International Journal of Finance and Accounting 2024, 13(1): 1-19
DOI: 10.5923/j.ijfa.20241301.01

Industry-Specific Prior Accuracy as a Measure for Sell-Side Analysts' Industry Knowledge

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Abstract Analysts' earnings forecasts are of high importance in multiple areas as, e.g., company valuation or asset management. In addition, analysts vary significantly in their earnings forecast accuracy. While existing literature finds that analysts' relative earnings forecast accuracy is influenced by a variety of analyst and forecast characteristics such as the number of companies followed, both academics and practitioners emphasize the value of analysts' industry knowledge. In this paper, I introduce industry-specific prior accuracy as a forecast-based proxy for industry knowledge and show that this characteristic is an important determinant of analysts' relative performance. In addition, superior forecast-based industry knowledge has important implications for analysts: In particular, analysts with higher industry-specific prior accuracy are more likely to issue more informative forecasts, are more likely to be All-Stars and have more favorable career outcomes, respectively.

Keywords Sell-side analysts, Forecast accuracy, Industry knowledge

1. Literature Review

Sell-side analysts are highly important for financial markets.[1] Employed by brokerage houses and investment banks, they serve as information intermediaries between the companies they cover and market participants such as investors (e.g., Schipper (1991)).[2] Analysts' main task is to issue written research reports which typically contain three key elements: A forecast for the company's future earnings, a stock price target and a stock recommendation (e.g., Bradshaw (2002), Bradshaw, Brown and Huang (2013)). Of these three components, the earnings forecast is the most fundamental one. This is because analysts frequently base their price targets and stock recommendations on simple earnings multiples (Asquith, Mikhail and Au (2005), Brown et al. (2015)). For example, analysts often use heuristics such as the price to earnings ratio or the price to earnings growth ratio to derive an estimate for the equity value. Correspondingly, Gleason, Johnson and Li (2013) relate the accuracy of analysts' earnings forecasts to the quality of their price targets. Similarly, Loh and Mian (2006) as well as Ertimur, Sunder and Sunder (2007) find that forecast accuracy is positively associated with the profitability of analysts' stock recommendations.[3]

Sell-side analysts in general and their earnings forecasts in particular are a promising field of study for three reasons. First, it has long been established that analysts' earnings forecasts outperform time-series models in terms of accuracy and function as superior proxies for market expectations (Brown and Rozeff (1980), Fried and Givoly (1982)). Second, analysts' forecasts of future earnings are widely used by academics and practitioners as inputs for equity valuation models and to calculate implied cost of capital estimates (e.g., Dechow, Hutton and Sloan (1999), Claus and Thomas (2001), Gebhardt, Lee and Swaminathan (2001)). Third, existing literature suggests that sell-side analysts' research is used by buy-side analysts as well who work for money management firms such as mutual funds (Groysberg, Healy and Chapman (2008), Ljungqvist et al. (2007)). That is, the output generated by sell-side analysts might also influence the investment decisions of the portfolio managers of these funds. Thus, sell-side analysts' earnings forecasts play a crucial role in capital markets and constitute an interesting topic for future research.

Prior literature, however, finds that sell-side analysts are not equally skilled in terms of their forecasting abilities.That

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Received: Feb. 23, 2024; Accepted: Mar. 27, 2024; Published: Apr. 10, 2024
Published online at http://journal.sapub.org/ijfa

[1] The terms "sell-side analysts" and "analysts" are used interchangeably. The same holds for the terms "relative accuracy" and "relative performance".

[2] For example, Kelly and Ljungqvist (2012) as well as Bradley, Gokkaya and Liu (2017) find that closures of brokerage houses as a proxy for exogenous stock coverage terminations by analysts increase information asymmetries.

[3] In addition, the results by Park and Stice (2000) and by Clement and Tse (2003) indicate that earnings forecasts by accurate analysts generate more pronounced stock market reactions than the forecasts by their inaccurate peers.

is, prior literature has established that individual analysts vary substantially in their forecast accuracy (e.g., Sinha, Brown and Das (1997)) and that these differences can be explained by various analyst and forecast characteristics. For instance, analysts' relative forecast accuracy has been linked to their working experience, to their employer size, to their portfolio complexity (e.g., Clement (1999)) or to the effort they exert to the forecasting task (e.g., Jacob, Lys and Neale (1999)). Besides, more recent papers even associate analysts' accuracy with their political views (Jiang, Kumar and Law (2016)) or show that analysts located near terroristic attacks are less optimistic and, thus, more accurate (Antoniou, Kumar and Maligkris (2016)).

While the explanation of differences in analysts' relative earnings forecast accuracy has been subject to a large body of research, academics and especially practitioners consistently highlight the importance of analysts' industry knowledge (e.g., Bagnoli, Watts and Zhang (2008), Bradley, Gokkaya and Liu (2017)). For example, Brown et al. (2015) note that surveys by the Institutional Investor (II) Magazine emphasize the value of analysts' industry knowledge. Moreover, a large survey by Brown et al. (2015) themselves supports this notion. Among others, the authors find that industry knowledge is a major determinant of analysts' compensation.

