:

Debt-to-Equity is a measure of the company's capital structure, calculated as the Debt/Equity ratio at the time of the forecast for each firm year. Debt is measured as the book-value of interest bearing liabilities at the end of the fiscal year, and equity is measured by the market capitalization two days prior to the announcement date of the forecast.

Volatility is a measure of the standard deviation of logarithmic share-price returns, for the forecasted company over the last 365 days leading up to the forecast announcement date.

Information Environment is a measure of the number of analysts issuing last-revision forecasts for a firm during a particular year.

Figure 3 below provides a visual illustration of the timeline for forecast revisions. It identifies plausible decision-making criteria for the analyst issuing the forecast, as well as the evaluation criteria for investors and the analyst's employer. It also defines the cross-sectional measures of boldness; the distance in absolute terms between analyst's *i'*s forecast revision and the consensus forecast. The *Year-to-Date Distance* is the absolute distance between the revised forecast and the consensus immediately prior to the announcement date. The *Fiscal Year End Distance* is the absolute distance between the revised forecast and the consensus at the end of the fiscal year.



(Figure 3)

Scaled Characteristics

To attain the final variables used in the regression models, the calculated raw characteristics are scaled by each firm and year. This implies that for each variable, every observation will assume a value between 0 and 1. This is done to facilitate comparison between the coefficients of different variables and allows for comparisons between observations of different firm-years to be made. For the scaling of the analyst- and forecast-specific characteristics used by Clement and Tse (2005), Equation 1 is used.[8] The subscripts *i, j,* and *t* refers to each unique analyst, firm, and year respectively.

[8] Forecast-specific variables: *Days Elapsed, Forecast Horizon, Forecast Frequency, Broker Size, Firm Experience, General Experience, Companies, Industries, Fiscal Year End Distance and Year-To-Date Distance*

$$Characteristic_{ijt} = \frac{Raw\_Characteristic_{ijt} - Raw\_Characteristic\_min_{jt}}{Raw\_Characteristic\_max_{jt} - Raw\_Characteristic\_min_{jt}}$$

(Equation 1)

To illustrate the effect of the scaling process, consider an example where there are seven analysts (analysts A – G) covering firm *j* in year *t*. Their *Raw Firm Experience* are 1, 3, 3, 4, 5, 7 and 8 years, respectively. The scaled variable *Firm Experience* for each analyst will then take the following values:

$$Firm\ Experience_A = \frac{1-1}{8-1} = 0$$

$$Firm\ Experience_B = \frac{3-1}{8-1} = 0.286$$

$$Firm\ Experience_C = \frac{3-1}{8-1} = 0.286$$

$$Firm\ Experience_D = \frac{4-1}{8-1} = 0.429$$

$$Firm\ Experience_E = \frac{5-1}{8-1} = 0.571$$

$$Firm\ Experience_F = \frac{7-1}{8-1} = 0.857$$

$$Firm\ Experience_G = \frac{8-1}{8-1} = 1$$

Naturally, as the firm-specific characteristics are meant to capture differences across firms, they are therefore scaled within each industry and year. Equation 2, illustrated below, is used for the scaling of firm-specific characteristics; where *j* refers to each unique firm, *k* refers to each unique 2-digit SIC sector code, and *t* to each year. [9]

$$FS\_Characteristic_{jt} = \frac{Raw\_FS\_Characteristic_{jt} - Raw\_FS\_Characteristic\_min_{kt}}{Raw\_FS\_Characteristic\_max_{kt} - Raw\_FS\_Characteristic\_min_{kt}}$$

(Equation 2)

Since there exists a negative relationship between the variable *Absolute Forecast Error* and the constructed variable *Accuracy* – a higher forecast error implies a lower accuracy – it is scaled in a different way. Equation 3 below is used, where *i* refers to each unique analyst, *j* to each unique firm and *t* to each year.

$$Accuracy_{ijt} = \frac{AbsoluteForecastError\_max_{jt} - AbsoluteForecastError_{ijt}}{AbsoluteForecastError\_max_{jt} - AbsoluteForecastError\_min_{jt}}$$

(Equation 3)

Hence *Accuracy* is calculated by taking the maximum *Absolute Forecast Error* for all forecasts for firm *j* in year *t* and subtracting from that the *Absolute Forecast Error* by analyst *i* for firm *j* in year *t*, scaled

[9] Firm-specific variables*: Debt-to-Equity, Volatility and Information Environment*

by the range of the absolute forecast errors in the same firm-year. This leads to the most accurate forecasts receiving a value of 1 and the least accurate forecasts receiving a value of 0.

The Association Between Firm-Specific Characteristics and Forecast Boldness

To test our first hypothesis, we follow the method applied by Clement and Tse (2005) and run a logit regression with *Bold* as the dependent variable. As illustrated by Regression 1 below, we extend prior research by explaining forecast boldness using firm-specific characteristics. The variables used by Clement and Tse (2005) are also included to control for analyst and forecast characteristics.

$$\begin{aligned} Bold_{ijt} = {} & \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} \\ & + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} \\ & + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} \\ & + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} + \varepsilon_{ijt} \end{aligned}$$

(Regression 1)

We further examine boldness and its causes by looking at how these characteristics affect optimistic forecast boldness. For Regression 2 we replace the dependent variable *Bold* in the first regression with *Optimistic Bold.*

$$\begin{aligned} OptimisticBold_{ijt} = {} & \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} \\ & + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} \\ & + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} \\ & + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} + \varepsilon_{ijt} \end{aligned}$$

(Regression 2)

The Association Between Forecast Boldness and Forecast Accuracy

To test our second research question regarding the effect of boldness on forecast accuracy we run a multivariate OLS regression with *Accuracy* as the dependent variable. We control for outside effects by including all the variables used in Regression 1 & 2, as well as the variables *Year-To-Date Distance* and *Fiscal Year End Distance*. These variables are included as additional measures of boldness, as they indicate how far the particular forecast deviates from either the current or year-end consensus. A positive association between *Year-To-Date Distance,* (*Fiscal Year End Distance)* and *Accuracy* would suggest that analysts whose last-forecast revisions deviate from the consensus (at year-end) incorporate more relevant information in their forecasts than other analysts.

Finally, we add the variable of interest, *Bold* as an independent variable. If analysts incorporate a higher degree of relevant private information in bold forecasts compared to herding forecasts, there should be a positive association between *Accuracy* and *Bold* after controlling for other characteristics.

$$\begin{aligned} Accuracy_{ijt} = {} & \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} \\ & + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} \\ & + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} \\ & + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} \\ & + \beta_{13} YTD\_Dist_{ijt} + \beta_{14} FYE\_Dist_{ijt} + \beta_{15} Bold_{ijt} + \varepsilon_{ijt} \end{aligned}$$

(Regression 3)

Previous studies have shown that the career-related consequences of issuing bold forecasts are very different for experienced and non-experienced analysts (Hong et al. 2000). To further explore this and examine the incremental effect on forecast accuracy of one additional year of general experience for bold forecasts, Regression 4 is tweaked to include an interaction term between *Bold* and *General Experience: (Bold x General Experience)*. A positive coefficient on the interaction term would suggest that there is an additional positive effect on accuracy of being bold for experienced analysts compared to in-experienced analysts. That would indicate that bold forecasts of experienced analysts are based on more relevant private information, as opposed to the forecasts of inexperienced analysts which are based on some other factor. A negative coefficient, however, would suggest that since inexperienced analysts are punished to a higher extent than experienced analyst's for issuing bold forecasts, in line with the findings of Hong et al. (2000); they will be more selective in exhibiting boldness. The bold forecasts that they do choose to issue will then be based on valuable private information, since they will have to withstand intense scrutiny from their employers.

$$\begin{aligned} Accuracy_{ijt} = {} & \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} \\ & + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} \\ & + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} \\ & + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} \\ & + \beta_{13} YTD\_Dist_{ijt} + \beta_{14} FYE\_Dist_{ijt} + \beta_{15} Bold_{ijt} \\ & + \beta_{16} (Bold\ x\ GeneralExperience)_{ijt} + \varepsilon_{ijt} \end{aligned}$$

(Regression 4)

The Association Between Optimistic Forecast Boldness and Forecast Accuracy

To examine the incremental effect of optimism among bold forecasts, we apply the same regression model as for the third research question but replace the independent variable *Bold* with *Optimistic Bold.* Additionally, since the aim is to compare the forecast accuracy of pessimistic bold and optimistic bold forecasts, no herding forecasts are included when running the regression. If optimistic bold forecasts are based on a larger than efficient weight being placed on private information in relation to pessimistic bold forecasts, there should be a negative association between optimistic boldness and forecast accuracy. However, if the analysts issuing systematically optimistic bold forecasts are rewarded by corporate managers with more access to relevant private information, the association may be positive.