In this paper, I bring these two strands of literature together. That is, I introduce analysts' industry-specific prior accuracy as a determinant of current relative accuracy and, at the same time, as a forecast-based measure for industry knowledge. Using a sample of 178,836 one-year ahead earnings forecasts issued within 1990 and 2011, I regress analysts' industry-specific prior accuracy on relative performance.[4] Thereby, I control for a comprehensive set of analyst and forecast characteristics such as analysts' experience, broker size or the number of covered companies and industries, which are known to be linked to relative accuracy (e.g., Blümke, Hess and Stolz (2017)).

First, the results indicate that analysts' industry-specific prior accuracy is an important determinant of relative performance. The coefficient estimate is not only highly significant but also third largest in absolute values, as compared to the remaining analyst and forecast characteristics.[5] For example, the coefficient on industry-specific prior accuracy surpasses the coefficient estimates on other well-known determinants of relative accuracy such as forecast frequency, general experience or the size of the brokerage.[6] This result is in line with Bradley, Gokkaya and Liu (2017) who show that preanalyst industry working experience, as an alternative measure for industry knowledge, increases accuracy.

Second, the association of industry-specific prior accuracy with relative performance does not diminish after the introduction of the Regulation Fair Disclosure (Reg FD). Thus, the effect does not seem to be influenced by managements' selective disclosure of private information to certain analysts. In contrast, some of the established determinants of analysts' relative accuracy such as an analysts' forecast frequency, for instance, lose their significance in the post-Reg FD period. This is consistent with Keskek et al. (2017) who report a decrease in the explanatory power of some common analyst and forecast characteristics after the introduction of Reg FD but an increase in the importance of firm-specific prior accuracy.

Third, I examine whether industry-specific prior accuracy is more helpful to explain differences in relative accuracy when uncertainty is high. That is, when the identification such differences is most interesting. In particular, I divide the sample into two parts. On the one hand, I run the regression separately for companies with a low or a high dispersion of analysts' forecasts (e.g., Blümke, Hess and Stolz (2017)). On the other hand, I estimate the effect the forecast-based measure for industry knowledge separately in periods of business cycle expansions and contractions, respectively. The results suggest that the influence of industry-specific prior accuracy on relative performance is more pronounced for high dispersion companies and in contraction periods, respectively. In other words, industry-specific prior accuracy seems to be particularly helpful to explain analysts' relative accuracy when uncertainty is high, that is, when it is most interesting.

Having established the positive association between industry-specific prior accuracy and current relative accuracy, I next assess the connection between forecast-based industry knowledge and the informativeness of analysts' forecasts, their All-Star status and their career outcomes, respectively.

First, I follow Clement and Tse (2005) and explain analysts' boldness by industry-specific prior accuracy while additionally including the remaining analyst and forecast characteristics. An analyst's boldness is an indicator variable equal to one if her forecast is above (or below) both her previous forecast and the outstanding consensus. Otherwise, it is equal to zero. Clement and Tse (2005) suggest that bold forecasts are issued by analysts with superior private information. I find that industry-specific prior accuracy is a significant determinant of analysts' boldness, even after taking into account the comprehensive set of control variables. For example, analysts with the highest level of industry-specific prior accuracy are 1.072 times more likely to issue a bold forecast than analysts with the lowest level of industry-specific prior accuracy.

Second, following Kumar (2010), I examine the relation between industry-specific prior accuracy and reputation as measured by the likelihood of being an II All-Star analyst. Every year in October, the II Magazine publishes the so-called All-America Research Team. Existing studies find that All-Star analysts possess fundamentally different

4 In this context, the terms "(relative) accuracy" and "(relative) performance" are used interchangeably.

5 As explained in Chapter 2, the dependent variable as well as the independent variables are adjusted and range from zero to one. Therefore, the absolute values of the coefficient estimates are directly comparable (Klettke, Homburg and Gell (2015)).

6 Only the coefficient estimates on boldness and the control variable forecast horizon are larger in absolute values.

characteristics than their peers. For example, Stickel (1992) shows that analysts nominated as All-Stars outperform their non-All-Star peers. In addition, Groysberg, Healy and Maber (2011) find that All-Star analysts earn a substantially higher compensation. Most importantly, my results indicate that industry-specific prior accuracy has a significant and positive effect on an analyst's chance to be a member of the All-America Research Team.

Third, similar to Keskek et al. (2017), I evaluate the degree to which industry-specific prior accuracy influences analysts' career outcomes. That is, I define an indicator variable equal to one if an analyst works at a top size decile brokerage in terms of the number of analysts employed in the following year. Otherwise, the variable is set to zero (e.g., Clement (1999)). I choose this variable since the size of the brokerage is related to its status and because analysts employed at larger brokers earn a higher compensation (Hong and Kubik (2003)). I find that the likelihood of a favorable career outcome significantly increases with analysts' forecast-based industry knowledge. In summary, industry-specific prior accuracy is an important determinant of current relative performance. This relation holds both before and after the introduction of Reg FD, for low and high dispersion companies and in business cycle expansions and contractions, respectively. Furthermore, analysts with superior forecast-based industry knowledge issue more informative forecasts, are more likely to be All-Stars and have more favorable career outcomes, respectively.

Closely related to my research is the paper by Bradley, Gokkaya and Liu (2017). The authors hand-collect biographical information on analysts' employment before becoming an analyst and match this data to the firms being followed. Analysts are then classified as industry experts if they have previously worked in the industry of the covered firm. Among others, Bradley, Gokkaya and Liu (2017) show that these analysts issue more accurate earnings forecasts, are more likely to be elected as All-Stars and generate stronger market reactions. While the results of Bradley, Gokkaya and Liu (2017) are in line with the findings provided in this paper, my forecast-based measure for industry knowledge is more readily observable. That is, I claim that is it generally easier to find information on (industry-specific) prior accuracy than to hand-collect each analyst's previous employment data from LinkedIn.com, for instance. Correspondingly, Bradley, Gokkaya and Liu (2017) themselves state that "*[…] industry knowledge is inherently difficult to measure*". I propose an intuitive and easy solution to this issue by computing analysts' industry-specific prior accuracy as a forecast-based measure of industry knowledge. Moreover, Bradley, Gokkaya and Liu (2017) do not evaluate the effect of preanalyst industry experience on boldness and do not differentiate between companies with a low or high forecast dispersion as well as between business cycle expansion and business cycle contraction periods, respectively. Besides, my study is related to Brown and Mohammad (2010) who show that analysts' general forecasting abilities are incremental to their firm-specific forecasting abilities.[7] While controlling for firm-specific lagged accuracy, the authors find that general lagged accuracy for all other covered firms also helps to explain relative performance.[8] In contrast, I evaluate the effect of industry-specific prior accuracy both before and after the introduction of Reg FD, for low and high dispersion firms as well as in expansions and contractions, respectively. In addition, I examine whether forecast-based industry knowledge influences an analyst's boldness, her All-Star status and her career outcomes, respectively.

I make three contributions to the existing literature on sell-side analysts. First, I introduce industry-specific prior accuracy as an important determinant of current relative performance and as a forecast-based proxy for industry knowledge. Second, I show that the influence of this characteristic is pronounced not only during the pre-Reg FD period but afterwards as well. Likewise, it does not diminish for low or high dispersions companies and in periods of expansions and contractions, respectively. Third, I find that this forecast-based measure for industry knowledge is also associated positively with the likelihood of issuing more informative forecasts, being an All-Star and working at a high-status brokerage in the future, respectively.

Besides, my study has three major theoretical and practical implications. First, the usefulness of industry-specific prior accuracy in explaining current relative accuracy implies that superior consensus forecasts could be created. In turn, these consensus forecasts could be used to enhance firm valuations or estimations of a company's implied cost of capital. Second, prior studies find that analysts' earnings forecast accuracy is related to the accuracy of their stock price target forecasts and to the performance of their stock recommendations (e.g., Loh and Mian (2006), Ertimur, Sunder and Sunder (2007), Gleason, Johnson and Li (2013)). Thus, to follow analysts with superior forecast-based industry knowledge might also enable the identification of profitable trading strategies. Third, the results suggest for brokerages to hire analysts with superior industry-specific prior accuracy as these analysts outperform their peers.

The remainder of the paper is organized as follows. Chapter 2 describes the research design. Chapter 3 explains the data and sample selection restrictions. Chapter 4 reports the empirical results and Chapter 5 concludes.

2. Research Design

[7] Similarly, Brown (2001) finds that firm-specific lagged accuracy is a major determinant of current relative accuracy.

[8] When I additionally include analysts' prior accuracy for all covered firms except those from the given firm's industry as an alternative measure for general forecasting ability into the regression equation, industry-specific prior accuracy is still highly significant. Furthermore, the coefficient estimate is more than twice as high, indicating that industry-specific prior accuracy is more important than non-industry-specific prior accuracy. Even when I include general forecasting ability as measured in Brown and Mohammad (2010), the coefficient estimate on industry-specific prior accuracy is still positive and significant (cf. Chapter 4).

I am interested in the effect of analysts' industry-specific prior accuracy on their current accuracy, relative to all analysts following the company in a given fiscal year. Thus, I standardize analyst i's last forecast for company j issued in fiscal year t to obtain a relative accuracy measure (e.g., Clement and Tse (2005)).

$$\mathrm{ACCURACY}_{ijt} = \frac{\mathrm{AFE\ max}_{jt} - \mathrm{AFE}_{ijt}}{\mathrm{AFE\ max}_{jt} - \mathrm{AFE\ min}_{jt}} \tag{1}$$

Where AFE_{ijt} is analyst i's absolute forecast error for company j in fiscal year t. $\mathrm{AFE\ max}_{jt}$ and $\mathrm{AFE\ min}_{jt}$ are the maximum and minimum absolute forecast errors of all analysts covering company j in fiscal year t. Correspondingly, the independent variables are range-adjusted as follows.[9]

$$\mathrm{Characteristic}_{ijt} = \frac{\mathrm{Raw\ Characteristic}_{ijt} - \mathrm{Raw\ Characteristic\ min}_{jt}}{\mathrm{Raw\ Characteristic\ max}_{jt} - \mathrm{Raw\ Characteristic\ min}_{jt}} \tag{2}$$

Where Raw $\mathrm{Characteristic}_{ijt}$ is analyst i's unadjusted characteristic (e.g., her forecast frequency) for company j in fiscal year t. Raw Characteristic max_{jt} and Raw Characteristic min_{jt} are the maximum and minimum unadjusted characteristics of all analysts following company j in fiscal year t.