$$\begin{aligned} Accuracy_{ijt} = {} & \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} \\ & + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} \\ & + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} \\ & + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} \\ & + \beta_{13} YTD\_Dist_{ijt} + \beta_{14} FYE\_Dist_{ijt} + \beta_{15} OptimisticBold_{ijt} + \varepsilon_{ijt} \end{aligned}$$

(Regression 5)

Consistent with the process of examining the third research question, we examine the incremental effect of one additional year of general experience for optimistic bold forecasts, by adding an interaction term between *General Experience* and *Optimistic Bold: (Optimistic Bold x General Experience).* See Regression 6 below.

$$\begin{aligned} Accuracy_{ijt} = {} & \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} \\ & + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} \\ & + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} \\ & + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} \\ & + \beta_{13} YTD\_Dist_{ijt} + \beta_{14} FYE\_Dist_{ijt} + \beta_{15} OptimisticBold_{ijt} \\ & + \beta_{16} (OptimisticBold\ x\ GeneralExperience)_{ijt} + \varepsilon_{ijt} \end{aligned}$$

(Regression 6)

The Impact of the Markets in Financial Instruments Directive (MiFID)

To test our fourth research question, we use Regression 7 illustrated below. The variable of interest is the interaction variable between *Optimistic Bold* and *Post: (Optimistic Bold x Post)*. A positive association would suggest that optimistic bold forecasts have become more accurate relative to pessimistic bold forecasts after the implementation of MiFID. We control for changes in our original control variables by adding interaction terms between all control variables and *Post.* Furthermore, to control for the tumultuous market conditions during the Global Financial Crisis and the Euro Crisis, we add another set of dummy variables.

Post is a dummy variable which takes the value of 1 if the fiscal year of firm *j* is 2008 or later.[10] For Austria it takes the value of 1 if the fiscal year is 2007 or later since MiFID was passed at an earlier date.

Global Financial Crisis is a dummy variable added to control for the effects of the global financial crisis. It takes the value 1 if the forecast announcement date is between the 1st December 2007 and the 1st June 2009, in accordance to the NBER classification. Otherwise it takes the value 0.

Euro Crisis is a dummy variable added to control for the effects of the Eurozone debt crisis. It takes the value of 1 if the forecast announcement date is between the 2nd May 2010 and 6th September 2012.[11] Otherwise it takes the value 0.

[10] MiFID was implemented on Nov 30th, 2007 (for all EU member states except Austria). However, we choose to separate our sample into post-MiFID after 2007 since the effects the first month likely are negligible and since most of these forecasts are already excluded.

[11] The timing restriction is motivated by: start-date for the crisis proxied by the date when Greece received the first debt-bailout package, end-date is proxied by the date when the ECB announced free-unlimited support for all eurozone member nations.

$$
\begin{aligned}
Accuracy_{ijt} = {} & \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} \\
& + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} \\
& + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} + \beta_{10} YTD\_Dist_{ijt} \\
& + \beta_{11} FYE\_Dist_{ijt} + \beta_{12} DebtToEquity_{jt} + \beta_{13} Volatility_{jt} \\
& + \beta_{14} InformationEnvironment_{jt} \\
& + \beta_{15} GlobalFinancialCrisis + \beta_{16} EuroCrisis + \beta_{17} Bold2_{ijt} \\
& + \beta_{18} DaysElapsed\ x\ Post_{ijt} + \beta_{19} ForecastHorizon\ x\ Post_{ijt} \\
& + \beta_{20} LaggedAccuracy\ x\ Post_{ijt} + \beta_{21} BrokerSize\ x\ Post_{ijt} \\
& + \beta_{22} ForecastFrequency\ x\ Post_{ijt} + \beta_{23} BrokerSize\ x\ Post_{ijt} \\
& + \beta_{24} FirmExperience\ x\ Post_{ijt} + \beta_{25} GeneralExperience\ x\ Post_{ijt} \\
& + \beta_{26} Companies\ x\ Post_{ijt} + \beta_{27} Industries\ x\ Post_{ijt} + \beta_{28} YTD_{Dist} x\ Post_{ijt} \\
& + \beta_{29} FYE_{Dist} x\ Post_{ijt} + \beta_{30} DebtToEquity\ x\ Post_{jt} + \beta_{31} Volatility\ x\ Post_{jt} \\
& + \beta_{32} InformationEnvironment\ x\ Post_{jt} + \beta_{33} (Optimistic\ Bold\ x\ Post)_{ijt} + \varepsilon_{ijt}
\end{aligned}
$$

(Regression 7)

V. Results

A. Descriptive Statistics

Descriptive statistics for variables and characteristics are presented in Table I. Panel A shows summary statistics for the raw characteristics. We get noticeably different mean and quantile values for some characteristics compared to Clement and Tse (2005), especially for *Forecast Horizon, Broker Size* and *Companies*. Since our results are based on an entirely different sample, representing a different geographical region as well as over a more recent time-period, some differences are to be expected. Looking at for example *Forecast Horizon,* Clement and Tse record a mean of 97.9 days compared to 176.3 days for our data. This suggests that within the confines of our timing-restriction (which is identical to the one of Clement and Tse), analysts issue last-revision forecasts considerably earlier in the fiscal year for European companies compared to U.S. companies. Furthermore, our mean for *Broker Size* was 53.2 analysts compared to Clement and Tse's 29.8, indicating that brokerage houses issuing forecasts for European companies are roughly twice the size of brokerage houses covering US companies. Naturally, it is necessary to consider the fact that the difference could be explained by the different time-periods.

Panel B reports the summary statistics for the scaled variables. These variables have been scaled so that observations assume values between 0 and 1, while retaining their relative position in the sample. Means range from a minimum of 0.17 for *Debt-to-Equity* to a maximum of 0.65 for *Accuracy*. Most variables are hence skewed.[12] Panel C reports the means and their differences between bold and herding forecasts for the scaled variables. Five of the variables show a difference in means significant at a 1% level, while the rest of the variables are not significant at a 5% level.[13] *Accuracy* has a larger mean for herding forecasts than for bold forecasts which might suggest that herding forecasts are more accurate. This will be explored further through the regressions. As is to be expected, the means for *Year-to-Date Distance* and *Fiscal Year End Distance* are considerably larger for bold forecasts compared to herding, since bold forecasts by design are ones that deviate from the consensus. Other notable differences are that herding forecasts are on average (i) issued earlier than bold forecasts and (ii) by more experienced analysts.

Panel D reports the means of the scaled variables for optimistic and pessimistic bold forecasts, as well as the significance of the differences between them. Eight of the variables suggest differences significant at a 1% level, and *Volatility* is significant at a 5% level.[14] Pessimistic bold forecasts have a higher mean accuracy than optimistic bold forecasts, which is explored more in detail in the results relating to the

[12] No skewedness would require means of 0.50 for all variables.

[13] *Accuracy, Days Elapsed, Forecast Horizon, Year-to-Date Distance* and *Fiscal Year End Distance* all show a difference in means at a 1% significance level.

[14] *Accuracy, Forecast Horizon, Broker Size, Industries, Market Capitalization, Debt-to-Equity, Year-to-Date Distance* and *Fiscal Year End Distance* all show a difference in means at a 1% significance level.

third research question. Another notable difference is that optimistic bold forecasts seem to be more prevalent at larger brokerage houses and are also issued earlier during the fiscal year than pessimistic bold forecasts. This is in line with findings of prior studies as analysts have a tendency to issue optimistic forecasts early in the fiscal year and later revise them pessimistically (Ke and Yu 2006). Optimistic bold forecasts are also more common relative to pessimistic bold forecasts for companies with (i) a lower leverage ratio and (ii) a lower volatility in stock returns. The differences in means for *Year-to-Date Distance* and *Fiscal Year End Distance* suggests that optimistic bold forecasts are, on average, issued closer to the consensus immediately prior to the forecast compared to pessimistic bold forecasts, but further away from the fiscal year-end consensus.

Panel E looks at the difference in means of the scaled variables between the time periods pre-MiFID (1996-2007) and post-MiFID (2008-2017). With the exception for *Days Elapsed, Forecast Frequency* and *Industries* which are not significant at a 5% level, and *Year-to-Date Distance* and *Optimistic Bold* which are significant at a 5% level, all variables have a difference significant at a 1% level. The mean for *Broker Size* has increased substantially after 2007, likely explained by industry consolidation following the financial crisis, which in part has been driven by needs to meet the larger corporate governance costs arising from regulation such as MiFID. Finally, the descriptive statistics suggest that bold forecasts have become less common in relation to herding forecasts after the implementation of MiFID, and likewise optimistic bold forecasts have become less common compared to pessimistic bold forecasts.

Panel F shows a correlation matrix for selected analyst, forecast and firm characteristics. Consistent with the prior study of Clement and Tse (2005), forecast accuracy is negatively correlated with *Days Elapsed, Forecast Horizon, Companies* as well as *Industries,* and positively correlated with *Broker Size.* Unlike the findings of Clement and Tse, we find that *Forecast Frequency, Firm Experience* and *General Experience* are all negatively associated with forecast accuracy.[15] Three variable pairs indicate a strong correlation: *Firm Experience* & *General Experience*, *Companies* & *Industries*, and *Fiscal Year End Distance & Year-To-Date Distance* with correlations of 0.466, 0.634, and 0.504, respectively. Given the classifications of these variables, presented in Section IV, the correlations noted above are not surprising.

[15] Clement and Tse (2005) found positive correlations between *Accuracy* and: *Forecast Frequency, Firm Experience* & *General Experience*.

Table I

Descriptive Statistics on Analyst, Forecast and Firm Characteristics

Descriptive statistics for 41,636 observations of analyst forecasts between 1996 - 2017. The I/B/E/S International Detail History file has been used to derive the forecast and analyst characteristics. Firm-specific characteristics have been derived from share-prices, interest-bearing debt, and common shares outstanding collected from Compustat Global's Security Daily and Fundamentals Annual files. The sample is restricted to forecasts issued less than 1 year ahead of and more than 30 days prior to the fiscal year end. Observations where only one analyst issued forecasts in a firm-year have been dropped. Only the last forecast issued by each analyst in a firm-year is kept for the final sample. The characteristics are: *Days Elapsed* - the number of days since the last forecast issued by any analyst; *Forecast Horizon* - number of days until fiscal year end*; Broker Size* - number of analysts issuing forecasts for a brokerage house in a firm-year; *Forecast Frequency* - number of forecasts made during the year; *Firm Experience* - years of firm specific experience; *General Experience* - years of experience in I/B/E/S database; *Companies* number of companies covered in each year; *Industries* - number of 2-digit SIC industries covered in each year; *Debt-to-Equity* - Interest-bearing debt at fiscal year end divided by market capitalization two days prior to forecast; *Volatility* - standard deviation of logarithmic share-price returns 1 year prior to forecast; *Information Environment* - number of analysts covering each firm during the year. Panel A reports summary statistics for the raw (unscaled) characteristics. Panel B reports summary statistics for the scaled analyst, forecast and firm characteristics as well as *Accuracy* and *Lagged Accuracy* variables, which are scaled to take values between 0 - 1. Panel C reports a comparison of the characteristics' means and their differences between Bold and Herding forecasts. Panel D reports a comparison of the characteristics' means and their differences between optimistic bold and pessimistic bold forecasts. Panel E reports a comparison of the characteristics' means and their differences between the pre- and post-MiFID time periods. Summary statistics are also provided for *Year-To-Date Distance* - absolute distance from forecast to prior consensus; and *Fiscal Year End Distance* - absolute distance from forecast to fiscal year end consensus.

Panel A: Descriptive Statistics of Raw (Unscaled) Anlalyst, Forecast and Firm Characteristics

	Mean	25th Percentile	Median	75th Percentile	Minimum	Maximum	Standard Deviation
Days Elapsed : Days since previous forecast	4.3	0	1	5	0	126	8.4
Forecast Horizon : Days to fiscal year end	176.3	103	169	248	30	355	84.4
Broker Size : Number of analysts at brokerage	53.2	19	48	80	1	190	36.5
Forecast Frequency : Number of forecasts made	5.0	3	4	6	1	311	4.1
Firm Experience : Years of firm experience	4.6	3	4	6	2	21	2.6
General Experience : Years of general experience	7.8	4	7	10	2	25	4.3
Companies : Number of companies covered	6.6	4	6	9	1	44	3.7
Industries : Number of industries covered	3.2	1	3	4	1	26	2.3
Debt-to-Equity	1.0	0	0	1	0	100[a]	3.1
Volatility : 1 year stock-return volatility %	2.3	1	2	3	0	47	2.1
Information Environment : Number of analysts covering firm	24.8	16	24	33	3	75	11.1

[a] *Debt-to-Equity ratios over* 100 are deemed outliers

Panel B: Descriptive Statistics of Scaled Analyst, Forecast and Firm Characteristics

	Mean	25th Percentile	Median	75th Percentile	Standard Deviation
Accuracy	0.65	0.46	0.69	0.87	0.26
Lagged Accuracy	0.65	0.46	0.70	0.87	0.26
Days Elapsed	0.20	0.00	0.07	0.29	0.29
Forecast Horizon	0.49	0.20	0.48	0.76	0.32
Broker Size	0.40	0.11	0.35	0.65	0.31
Forecast Frequency	0.49	0.25	0.45	0.70	0.29
Firm Experience	0.58	0.33	0.53	0.89	0.31
General Experience	0.50	0.27	0.47	0.71	0.28
Companies	0.42	0.20	0.38	0.60	0.28
Industries	0.33	0.00	0.25	0.50	0.31
Debt-to-Equity	0.17	0.04	0.10	0.22	0.21
Volatility	0.18	0.05	0.11	0.24	0.20
Information Environment	0.68	0.47	0.72	0.93	0.27
Year-To-Date Distance	0.30	0.08	0.22	0.44	0.28
Fiscal Year End Distance	0.28	0.08	0.22	0.42	0.25

Panel C: Comparison of Scaled Analyst, Forecast and Firm Characteristics Between Bold and Herding Forecasts				
	Bold Forecast Revisions	Herding Forecast Revisions	t-Value for Difference	Significance
	N = 24,409	N = 17,227		
Accuracy	0.6402	0.6531	5.04	<0.001
Lagged Accuracy	0.6501	0.6474	-1.02	0.309
Days Elapsed	0.2005	0.2080	2.57	0.010
Forecast Horizon	0.4770	0.5161	12.28	<0.001
Broker Size	0.4005	0.4053	1.51	0.132
Forecast Frequency	0.4961	0.4920	-1.39	0.164
Firm Experience	0.5773	0.5795	0.78	0.437
General Experience	0.4941	0.5022	2.88	0.004
Companies	0.4188	0.4237	1.73	0.084
Industries	0.3242	0.3300	1.84	0.066
Debt-to-Equity	0.1694	0.1709	0.69	0.488
Volatility	0.1810	0.1824	0.66	0.512
InformationEnvironment	0.6796	0.6751	-1.65	0.098
Year-To-Date Distance	0.3193	0.2650	-20.19	<0.001
Fiscal Year End Distance	0.3214	0.2278	-39.05	<0.001

Panel D: Comparison of Scaled Variables Between Optimistc Bold and Pessimistic Bold Forecasts				
	Optimistic Bold Forecasts	Pessimistic Bold Forecasts	t-Value for Difference	Significance
	N = 11,295	N = 13,114		
Accuracy	0.6344	0.6453	3.16	0.002
Lagged Accuracy	0.6494	0.6508	0.42	0.672
Days Elapsed	0.1998	0.2010	0.33	0.743
Forecast Horizon	0.5081	0.4502	-14.22	<0.001
Broker Size	0.4071	0.3952	-2.94	0.003
Forecast Frequency	0.4980	0.4945	-0.92	0.356
Firm Experience	0.5770	0.5769	-0.02	0.986
General Experience	0.4971	0.4915	-1.57	0.117
Companies	0.4170	0.4207	1.02	0.310
Industries	0.3181	0.3299	2.93	0.003
Debt-to-Equity	0.1647	0.1807	6.12	<0.001
Volatility	0.1777	0.1851	2.86	0.004
InformationEnvironment	0.6826	0.6770	-1.65	0.099
Year-To-Date Distance	0.3088	0.3282	5.35	<0.001
Fiscal Year End Distance	0.3355	0.3092	-7.72	<0.001

Panel E: Comparison of Scaled Variables Between Pre- and Post-MiFID				
	Pre-MiFID 1996-2007	Post-MiFID 2008-2017	t-Value for Difference	Significance
	N = 13,858	N = 27,778		
Accuracy	0.6262	0.6552	-10.56	<0.001
Lagged Accuracy	0.6330	0.6570	-8.74	<0.001
Days Elapsed	0.2039	0.2034	0.17	0.867
Forecast Horizon	0.5083	0.4855	6.84	<0.001
Broker Size	0.3216	0.4431	-39.55	<0.001
Forecast Frequency	0.4923	0.4956	-1.07	0.286
Firm Experience	0.6288	0.5526	24.29	<0.001
General Experience	0.5052	0.4935	4.07	<0.001
Companies	0.3947	0.4341	-13.37	<0.001
Industries	0.3220	0.3292	-2.19	0.286
Debt-to-Equity	0.2084	0.1567	22.37	<0.001
Volatility	0.1626	0.1920	-14.02	<0.001
InformationEnvironment	0.6864	0.6735	4.53	<0.001
Year-To-Date Distance	0.3008	0.2947	2.13	0.034
Fiscal Year End Distance	0.2928	0.2776	5.73	<0.001
Bold	0.5994	0.5797	3.87	<0.001
Optimistic Bold	0.4737	0.4571	2.46	0.014