This measurement is advantageous for two reasons. First, it controls for firm-year effects which make analysts' forecasting task more or less difficult in certain firm-years (e.g., Klettke, Homburg and Gell (2015)). Second, it adjusts analysts' accuracy as well as the explanatory variables such that they range from zero to one. For example, an analyst with a $\mathrm{ACCURACY}_{ijt}$ of zero (one) is least (most) accurate in a given fiscal year, relative to all analysts following the firm. The same holds for the independent variables. For instance, an analyst with a range-adjusted forecast frequency of zero (one) has issued the least (most) forecasts of all analysts covering the company in a given fiscal year. This range-adjustment between zero and one now allows to directly compare the estimated regression coefficients and, thereby, the influence of each explanatory variable on relative accuracy.

I then regress analysts' relative performance on their industry-specific prior accuracy as well as on a comprehensive set of control variables (e.g., Blümke, Hess and Stolz (2017)).

$$\begin{aligned}\mathrm{ACCURACY}_{ijt} &= \beta_0 \\ &+ \beta_1 \cdot \mathrm{FOR\_HORIZON}_{ijt} + \beta_2 \cdot \mathrm{LAG\_ACCURACY}_{ijt} \\ &+ \beta_3 \cdot \mathrm{BROKER\_SIZE}_{ijt} + \beta_4 \cdot \mathrm{EXPERIENCE}_{ijt} \\ &+ \beta_5 \cdot \mathrm{COMPANIES}_{ijt} + \beta_6 \cdot \mathrm{INDUSTRIES}_{ijt} \\ &+ \beta_7 \cdot \mathrm{FOR\_FREQUENCY}_{ijt} + \beta_8 \cdot \mathrm{BOLDNESS}_{ijt} \\ &+ \beta_9 \cdot \mathrm{ALLSTAR}_{it} + \beta_{10} \cdot \mathrm{ILAG\_ACCURACY}_{ijt} \\ &+ \varepsilon_{ijt}\end{aligned} \tag{3}$$

The main coefficient of interest is β_{10} which I expect to be positive and significant. Following Klettke, Homburg and Gell (2015), I compute analysts' industry-specific prior accuracy based on their *range-adjusted* firm-specific prior accuracy.[10] Specifically, I calculate the forecast-based proxy for industry knowledge as the average range-adjusted prior accuracy for all firms operating in the given firm's industry, excluding that firm.[11] I separately include analysts' firm-specific prior performance (e.g., Brown (2001)) since I am interested in the incremental effect of industry-specific prior accuracy.

Besides, I use an analyst's forecast horizon, broker size, experience, portfolio complexity, forecast frequency, boldness and All-Star status as additional explanatory variables. The forecast horizon functions as an important control variable for the information available to the analyst at the time the forecast is issued (e.g., Brown and Mohd (2003)). Broker size in terms of the number of analysts employed captures the amount of resources available to the analyst, among others (e.g., Clement and Tse (2005)). The natural logarithm of the number of years of an analyst's working experience proxies for her learning curve (e.g., Mikhail, Walther and Willis (1997), Jacob, Lys and Neale (1999)). Portfolio complexity, measured by the number of covered companies and industries, respectively, accounts for the difficulty of the forecasting task (e.g., Jacob, Lys and Neale (1999)). Forecast frequency is a proxy for the effort the analyst devotes to forecasting the covered company's earnings (e.g., Klettke, Homburg and Gell (2015)). An analyst's boldness indicates if she deviates from her previous forecast and from the outstanding consensus. It is associated with the amount of private information available to the analyst (e.g., Clement and Tse (2005)). An analyst's All-Star status proxies for her reputation (e.g., Stickel (1992)). More precise variable definitions can be found in Appendix Table A1.

In line with the findings by previous research, I expect firm-specific prior accuracy, broker size, experience, forecast frequency, boldness and All-Star status to have a significantly positive effect on relative accuracy. In contrast, forecast horizon as well as the number of covered companies and industries are supposed to have a significantly negative influence (e.g., Blümke, Hess and Stolz (2017)).

3. Data and Sample Selection

My primary data source is the Institutional Brokers' Estimate System (I/B/E/S) from which I obtain analysts' annual earnings per share forecasts and the corresponding actual earnings in the period between 1990 and 2011.[12] Besides, I use COMPUSTAT and the Center for Research in Security Prices (CRSP). From COMPUSTAT, I retrieve

[9] Except for analysts' firm-specific prior accuracy which is adjusted as the dependent variable, the two indicator variables boldness and All-Star status which already range from zero to one and industry-specific prior accuracy (see next page).

[10] Note that only the range-adjusted variables account for firm-year effects and can thus be reasonably compared (Klettke, Homburg and Gell (2015)).

[11] Of course, analysts' industry-specific prior accuracy ranges from zero to one as well.

[12] To measure analysts' experience more reliably and to calculate analysts' prior accuracy in 1990, I initially retrieve forecasts issued as early as 1981.

annual earnings announcement dates, following Acker and Duck (2009).[13] From CRSP, I obtain stock prices to deflate absolute forecast errors as well as adjustment factors to account for stock splits.

Consistent with previous literature, I focus my analyses on analysts' last active one-year ahead forecasts issued before the earnings reporting date (e.g., Brown (2001), Call, Chen and Tong (2009), Brown and Mohammad (2010)).[14] Moreover, only forecasts by uniquely identifiable analysts are considered. That is, I drop analysts whose identification code refers to a team, is missing or equal to zero (e.g., Clement (1999), Jacob, Lys and Neale (1999)). Besides, I exclude observations with missing actual earnings, stock prices, adjustment factors and Standard Industrial Classification (SIC) codes. Two-digit SIC codes are needed to categorize the industry a given company operates in (e.g., Clement (1999), Clement and Tse (2005)). Ambiguous forecasts as well as forecasts with inconsistent activation or revision dates, respectively, are classified as data errors and therefore dropped. The same is done with forecasts which do not use the same accounting basis as the majority of the estimates.[15] Moreover, in line with O'Brien (1990), Sinha, Brown and Das (1997) and Brown and Mohammad (2010), the sample is restricted to companies with fiscal year-ends in December. Likewise, I delete the first firm-year after a fiscal year-end change as well as the following transition firm-years. Consistent with Clement and Tse (2005), I exclude outliers defined as forecasts with an absolute forecast error of 40.0 percent or more of a company's stock price. Finally, a minimum of two analysts is required to cover a company as I evaluate the influence of industry-specific prior accuracy on analysts' relative performance (e.g., Clement, Koonce and Lopez (2007)).[16]

The final sample comprises 178,836 annual earnings forecasts for 4,051 companies issued by 6,115 analysts who are employed by 486 brokerage houses. As shown in Table 1, the number of forecasts increases from 5,038 in 1990 to 11,834 in 2011.

Table 1. Summary statistics – Number of analysts, brokers, companies and forecasts by fiscal year

Table 1 shows the number of distinct analysts, brokers, companies and forecasts by fiscal year. The sum of the number of distinct analysts, brokers and companies, respectively, over the fiscal years does not match the total number in the last row as analysts, brokers and companies appear in multiple fiscal years during the sample period.

Fiscal year	Analysts	Brokers	Companies	Forecasts
1990	816	122	650	5,038
1991	954	123	761	6,950
1992	950	124	800	7,249
1993	992	136	835	7,350
1994	1,027	145	921	7,401
1995	1,084	138	977	7,415
1996	1,173	149	1,049	7,667
1997	1,205	146	1,092	7,340
1998	1,351	150	1,167	7,780
1999	1,405	150	1,143	7,852
2000	1,281	132	996	6,472
2001	1,188	109	929	5,884
2002	1,236	120	1,062	6,570
2003	1,373	140	1,150	7,990
2004	1,517	168	1,188	8,826
2005	1,621	166	1,290	9,486
2006	1,679	168	1,419	9,995
2007	1,648	167	1,421	9,763
2008	1,473	166	1,346	8,725
2009	1,579	184	1,438	9,809
2010	1,727	173	1,484	11,440
2011	1,779	165	1,468	11,834
Total	6,115	486	4,051	178,836

4. Results

Descriptive statistics

Before examining the relation between industry-specific prior accuracy and current relative performance, I first provide some descriptive statistics. Table 2 shows the distribution of the unadjusted variables (Panel A), the distribution of the range-adjusted variables (Panel B) and the correlations among the range-adjusted variables (Panel C). The distribution of the variables before applying the range-adjustment in Panel A of Table 1 is comparable to existing literature (e.g., Clement and Tse (2005), Klettke, Homburg and Gell (2015)). For example, analysts issue almost five forecasts in a given firm-year and follow around 22 companies operating in about four industries, on average. While the average brokerage size of about 67 analysts is larger than in prior studies (e.g., Clement and Tse (2003)), more recent papers report similar figures (e.g., Klettke, Homburg and Gell (2015)). Panel B of Table 2 shows the distribution of the variables after the adjustment. Correspondingly, all variables range from zero to one. The distribution is broadly consistent with prior literature as well (e.g., Clement and Tse (2005)). Last, Panel C of Table 2 reports the correlations among the adjusted variables. Analysts' relative accuracy is significantly correlated with all explanatory variables, including industry-specific prior accuracy. In particular, there is a positive correlation between accuracy and analysts' firm-specific prior accuracy, working

13 Besides, I require earnings announcement dates to be consistent. For example, I drop firm-years in which companies report their earnings more than 90 days after the fiscal year-end as this violates the U.S. Securities and Exchange Commission disclosure rules (cf. https://www.sec.gov/answers/form10k.htm). The filter, however, affects only less than one percent of all observations. Moreover, the results remain unchanged if I do not apply the filter.