Panel F: Correlations among scaled variables

Significance levels in parentheses

	Accuracy	*Days Elapsed*	*Forecast Horizon*	*Broker Size*	*Forecast Frequency*	*Firm Experience*	*General Experience*	*Companies*	*Industries*	*Debt-to-Equity*	*Volatility*	*Information Environment*	*Year To Date Distance*
Days Elapsed	-0.033												
	(0.000)												
Forecast Horizon	-0.150	-0.033											
	(0.000)	(0.000)											
Broker Size	0.020	-0.010	-0.012										
	(0.000)	(0.040)	(0.012)										
Forecast Frequency	-0.016	0.051	-0.074	0.010									
	(0.001)	(0.000)	(0.000)	(0.041)									
Firm Experience	-0.012	0.016	-0.009	-0.056	0.054								
	(0.012)	(0.001)	(0.076)	(0.000)	(0.000)								
General Experience	-0.013	0.013	-0.016	-0.013	0.025	0.466							
	(0.008)	(0.007)	(0.001)	(0.009)	(0.000)	(0.000)							
Companies	-0.022	0.044	-0.022	-0.051	0.087	0.047	0.165						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
Industries	-0.041	0.045	-0.022	-0.141	0.091	0.065	0.155	0.634					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Debt-to-Equity	-0.040	0.026	-0.018	-0.022	-0.006	0.005	0.029	-0.005	0.037				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.192)	(0.353)	(0.000)	(0.277)	(0.000)				
Volatility	-0.021	0.014	0.023	-0.018	0.005	0.024	-0.010	-0.004	0.039	0.208			
	(0.000)	(0.004)	(0.000)	(0.000)	(0.301)	(0.000)	(0.034)	(0.366)	(0.000)	(0.000)			
Information Environment	0.085	-0.129	0.054	0.023	-0.159	-0.102	-0.089	-0.166	-0.180	0.060	0.038		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Year-To-Date Distance	-0.129	0.008	0.029	-0.019	0.018	0.022	0.029	0.038	0.042	0.016	0.010	-0.097	
	(0.000)	(0.120)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.036)	(0.000)	
Fiscal Year End Distance	-0.325	0.013	-0.000	-0.035	0.010	0.016	0.007	0.024	0.032	0.011	0.020	-0.053	0.504
	(0.000)	(0.011)	(0.986)	(0.000)	(0.038)	(0.001)	(0.158)	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)	(0.000)

B. The Association Between Firm-Specific Characteristics and Forecast Boldness

Table II shows the results for our first research question. In Regression 1 we find, like Clement and Tse (2005), a negative and significant relationship between *Days Elapsed* and forecast boldness, with an odds ratio of roughly the same magnitude. Two other significant variables are *Forecast Horizon* and *Broker Size*, which both have negative coefficients unlike Clement and Tse (2005) who find positive associations. Unsurprisingly, these are the variables where we also find the largest difference in the descriptive statistics. The means for our sample of *Broker Size* and *Forecast Horizon* is 53.2 analysts and 176.3 days, respectively compared to Clement and Tse's 29.8 analysts and 97.9 days, respectively. Thus, the results indicate that the associations rooted in existing theory are not that clear-cut, and are not supported for a more recent dataset of European companies. Interestingly, we also find that *General Experience* is negatively associated with forecast boldness which contradicts the findings of Clement and Tse (2005) and Hong et al. (2000). However, we do not deem this finding to be robust enough to dispute existing theory, as the association is significant only at a 5% level. The discrepancy could be related to the smaller size of our sample, which is further discussed in the Potential Issues section below. Our results suggest that the odds of observing a bold forecast from an analyst with the highest level of general experience is 0.90 times those compared to an analyst with the lowest level of general experience. None of the firm-specific characteristics are significant at a 10% level, suggesting that there is not sufficient evidence to state that forecast boldness is affected by the characteristics of the covered firm. However, *Information Environment* is positive and significant at a level of 10.9%, hinting at the existence of some association.

In Regression 2 we find *Forecast Horizon* to be positively associated with optimistic boldness which is in line with previous findings by Ke and Yu (2006). The odds of a forecast issued 355 days ahead of the fiscal year end being optimistically bold is 1.78 times higher than for a forecast issued 30 days prior to fiscal year end. [16] The coefficient for *Broker Size* is positive and significant which indicates that analysts' bold forecasts at larger brokerage houses tend to be more optimistic compared to smaller brokerages. A possible explanation for this finding is that larger brokerage houses tend to also conduct more investment banking business which could result in a larger proportion of affiliated analysts, who are incentivized to issue optimistic forecasts (Michaely & Womack, 1999). *Forecast Frequency, General Experience* and *Industries* are all significant at a 5% level.[17] *Debt-to-Equity* is negative and significant at a 1% level, suggesting that optimistic bold forecasts are less frequent compared to pessimistic bold forecasts for highly leveraged firms. *Volatility* is also negatively associated with optimistic boldness but significant only at a 10% level.

[16] The maximum *Forecast Horizon* for our sample was 355 days.
[17] *Forecast Frequency* and *General Experience:* positive coefficients. *Industries:* negative coefficient.

Table II

The Association Between Boldness and Analyst, Forecast and Firm-specific Characteristics

Table II reports the association between Boldness and various exploratory variables. All variables are scaled within each firm-year to take values between 0 - 1. The variables are: *Days Elapsed* - the number of days since the last forecast issued by any analyst; *Forecast Horizon* - number of days until fiscal year end; *Broker Size* - number of analysts issuing forecasts for a brokerage house in a firm-year; *Forecast Frequency* - number of forecasts made during the year; *Firm Experience* - years of firm specific experience; *General Experience* - years of experience in I/B/E/S database; *Companies* - number of companies covered in each year; *Industries* - number of 2-digit SIC industries covered in each year; *Debt-to-Equity* - Interest-bearing debt at fiscal year end divided by market capitalization two days prior to forecast; *Volatility* - standard deviation of logarithmic share-price returns 1 year prior to forecast; *Information Environment* - number of analysts covering each firm during the year. Regression 1 examines the association between bold forecast revisions and various analyst-, forecast-, and firm-specific characteristics. Regression 2 examines the association between optimistic bold forecast revisions and the same analyst-, forecast-, and firm-specific characteristics as in Regression 1. Regression 1 uses our total sample of 41,636 observations while Regression 2 uses 24,409 observations as only bold forecast revisions are considered.

$$Bold_{ijt} = \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} + \varepsilon_{ijt}$$

(Regression 1)

$$OptimisticBold_{ijt} = \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} + \varepsilon_{ijt}$$

(Regression 2)

	Regression 1: Logit Probability of Boldness		**Regression 2: Logit Probability of Optimistic Boldness**	
	N = 41,636		N = 24,409	
VARIABLES	Parameter	Odds Ratio	Parameter	Odds Ratio
Intercept	0.5715***		-0.4757***	
	(10.07)		(-6.46)	
Days Elapsed	-0.0937***	0.9105***	0.0155	1.0156
	(-2.69)	(-2.69)	(0.34)	(0.34)
Forecast Horizon	-0.3899***	0.6772***	0.5766***	1.7800***
	(-12.40)	(-12.40)	(14.10)	(14.10)
Lagged Accuracy	0.0358	1.0365	-0.0474	0.9537
	(0.93)	(0.93)	(-0.95)	(-0.95)
Broker Size	-0.0630**	0.9390**	0.1015**	1.1069**
	(-1.96)	(-1.96)	(2.44)	(2.44)
Forecast Frequency	0.0381	1.0388	0.0987**	1.1038**
	(1.09)	(1.09)	(2.18)	(2.18)
Firm Experience	0.0216	1.0219	-0.0245	0.9758
	(0.59)	(0.59)	(-0.52)	(-0.52)
General Experience	-0.1041**	0.9011**	0.1267**	1.1351**
	(-2.56)	(-2.56)	(2.39)	(2.39)
Companies	-0.0197	0.9805	0.0379	1.0386
	(-0.43)	(-0.43)	(0.63)	(0.63)
Industries	-0.0389	0.9618	-0.1184**	0.8884**
	(-0.93)	(-0.93)	(-2.17)	(-2.17)
Debt-to-Equity	-0.0384	0.9623	-0.3415***	0.7107***
	(-0.77)	(-0.77)	(-5.24)	(-5.24)
Volatility	-0.0119	0.9882	-0.1183*	0.8884*
	(-0.23)	(-0.23)	(-1.79)	(-1.79)
InformationEnvironment	0.0624	1.0644	0.0624	1.0643
	(1.60)	(1.60)	(1.23)	(1.23)

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

C. The Association Between Forecast Boldness and Forecast Accuracy

Table III reports the results concerning our second research question. Looking at Regression 3 we find a positive association between forecast boldness and *Accuracy*, significant at a 1% level. This suggests that bold forecast revisions indeed are more accurate than herding forecasts in Europe, reaffirming the results found by Clement and Tse (2005) for U.S. companies. However, the coefficient we find is roughly a fifth of the size of the coefficient Clement and Tse (2005) record in their study.[18] This suggests that while the same phenomenon and association exists in Europe, the effect is not nearly as prominent as in the U.S. Observing the alternative measures of boldness, *Year-to-Date Distance* and *Fiscal Year End Distance* are positively and negatively associated with forecast accuracy, respectively. This implies that forecast revisions that are farther from the consensus at the revision date are on average more accurate, but that forecasts that deviate from the year-end consensus are less accurate. The positive coefficient on *Year-to-Date Distance* suggest that forecasts which deviate from the consensus at the time of the revision (i.e. bold forecasts) incorporate more relevant private information compared to forecasts issued closer to the consensus. The negative coefficient on *Fiscal Year End Distance* is likely explained by a timing-perspective. As the fiscal year progresses, more information is disseminated to analysts and investors through company signaling. The consensus will thus progressively incorporate more information-content, and the year-end consensus will unsurprisingly be closer to the actual disclosed earnings than a consensus at an earlier date. Naturally, a forecast issued with 169 days left to the announcement date for corporate earnings (which is the median for our sample) will not incorporate as much information as one issued at the fiscal year end, since many crucial events or news have not been disclosed, or even occurred, at that time. The timing issue described above leads us to question the usefulness of the *Fiscal Year End Distance* metric as an indicator for boldness. After all, a forecast issued exactly at the same value as the consensus can hardly be considered bold, yet might register a high *Fiscal Year End Distance* if it is not updated later during the fiscal year.

Of the firm-specific characteristics; *Debt-to-Equity* and *Information Environment* are both significantly associated with *Accuracy* at a 1% level. The coefficient of *Debt-to-Equity* is negative, suggesting that analysts are less accurate when forecasting earnings for highly leveraged firms, which makes intuitive economic sense. *Information Environment* records a positive coefficient, meaning that forecasts are more accurate for more intensely covered firms. A likely explanation for this is that more analysts covering a firm leads to more relevant information being available and a more informed consensus.

In Regression 4 the interaction variable between *Bold* and *General Experience* did not provide sufficient evidence of a significant association.

[18] Clement and Tse's coefficient for *Bold* is 0.0569 while our coefficient is 0.0124.

D. The Differences in Forecast Accuracy Between Optimistic and Pessimistic Bold Forecasts

In Table IV we examine our third research question regarding the incremental effect of optimism among bold forecasts on forecast accuracy. In Regression 5 it can be observed that the coefficient of *Optimistic Bold* is positive and significant at a 5% level. This suggests that optimistic bold forecasts are on average more accurate than pessimistic bold forecasts, in line with the findings of Brun and Nyh (2014). It should be noted however that the coefficient is rather small and significant only at a 5% level. The results suggest that the effect of optimistic analysts receiving private information from managers outweighs their potential overweighting of that information.

In Regression 6 it can be observed that the interaction term between *Optimistic Bold* and *General Experience* is not significant at a 10% level. The coefficient for the interaction variable is negative which might suggest an adverse effect on forecast accuracy, but we cannot draw any definitive conclusions. It would be interesting to study this potential relationship further with a more complete dataset.

Table III

The Effect of Boldness on Forecast Accuracy

Table III reports the association between Boldness and forecast accuracy. The variable of interest is ***Bold:*** a positive and significant coefficient indicates that bold forecasts are on average more accuracte than herding forecasts. Regression 4 adds the interaction variable *Bold x General Experience* . The variable of interest in Regression 4 is the interaction variable ***Optimistic Bold x General Experience*** , which shows the incremental effect of one additional year of general experience for the accuracy of optimistic bold forecasts. All variables except the dummy variable *Bold* are scaled within each firm-year and takes on values between 0 - 1. The following variables are included in the model: *Days Elapsed* - the number of days since the last forecast issued by any analyst; *Forecast Horizon* - number of days until fiscal year end; *Broker Size* - number of analysts issuing forecasts for a brokerage house in a firm-year; *Forecast Frequency* - number of forecasts made during the year; *Firm Experience* - years of firm specific experience; *General Experience* - years of experience in I/B/E/S database; *Companies* - number of companies covered in each year; *Industries* - number of 2-digit SIC industries covered in each year; *Debt-to-Equity* - Interest-bearing debt at fiscal year end divided by market capitalization two days prior to forecast; *Volatility* - standard deviation of logarithmic share-price returns 1 year prior to forecast; *Information Environment* - number of analysts covering each firm during the year; *Bold* - dummy variable that takes the value of 1 if a forecast is either above both the prior consensus and previous estimate or else below both. Also included are the variables: *Year-To-Date Distance* - absolute distance between the forecast and the prior consensus; *Fiscal Year End Distance* - absolute distance between the forecast and the consensus at fiscal year end. The number of observations is 41,636.

$$Accuracy_{ijt} = \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} + \beta_{13} YTD\_Dist_{ijt} + \beta_{14} FYE\_Dist_{ijt} + \beta_{15} Bold_{ijt} + \varepsilon_{ijt}$$

(Regression 3)

VARIABLES	Regression 3: Accuracy & Boldness N = 41,636	Regression 4: Boldness & Experience N = 41,636
Intercept	0.7374***	0.7363***
	(103.52)	(98.58)
DaysElapsed	-0.0198***	-0.0198***
	(-4.70)	(-4.70)
Forecast Horizon	-0.1277***	-0.1277***
	(-33.63)	(-33.63)
Lag Accuracy: Accuracy previous period	0.0342***	0.0342***
	(7.35)	(7.36)
Broker Size	0.0012	0.0012
	(0.31)	(0.31)
Forecast Frequency	-0.0094**	-0.0094**
	(-2.24)	(-2.24)
Firm Experience	0.0032	0.0032
	(0.73)	(0.73)
General Experience	-0.0047	-0.0026
	(-0.96)	(-0.38)
Companies	0.0098*	0.0099*
	(1.78)	(1.78)
Industries	-0.0192***	-0.0192***
	(-3.82)	(-3.82)
FiscalYearEndDistance	-0.3652***	-0.3652***
	(-58.63)	(-58.62)
YearToDateDistance	0.0585***	0.0585***
	(10.82)	(10.82)
Debt-to-Equity	-0.0524***	-0.0524***
	(-8.37)	(-8.37)
Volatility	-0.0030	-0.0030
	(-0.50)	(-0.50)
InformationEnvironment	0.0709***	0.0709***
	(14.79)	(14.79)
Bold	**0.0124*** **	**0.0142*** **
	(5.14)	**(2.93)**
Bold x General Experience		**-0.0036**
		(-0.42)
R-squared	0.142	0.142

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IV

Optimistic Boldness & Forecast Accuracy

Table IV reports the effect of optimistic boldness on forecast accuracy. The variable of interest in Regression 5 is ***Optimistic Bold.*** A positive coefficient indicates that optimistic bold forecasts are more accurate than pessimistic bold forecasts, and vice versa. Regression 6 is the same as Regression 5 below, but with the addition of the interaction variable *Optimstic Bold x General Experience.* The variable of interest in Regression 6 is the interaction variable ***Optimistic Bold x General Experience,*** which shows the incremental effect of one additional year of general experience for the accuracy of optimistic bold forecasts. All variables except the dummy variable Optimistic Bold are scaled within each firm-year and take on values between 0 - 1. The variables included are: *Days Elapsed* - the number of days since the last forecast issued by any analyst; *Forecast Horizon* - number of days until fiscal year end; *Broker Size* - number of analysts issuing forecasts for a brokerage house in a firm-year; *Forecast Frequency* - number of forecasts made during the year; *Firm Experience* - years of firm specific experience; *General Experience* - years of experience in I/B/E/S database; *Companies* - number of companies covered in each year; *Industries* - number of 2-digit SIC industries covered in each year; *Debt-to-Equity* - Interest-bearing debt at fiscal year end divided by market capitalization two days prior to forecast; *Volatility* - standard deviation of logarithmic share-price returns 1 year prior to forecast; *Information Environment* - number of analysts covering each during the year; *Optimistic Bold* - dummy variable that takes the value of 1 if a forecast is bold and above the prior consensus. Also included are the variables: *Year-To-Date Distance* - absolute distance between the forecast and the prior consensus; *Fiscal Year End Distance* - absolute distance between the forecast and the consensus at fiscal year end. The number of observations in both Regression 5 & 6 are 24,409 since only bold forecasts are included.

$$Accuracy_{ijt} = \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} + \beta_{13} YTD\_Dist_{ijt} + \beta_{14} FYE\_Dist_{ijt} + \beta_{15} OptimisticBold_{ijt} + \varepsilon_{ijt} \quad \text{(Regression 5)}$$