14 Duplicates are already dropped in the initial sample.

15 These forecasts are labeled as excluded by I/B/E/S (cf. Thomson Reuters (2013)).

16 The application of the filters is specific to the unadjusted variable being calculated. For more details regarding the sample construction, see Blümke, Hess and Stolz (2017).

experience, forecast frequency, boldness, All-Star status and, most importantly, industry-specific prior accuracy. Likewise, accuracy is negatively correlated with the forecast horizon, the number of covered companies and industries, as well as with the size of analysts' brokerages.[17]

As broker size is a proxy for the available resources and for the access to the management of the followed firm (e.g., Clement (1999)), the latter result is somewhat surprising.[18] Note, however, that there is also evidence on a negative relation between analysts' relative accuracy and the size of their employers (e.g., Bonner, Walther and Young (2003), Sonney (2009)). In this context, Keskek et al. (2017) show that broker size positively affects analysts' performance only before the introduction of Regulation Fair Disclosure (Reg FD). In the post-Reg FD period, the coefficient estimate becomes significantly negative. The authors explain this finding with the restricted access of analysts employed by large brokerages to the covered company's management after the enactment of Reg FD.

Industry-specific prior accuracy, on the other hand, is also significantly correlated with the remaining analyst and forecast characteristics. For instance, a higher industry-specific prior accuracy is associated with a lower forecast horizon and a lower task complexity. In turn, analysts with superior forecast-based industry knowledge work at larger brokers, are more experienced, issue more forecasts and are more likely to be bold and All-Stars, respectively.[19]

Table 2. Descriptive statistics

Table 2 shows descriptive statistics on the distribution of the unadjusted variables (Panel A), on the distribution of the range-adjusted variables (Panel B) and on the correlations among the range-adjusted variables (Panel C). In Panel A and Panel B, respectively, p25, p50 and p50 are the 25th, 50th and 75th percentiles. In Panel C, the abbreviations ACC, FH, LA, BS, EX, CO, IN, FF, BO, AS and ILA stand for ACCURACY, FOR_HORIZON, BROKER_SIZE, EXPERIENCE, COMPANIES, INDUSTRIES, FOR_FREQUENCY, BOLDNESS, ALLSTAR and ILAG_ACCURACY. Precise definitions of the range-adjusted variables can be found in Appendix Table A1. Two-sided p-values in parentheses indicate the statistical significances among the correlations.

Final sample (1990–2011)				
n = 178,836				
Panel A: Distribution of unadjusted variables				
Variable	Mean	p25	p50	p75
AFEP in %	0.7	0.1	0.2	0.5
FOR_HORIZON	106.9	48.0	94.0	120.0
BROKER_SIZE	66.9	22.0	50.0	95.0
EXPERIENCE	8.7	5.0	8.0	12.0
COMPANIES	22.2	14.0	18.0	25.0
INDUSTRIES	3.8	2.0	3.0	5.0
FOR_FREQUENCY	4.9	3.0	4.0	6.0
BOLDNESS	0.8	1.0	1.0	1.0
ALLSTAR	0.0	0.0	0.0	0.0

Table 2. Descriptive statistics (continued)

Final sample (1990–2011)				
n = 178,836				
Panel B: Distribution of range-adjusted variables				
Variable	Mean	p25	p50	p75
ACCURACY	0.669	0.485	0.788	0.952
FOR_HORIZON	0.384	0.099	0.282	0.599
LAG_ACCURACY	0.615	0.333	0.714	0.964
BROKER_SIZE	0.342	0.085	0.265	0.491
EXPERIENCE	0.649	0.467	0.698	0.889
COMPANIES	0.426	0.180	0.367	0.630
INDUSTRIES	0.342	0.000	0.250	0.500
FOR_FREQUENCY	0.509	0.273	0.500	0.750
BOLDNESS	0.758	1.000	1.000	1.000
ALLSTAR	0.044	0.000	0.000	0.000
ILAG_ACCURACY	0.614	0.500	0.633	0.750

The effect of forecast-based industry knowledge on accuracy

To get a first glimpse on the association between the forecast-based measure for industry knowledge and analysts' relative performance, I divide the sample into three parts based on industry-specific prior accuracy (Klettke, Homburg and Gell (2015)).[20] Within each tercile, I compute the mean relative forecast accuracy. As indicated by Table 3, analysts' mean accuracy increases linearly from the bottom (T1) to the top tercile (T3). Furthermore, the difference in mean accuracy between tercile T3 and tercile T1 is positive and significant at the 1 percent level. Thus, analysts in the top tercile in terms of their industry-specific prior accuracy perform significantly better than analysts in the bottom tercile.