VARIABLES	Regression 5: Accuracy & Optimistic Boldness N = 24,409	Regression 6: Optimistic Boldness & Experience N = 24,409
Intercept	0.7677***	0.7641***
	(80.77)	(77.56)
DaysElapsed	-0.0248***	-0.0248***
	(-4.34)	(-4.34)
Forecast Horizon	-0.1581***	-0.1581***
	(-30.99)	(-31.00)
Lag Accuracy: Accuracy previous period	0.0299***	0.0298***
	(4.79)	(4.78)
Broker Size	-0.0023	-0.0023
	(-0.44)	(-0.45)
Forecast Frequency	-0.0044	-0.0044
	(-0.79)	(-0.78)
Firm Experience	0.0047	0.0046
	(0.81)	(0.80)
General Experience	-0.0073	0.0002
	(-1.12)	(0.03)
Companies	0.0051	0.0051
	(0.69)	(0.69)
Industries	-0.0216***	-0.0215***
	(-3.21)	(-3.20)
FiscalYearEndDistance	-0.3731***	-0.3730***
	(-47.02)	(-46.99)
YearToDateDistance	0.0701***	0.0700***
	(9.64)	(9.63)
Debt-to-Equity	-0.0611***	-0.0611***
	(-7.35)	(-7.36)
Volatility	0.0002	0.0002
	(0.02)	(0.03)
InformationEnvironment	0.0689***	0.0688***
	(10.73)	(10.73)
Optimistic Bold	**0.0079****	**0.0159****
	(2.47)	**(2.47)**
Optimistic Bold x General Experience		**-0.0162**
		(-1.41)
R-squared	0.155	0.155

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

E. Impact of the MiFID on the Association Between Optimistic Boldness and Accuracy

Table V reports the findings concerning our fourth research question relating to the impact of MiFID. In the left-hand column of Regression 7 – which is based on forecasts issued before MiFID – we see that the coefficient for *Optimistic Bold* is positive and significant at a 1% level. The coefficient is more than double the size compared to Regression 5, indicating that optimistic bold forecasts were more accurate – compared to pessimistic bold forecasts – before the implementation of MiFID. A likely explanation is that the change in the flow of private information from corporate managers disproportionally affects optimistic analysts.

The right-hand column of Regression 7 is based on all optimistic bold forecasts and shows the effect of MiFID on optimistic boldness and accuracy. Controlling for the global financial crisis and the eurozone debt crisis, we find that the interaction variable between *Optimistic Bold* and *Post* is negative and significant at a 1% level, indicating that optimistic bold forecasts have become less accurate in relation to pessimistic bold forecasts after the implementation of MiFID.

The adverse effect on forecast accuracy for optimistic bold forecasts of MiFID is likely due to the reduced access to private information disclosed by corporate managers, leading to an overall loss of relevant private information. It is difficult however, to isolate the effects of specifically the stricter set of internal governance rules related to MiFID, due to the comprehensive nature of the regulatory framework.

Table V
Impact of MiFID on Accuracy & Optimistic Boldness

Table V presents the impact of MiFID on optimistic boldness and its effect on forecast accuracy. The variable of interest here is the interaction variable ***Optimistic Bold x Post*** in the bottom of the right hand column. It shows the effect of MiFID on the accuracy of optimistic bold forecasts where a positive coefficient suggests optimistic bold forecasts have become more accurate after MiFID and a negative coefficient indicates they have become less accurate. All variables except the dummy variables *Optimistic Bold* and *Post* are scaled within each firm-year and take on values between 0 - 1. The variables included are: *Days Elapsed* - the number of days since the last forecast issued by any analyst; *Forecast Horizon* - number of days until fiscal year end; *Broker Size* - number of analysts issuing forecasts for a brokerage house in a firm-year; *Forecast Frequency* - number of forecasts made during the year; *Firm Experience* - years of firm specific experience; *General Experience* - years of experience in I/B/E/S database; *Companies* - number of companies covered in each year; *Industries* - number of 2-digit SIC industries covered in each year; *Debt-to-Equity* - Interest-bearing debt at fiscal year end divided by market capitalization two days prior to forecast; *Volatility* - standard deviation of logarithmic share-price returns 1 year prior to forecast; *Information Environment* - number of analysts covering each during the year. *Optimistic Bold - dummy variable that takes the value of 1 if a forecast is bold and above the prior consensus.* Also included are the variables: *Year-To-Date Distance* - absolute distance between the forecast and the prior consensus; *Fiscal Year End Distance* - absolute distance between the forecast and the consensus at fiscal year end. The number of observations used in Regression 7 is 24,409, or the total number of bold forecasts. In the left hand column Regression 7 is run for bold forecasts issued prior to the implementation of MiFID. Hence all interaction variables with Post are ommitted and the number of observations used is 8,307.

$$
\begin{aligned}
Accuracy_{ijt} = {} & \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} \\
& + \beta_6 FirmExperience_{ijt} + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} + \beta_{10} YTD\_Dist_{ijt} + \beta_{11} FYE\_Dist_{ijt} \\
& + \beta_{12} DebtToEquity_{jt} + \beta_{13} Volatility_{jt} + \beta_{14} InformationEnvironment_{jt} \\
& + \beta_{15} GlobalFinancialCrisis + \beta_{16} EuroCrisis + \beta_{17} Bold2_{ijt} + \beta_{18} DaysElapsed\,x\,Post_{ijt} + \beta_{19} ForecastHorizon\,x\,Post_{ijt} \\
& + \beta_{20} LaggedAccuracy\,x\,Post_{ijt} + \beta_{21} BrokerSize\,x\,Post_{ijt} + \beta_{22} ForecastFrequency\,x\,Post_{ijt} + \beta_{23} BrokerSize\,x\,Post_{ijt} \\
& + \beta_{24} FirmExperience\,x\,Post_{ijt} + \beta_{25} GeneralExperience\,x\,Post_{ijt} + \beta_{26} Companies\,x\,Post_{ijt} + \beta_{27} Industries\,x\,Post_{ijt} \\
& + \beta_{28} YTD_{Dist}\,x\,Post_{ijt} + \beta_{29} FYE_{Dist}\,x\,Post_{ijt} + \beta_{30} DebtToEquity\,x\,Post_{jt} + \beta_{31} Volatility\,x\,Post_{jt} \\
& + \beta_{32} InformationEnvironment\,x\,Post_{jt} + \beta_{33} Optimstic\,Bold\,x\,Post_{ijt} + \varepsilon_{ijt}
\end{aligned}
\qquad \text{(Regression 7)}
$$

Table V Continued

VARIABLES	Regression 7: Pre-MiFID (1996-2007) N = 8,307	Regression 7: Post-MiFID (2008-2017) N = 24,409
Intercept	0.7582***	0.7700***
	(44.71)	(79.95)
DaysElapsed	-0.0133	-0.0143
	(-1.29)	(-1.40)
Forecast Horizon	-0.1529***	-0.1545***
	(-16.78)	(-17.37)
Lag Accuracy: Accuracy previous period	0.0236**	0.0205**
	(2.19)	(2.03)
Broker Size	-0.0107	-0.0125
	(-1.03)	(-1.24)
Forecast Frequency	-0.0109	-0.0133
	(-1.11)	(-1.40)
Firm Experience	0.0065	0.0045
	(0.62)	(0.44)
General Experience	-0.0259**	-0.0273**
	(-2.21)	(-2.35)
Companies	-0.0059	-0.0076
	(-0.40)	(-0.53)
Industries	-0.0110	-0.0113
	(-0.82)	(-0.85)
FiscalYearEndDistance	-0.3570***	-0.3581***
	(-25.57)	(-25.73)
YearToDateDistance	0.0953***	0.0944***
	(7.30)	(7.27)
Debt-to-Equity	-0.0491***	-0.0497***
	(-3.98)	(-4.04)
Volatility	0.0025	0.0017
	(0.18)	(0.12)
InformationEnvironment	0.0524***	0.0483***
	(4.78)	(4.92)
Optimistic Bold	**0.0237*** **	**0.0231*** **
	(4.17)	**(4.10)**
GFC		-0.0104
		(-1.61)
EuroCrisis		0.0011
		(0.26)
DaysElapsed x Post		-0.0146
		(-1.19)
ForecastHorizon x Post		-0.0020
		(-0.19)
LagAccuracy x Post		0.0116
		(0.97)
BrokerSize x Post		0.0058
		(0.50)
ForecastFrequency x Post		0.0129
		(1.14)
FirmExperience x Post		0.0060
		(0.49)
GeneralExperience x Post		0.0268*
		(1.92)
Companies x Post		0.0136
		(0.82)
Industries x Post		-0.0133
		(-0.86)
FiscalYearEndDistance x Post		-0.0222
		(-1.31)
YearToDateDistance x Post		-0.0375**
		(-2.41)
Debt-to-Equity x Post		-0.0087
		(-0.52)
Volatility x Post		-0.0061
		(-0.36)
Information Environment x Post		0.0312***
		(2.74)
Optimistic Bold x Post		**-0.0233*** **
		(-3.43)
R-squared	0.127	0.157

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

F. Potential Issues

Quality of I/B/E/S International Data: A noteworthy issue related to examining herding behavior for forecasting of European companies is that the I/B/E/S international data is generally of lower quality compared to the U.S. data, which results in a higher proportion of missing values and thus a smaller final sample. This discrepancy is especially evident for non-recent data. However, we believe the fact that this study finds evidence of herding behavior consistent with that of prior studies examining the U.S. is testament to the prevalence and consequences of herding in forecasting. A possible solution to obtaining a more complete dataset is to include a lower number of control variables, as the creation of each new variable yields more missing values. This naturally comes at the expense of not being able to control for the characteristics those variables represent, leading to a trade-off. One example of the shortcomings of the I/B/E/S international dataset is how our end sample yields only 172 German firm-year observations out of a total of 9,049 firm-year observations. This corresponds to roughly 2% of all firm-year observations which is extraordinarily low considering that Germany is the largest economy in Europe.

Isolating the Effect of the MiFID: Our fourth research question relates to the consequences of MiFID on the behavior of research analysts. This thesis resorts to analyzing differences between two time-periods, separated by the implementation date of MiFID. While this method, considering the nature of our dataset and the scope of the research question, appears to be the most suitable it is not without shortcomings. From a statistical standpoint it becomes difficult to gauge the actual effects of the legislature, due to the dynamic nature of the financial markets. This is especially true for MiFID, since its implementation coincides with the subprime mortgage crisis, which would eventually escalate to a global financial crisis. After all, it is impossible to observe how the European financial market would look like had MiFID never been implemented. A preferred way to examine the effects of MiFID would be to use a Differences-in-Differences approach, but since we cannot observe any control group (untreated group), with regards to MiFID, this method would not work. Additionally, although the implementation date appears to be the most appropriate divider between the two periods, there might be a lagged-effect at play.

Variations in size of final sample: When calculating the prior consensus for each observation, we consider forecasts made within the last 90 days of the announcement date. This warrants the use of the user-supplied Stata program "rangerun". It considers each observation separately, and "[…] at each pass, the data in memory is cleared and replaced with observations that fall within the interval bounds specified for the current observation." The program is effective but yields marginally different end-samples when repeated. While this is odd, the variation of around 100 observations per run is rather negligible considering the size of our sample. We attain the same signs on all coefficients when running regressions 3-7 on the different

end-samples, as well as the significance levels of those coefficients. The only effect that we do notice are smaller variations in the size of the coefficients and their significance levels for Regressions 1 and 2. We do however urge others to keep this effect in mind when conducting similar studies and utilizing the same methodology.

Heteroscedasticity: We check our results for heteroscedasticity of the residuals. By performing White's Test on Regressions 3, 5 and 7 we find that all exhibit signs of heteroscedasticity. Furthermore, plotting the fitted values versus the residuals also suggests that the residuals are heteroscedastic, see Appendix Table I. We combat this issue by estimating all regression models with robust standard errors.

Imperfect Multicollinearity: We find that none of the independent variables used in Regressions 3 or 5 show signs of high imperfect multicollinearity, as the Variance Inflation Factors are all low, see Appendix Table II. In Appendix Table III we do however notice higher Variance Inflation Factors for Regression 7, but this is to be expected when using interaction variables and hence is not seen as an issue.

VI. Conclusion

The primary aim of this study has been to add to the existing literature of herding behavior in forecasting, and to examine its potential causes and consequences. Theory predicts that analyst- and forecast-characteristics explain forecast boldness, and we therefore additionally examine the association between boldness and firm-specific characteristics. This study is also motivated by the findings of Clement and Tse (2005) that a consensus based solely on bold forecasts may signal more valuable information to investors than a general one. We examine and reaffirm this association for our dataset and show that the consequences of herding are not exclusive to coverage of U.S. companies. The data used in our sample stems from analyst last-forecast earnings revisions for 16 European nations spanning over the period 1996 – 2017.

This thesis adds to the evidence of the causes of herding, by confirming the positive association between herding and *Days Elapsed* recorded by Clement and Tse (2005), while finding the opposite associations for *Forecast Horizon, Broker Size* and *General Experience.* Interestingly, though we question the robustness of the findings, our results indicate that an analyst's tendency to issue bold forecasts decreases with experience, unlike prior studies examining U.S. data. Additionally, we find that experience is positively associated with optimism among bold forecasts. While we did not find any statistically significant association between the firm-specific characteristics and boldness, we find that both *Debt-to-Equity* and *Volatility* are negatively associated with optimism among bold forecasts. The intuitive explanation of these findings anchored in economic theory suggest that higher leverage and volatility tend to warrant more pessimistic forecasts.

For our second research question we were able to reaffirm the findings of Clement and Tse (2005) that bold forecasts are on average more accurate than herding forecasts, while controlling for factors that previous studies have found to affect accuracy. Notably however, the association we find is weaker than the one of Clement and Tse (2005).

The results of our third research question show that optimistic bold forecasts are on average more accurate than pessimistic bold forecasts, thereby reaffirming the findings of Brun and Nyh (2014) for European companies. We do however call for further research to explore this association, since established theory does not provide a clear-cut explanation. Additionally, our results do not offer a definitive answer to the association, since the coefficient we find is small and the significance is at a 5% level.

This thesis also examines the incremental effect on forecast accuracy of one additional year of general experience for bold forecasts, and while the results hint at a possible negative association, the coefficient is not significant at a 10% level. We do however suggest further research to delve deeper into this subject with a larger and more complete dataset.

Our fourth research question examines the consequences of regulation, specifically MiFID, on the association between optimism and forecast accuracy among bold forecasts. The results indicate that optimistic bold forecasts have become less accurate relative to pessimistic bold forecasts since the implementation of MiFID.

Our main explanation for these results, rooted in theory, is that the most prominent consequence of MiFID on optimistic boldness has been to reduce the flow of private information from corporate managers to optimistic analysts. However, we do not deem the results to be conclusive with regards to the effect of stricter internal governance rules on resolving the potential conflict of interest within equity research. This is since we are (i) observing the differences in forecast accuracy between two different time periods, it is not definitive that this difference is a result of MiFID, although we attempt to control for as many different factors as we can, including the global financial crisis as well as the Eurozone Crisis, (ii) assuming the difference is a consequence of MiFID, due to the multifaceted nature of the regulation, existing theory suggests ambiguous effects. Additionally, while the research question addresses specifically MiFID, it is likely that other pieces of legislature such as MAD (adopted by member states between 2004 and 2006) have also had noteworthy consequences on analyst behavior.

To add to the discussion, we call for future research to examine the effect of the newly implemented MiFID II on analyst herding behavior after a sufficient amount of data becomes available. MiFID II is projected to substantially change the nature of the sell-side equity analyst profession in Europe and hence it would be interesting to investigate how this affects the propensity of herding and herding's effect on forecast accuracy.

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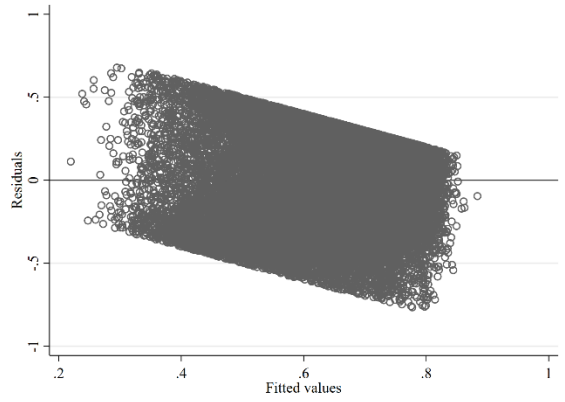
Appendix

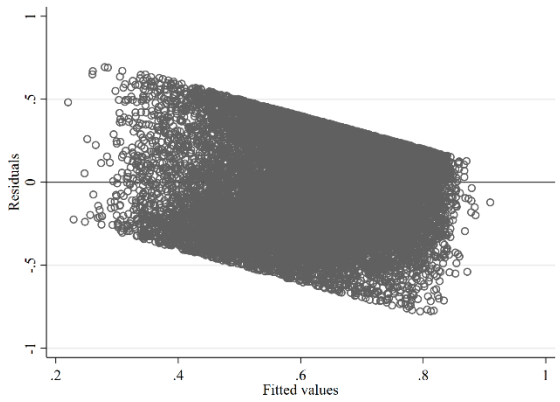
Appendix Table I
Residuals Versus Fitted Values Plots

Appendix Table I shows the residuals plotter versus the fitted value for Regression 3, 5 and 7 respectively. This is done to check for heteroscedasticity. Panel A shows the plot for Regression 3. Panel B shows the plot for Regression 5. Panel C shows the plot for Regression 7. All of the plots suggest there exists heteroscedasticity in the regression models.