[17] I find a significantly negative coefficient on broker size in the multivariate regression as well (see below).

[18] Correspondingly, several studies report a positive association between relative accuracy the size of analysts' brokerages (e.g., Clement, Rees and Swanson (2003), Dunn and Nathan (2005), Herrmann and Thomas (2005), Malloy (2005)). In contrast, Call, Chen and Tong (2009), Keung (2010) as well as Klettke, Homburg and Gell (2015) do not find that relative accuracy is significantly influenced by the broker size.

[19] These results are confirmed in a multivariate analysis in which I regress industry-specific prior accuracy on the remaining control variables (unreported). In particular, all coefficient estimates have the same signs as in the correlation matrix and are significant at the 1 percent level (except for analysts' boldness which is significant at the 10 percent level).

[20] I partition the whole sample in one step instead of splitting each firm-year separately. This is possible because all variables are adjusted such that they range from zero to one and thereby account for firm-year-specific influences (cf. Chapter 2 as well as Klettke, Homburg and Gell (2015)).

Table 2. Descriptive statistics (continued)

	ACC	FH	LA	BS	EX	CO	IN	FF	BO	AS
Final sample (1990–2011)										
n = 178,836										
Panel C: Correlations among range-adjusted variables										
FH	-0.330									
	(<0.001)									
LA	0.071	-0.053								
	(<0.001)	*(<0.001)*								
BS	-0.009	0.027	0.004							
	(<0.001)	*(<0.001)*	*(0.093)*							
EX	0.031	-0.041	0.011	0.040						
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*						
CO	-0.043	0.047	-0.051	0.013	0.180					
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*					
IN	-0.049	0.056	-0.046	-0.067	0.099	0.483				
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*				
FF	0.115	-0.325	0.010	0.059	-0.029	0.023	0.015			
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*			
BO	0.063	0.050	0.007	0.030	0.004	-0.002	-0.002	0.009		
	(<0.001)	*(<0.001)*	*(0.005)*	*(<0.001)*	*(0.116)*	*(0.486)*	*(0.309)*	*(<0.001)*		
AS	0.013	-0.015	0.011	0.142	0.110	0.052	-0.005	0.016	0.009	
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.040)*	*(<0.001)*	*(<0.001)*	
ILA	0.052	-0.050	0.072	0.041	0.016	-0.063	-0.060	0.027	0.007	0.018
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.005)*	*(<0.001)*

Table 3. Sample segmentation by industry-specific prior accuracy

Table 3 shows the sample segmentation into terciles based on analysts' industry-specific prior accuracy. The whole sample is divided into three parts in one step instead of partitioning each firm-year separately since the forecast-based measure for industry knowledge is adjusted such that it ranges from zero to one and thereby accounts for firm-year effects. For each tercile, the last column reports the mean range-adjusted accuracy. Precise definitions of the range-adjusted variables can be found in Appendix Table A1. The two-sided p-value in parentheses indicates the statistical significance of the accuracy difference between the first tercile and the third tercile. *, **, *** denote a significance level at the 10%, 5%, 1% level, respectively.

Tercile		n	Mean Accuracy
Final sample (1990–2011)			
n = 178,836			
Sample segmentation by industry-specific prior accuracy			
Low industry knowledge	T1	59,611	0.642
Medium industry knowledge	T2	59,613	0.677
High industry knowledge	T3	59,612	0.688
Difference	T3 – T1		0.046^{***} *(<0.001)*

To substantiate this preliminary finding, I first regress analysts' relative accuracy on their industry-specific prior accuracy and the set of control variables, pooled across all firm-years. Second, I investigate the relation between the forecast-based measure for industry knowledge and accuracy before and after the introduction of Reg FD. Third, I separately examine whether industry-specific prior accuracy is more or less able to explain relative accuracy differences for companies with a low or high forecast dispersion as well as in fiscal years in which the business cycle expands or contracts, respectively.

First, Table 4 reports the results for the pooled regression analysis. Most importantly and in line with the correlation matrix, the coefficient estimate on analysts' industry-specific prior accuracy is positive and significant at the 1 percent level.[21] In other words, analysts with superior knowledge of the industry the given firm operates in outperform their peers in terms of relative accuracy. This effect is evident even after controlling for a comprehensive set of analyst and forecast characteristics known to be linked to analysts' relative performance (e.g., Blümke, Hess and Stolz (2017)). Moreover, the coefficient estimate ranks third highest in absolute values and is only exceeded by the coefficient on the control variable forecast horizon and by the coefficient on boldness. That is, forecast-based industry knowledge is a more important determinant of relative performance than several other well-established analyst and forecast characteristics such as an analyst's task complexity or her working experience.

[21] The standard errors are heteroscedasticity-consistent. Note that the range-adjustment already controls for firm-year effects.