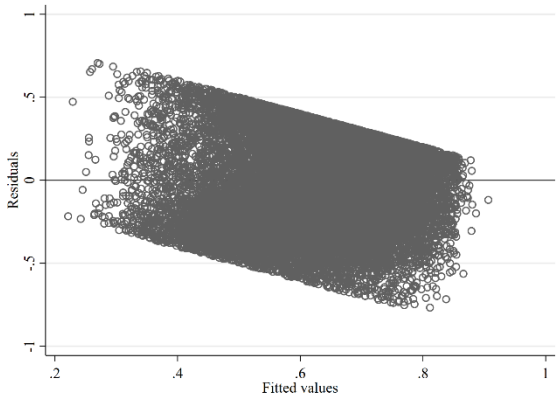
Panel A



Panel B



Panel C



Appendix Table II

Variance Inflation Factors - Test for imperfect multicollinearity

Appendix Table II reports the Variance Inflation Factors for the independent variables in Regressions 3 and 5 in order to test for imperfect multicollinearity. The variables included in Regression 3 and 5 are: *Days Elapsed* - the number of days since the last forecast issued by any analyst; *Forecast Horizon* - number of days until fiscal year end; *Broker Size* - number of analysts issuing forecasts for a brokerage house in a firm-year; *Forecast Frequency* - number of forecasts made during the year; *Firm Experience* - years of firm specific experience; *General Experience* - years of experience in I/B/E/S database; *Companies* - number of companies covered in each year; *Industries* - number of 2-digit SIC industries covered in each year; *Debt-to-Equity* - Interest-bearing debt at previous fiscal year end divided by market capitalization two days prior to forecast; *Volatility* - volatility of logarithmic share-price returns 1 year prior to forecast; *Information Environment* - number of analysts covering each during the year; *Year-To-Date Distance* - absolute distance between the forecast and the prior consensus; *Fiscal Year End Distance* - absolute distance between the forecast and the consensus at fiscal year end; *Bold* - dummy variable that takes the value of 1 if a forecast is either above both the prior consensus and previous estimate or else below both; *Optimistic Bold* - dummy variable that takes the value of 1 if a forecast is bold and above the prior consensus. The number of forecasts used in Regression 3 and 5 are 41,636 and 24,409 respectively. No Variance Inflation Factor or Tolerance is alarmingly high.

$$Accuracy_{ijt} = \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} + \beta_{13} YTD\_Dist_{ijt} + \beta_{14} FYE\_Dist_{ijt} + \beta_{15} Bold_{ijt} + \varepsilon_{ijt} \quad \text{(Regression 3)}$$

$$Accuracy_{ijt} = \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} + \beta_4 BrokerSize_{ijt} + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} + \beta_{10} DebtToEquity_{jt} + \beta_{11} Volatility_{jt} + \beta_{12} InformationEnvironment_{jt} + \beta_{13} YTD\_Dist_{ijt} + \beta_{14} FYE\_Dist_{ijt} + \beta_{15} OptimisticBold_{ijt} + \varepsilon_{ijt} \quad \text{(Regression 5)}$$

	Regression 3		Regression 5	
VARIABLE	VIF	Tolerance	VIF	Tolerance
Industries	1.74	0.574	1.75	0.571
Companies	1.7	0.587	1.72	0.582
Fiscal Year End Distance	1.38	0.726	1.47	0.681
Year To Date Distance	1.35	0.738	1.47	0.679
General Experience	1.32	0.757	1.32	0.758
Firm Experience	1.29	0.773	1.29	0.774
Information Environment	1.11	0.905	1.11	0.903
Debt-to-Equity	1.05	0.948	1.06	0.946
Volatility	1.05	0.950	1.05	0.950
Bold	1.04	0.962		
Forecast Requency	1.04	0.963	1.04	0.960
Broker Size	1.03	0.972	1.03	0.970
Days Elapsed	1.02	0.980	1.02	0.978
Forecast Horizon	1.02	0.985	1.02	0.980
Lagged Accuracy	1.01	0.989	1.01	0.989
Optimistic Bold			1.02	0.981
Mean VIF	1.21		1.23	

Appendix Table III

Variance Inflation Factors - Test for imperfect multicollinearity

Appendix Table III reports the Variance Inflation Factors for the independent variables in Regression 7 in order to test for imperfect multicollinearity. The variables included in Regression 7 are: *Days Elapsed* - the number of days since the last forecast issued by any analyst; *Forecast Horizon* - number of days until fiscal year end; *Broker Size* - number of analysts issuing forecasts for a brokerage house in a firm-year; *Forecast Frequency* - number of forecasts made during the year; *Firm Experience* - years of firm specific experience; *General Experience* - years of experience in I/B/E/S database; *Companies* - number of companies covered in each year; *Industries* - number of 2-digit SIC industries covered in each year; *Debt-to-Equity* - Interest-bearing debt at previous fiscal year end divided by market capitalization two days prior to forecast; *Volatility* - volatility of logarithmic share-price returns 1 year prior to forecast; *Information Environment* - number of analysts covering each during the year; *Year-To-Date Distance* - absolute distance between the forecast and the prior consensus; *Fiscal Year End Distance* - absolute distance between the forecast and the consensus at fiscal year end; *Bold* - dummy variable that takes the value of 1 if a forecast is either above both the prior consensus and previous estimate or else below both; *Optimistic Bold* - dummy variable that takes the value of 1 if a forecast is bold and above the prior consensus. The number of observations used in Regression 7 are 24,409. Some of the Variance Inflation Factors are rather high but this is to be expected since Regression 7 is using interaction variables. Hence, this does not represent an issue.

$$
\begin{aligned}
Accuracy_{ijt} = {} & \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForecastHorizon_{ijt} + \beta_3 LaggedAccuracy_{ijt} + \beta_4 BrokerSize_{ijt} \\
& + \beta_5 ForecastFrequency_{ijt} + \beta_6 FirmExperience_{ijt} + \beta_7 GeneralExperience_{ijt} + \beta_8 Companies_{ijt} \\
& + \beta_9 Industries_{ijt} + \beta_{10} YTD\_Dist_{ijt} + \beta_{11} FYE\_Dist_{ijt} + \beta_{12} DebtToEquity_{jt} + \beta_{13} Volatility_{jt} \\
& + \beta_{14} InformationEnvironment_{jt} + \beta_{15} GlobalFinancialCrisis + \beta_{16} EuroCrisis + \beta_{17} Bold2_{ijt} \\
& + \beta_{18} DaysElapsed\ x\ Post_{ijt} + \beta_{19} ForecastHorizon\ x\ Post_{ijt} + \beta_{20} LaggedAccuracy\ x\ Post_{ijt} \\
& + \beta_{21} BrokerSize\ x\ Post_{ijt} + \beta_{22} ForecastFrequency\ x\ Post_{ijt} + \beta_{23} BrokerSize\ x\ Post_{ijt} \\
& + \beta_{24} FirmExperience\ x\ Post_{ijt} + \beta_{25} GeneralExperience\ x\ Post_{ijt} + \beta_{26} Companies\ x\ Post_{ijt} \\
& + \beta_{27} Industries\ x\ Post_{ijt} + \beta_{28} YTD_{Dist}\ x\ Post_{ijt} + \beta_{29} FYE_{Dist}\ x\ Post_{ijt} + \beta_{30} DebtToEquity\ x\ Post_{jt} \\
& + \beta_{31} Volatility\ x\ Post_{jt} + \beta_{32} InformationEnvironment\ x\ Post_{jt} + \beta_{33} Optimstic\ Bold\ x\ Post_{ijt} + \varepsilon_{ijt}
\end{aligned}
$$

(Regression 7)

	Regression 7	
VARIABLE	VIF	Tolerance
Companies x Post	9.79	0.102
Industries x Post	7.91	0.126
General Experience x Post	7.86	0.127
Firm Experience x Post	7.64	0.131
Lagged Accuracy x Post	7.56	0.132
Information Environment x Post	7.12	0.140
Industries	6.35	0.158
Fiscal Year End Distance x Post	6.24	0.160
Year To Date Distance x Post	6.2	0.161
Companies	6.03	0.166
Broker Size x Post	5.65	0.177
Forecast Frequency x Post	5.3	0.189
Forecast Horizon x Post	4.84	0.207
Year To Date Distance	4.45	0.225
Fiscal Year End Distance	4.29	0.233
Volatility x Post	3.99	0.250
General Experience	3.83	0.261
Optimistic Bold	3.77	0.265
Firm Experience	3.69	0.271
Broker Size	3.62	0.277
Days Elapsed x Post	3.54	0.282
Days Elapsed	3.07	0.325
Volatility	3.01	0.333
Optimistic Bold	2.93	0.341
Debt-to-Equity x Post	2.84	0.352
Forecast Horizon	2.82	0.354
Forecast Frequency	2.76	0.362
Information Environment	2.48	0.404
Lagged Accuracy	2.46	0.407
Debt-to-Equity	2.27	0.441
Euro Crisis	1.22	0.817
GFC	1.14	0.875
Mean VIF	4.58	