Discussion of results and further analyses

Overall, this result is in line with existing literature. For example, Bradley, Gokkaya and Liu (2017) find that preanalyst industry working experience subsequently leads to a higher relative accuracy. Dunn and Nathan (2005) show that industry diversification, which may be viewed as an inverse measure for industry knowledge, reduces accuracy. Likewise, the results by Jacob, Lys and Neale (1999) indicate that an analyst's industry specialization as well as brokerage house industry specialization positively influence accuracy.[22] Finally, Brown et al. (2015) conduct a survey and find that industry knowledge serves as an important input for analysts' earnings forecasts as well as for their stock recommendations.

The result, however, is inconsistent with Park and Stice (2000). The authors classify analysts as superior based on their firm-specific prior performance and show that these analysts generate stronger stock price reactions than their peers. In turn, superior analysts are not generally able to move prices since the price effects are not observed for the remaining companies covered by an analyst. This might be due to the fact that Park and Stice (2000) solely examine potential spillover effects with regard to the two companies for which an analyst issued the most forecasts in the past. In addition, Sonney (2009) finds that analysts who are country-specialists outperform analysts who are sector-specialists. The author classifies an analyst as a sector-specialist based on the number of companies covered in a given sector, relative to all companies covered by the analyst in a given year. In contrast, I argue that industry knowledge should rather be based on prior forecasting performance in an industry and not merely on the relative number of firms followed.[23]

The coefficient estimates on the other analyst and forecast characteristics are significant at the 1 percent level as well, except for the coefficient on All-Star status which is significant only at the 5 percent level.[24] Besides, the signs of the coefficients are generally as expected. That is, relative accuracy increases with firm-specific prior accuracy, general experience, forecast effort, boldness and All-Star status. As opposed to that, a higher forecast horizon, a higher number of followed firms and followed industries as well as a larger broker size decrease relative accuracy. As examined in the correlation matrix, the latter finding appears surprising at first sight but can be explained by previous literature (e.g., Bonner, Walther and Young (2003), Sonney (2009), Keskek et al. (2017)).[25]

Table 4. Pooled regression results

Table 4 shows the pooled regression results. Precise definitions of the range-adjusted regression variables can be found in Appendix Table A1. Two-sided p-values in parentheses indicate the statistical significances of the coefficients. *, **, *** denote a significance level at the 10%, 5%, 1% level (heteroscedasticity-consistent standard errors), respectively. The regression equation reads:

$$\begin{aligned}
\mathrm{ACCURACY}_{ijt} &= \beta_0 \\
&+ \beta_1 \cdot \mathrm{FOR_HORIZON}_{ijt} + \beta_2 \cdot \mathrm{LAG_ACCURACY}_{ijt} \\
&+ \beta_3 \cdot \mathrm{BROKER_SIZE}_{ijt} + \beta_4 \cdot \mathrm{EXPERIENCE}_{ijt} \\
&+ \beta_5 \cdot \mathrm{COMPANIES}_{ijt} + \beta_6 \cdot \mathrm{INDUSTRIES}_{ijt} \\
&+ \beta_7 \cdot \mathrm{FOR_FREQUENCY}_{ijt} + \beta_8 \cdot \mathrm{BOLDNESS}_{ijt} \\
&+ \beta_9 \cdot \mathrm{ALLSTAR}_{it} + \beta_{10} \cdot \mathrm{ILAG_ACCURACY}_{ijt} \\
&+ \varepsilon_{ijt}
\end{aligned}$$

			Final sample (1990–2011)
		Exp.	n = 178,836
Intercept	β_0	N/A	0.686*** *(<0.001)*
FOR_HORIZON	β_1	-	-0.319*** *(<0.001)*
LAG_ACCURACY	β_2	+	0.045*** *(<0.001)*
BROKER_SIZE	β_3	+	-0.007*** *(0.004)*
EXPERIENCE	β_4	+	0.025*** *(<0.001)*
COMPANIES	β_5	-	-0.019*** *(<0.001)*
INDUSTRIES	β_6	-	-0.021*** *(<0.001)*
FOR_FREQUENCY	β_7	+	0.010*** *(<0.001)*
BOLDNES	β_8	+	0.061*** *(<0.001)*
ALLSTAR	β_9	+	0.009** *(0.013)*
ILAG_ACCURACY	β_{10}	+	0.045*** *(<0.001)*
Adj. R^2			12.04%

22 The results remain robust when I additionally include the industry specialization of the analyst, the industry specialization of the broker (Jacob, Lys and Neale (1999)) or the industry experience of the analyst into the regression equation (Mikhail, Walther and Willis (1997); cf. Chapter 4).

23 Specifically, Sonney (2009) uses an indicator variable for sector-specialists in his accuracy regression. This indicator variable is based on a Herfindahl Index (HI) which is computed for every analyst in every year in two steps. First, for each sector, the ratio of the number of companies covered by the analyst in the sector to the total number of companies covered in a given year is calculated. Second, the ratios are summed across sectors to obtain the HI.

24 Even though some of the remaining independent variables such as the number of covered companies and the number of covered industries exhibit a high and significant correlation, multicollinearity does not seem to be a problem. Specifically, no variance inflation factor (VIF) of any explanatory variable is greater than 2. According to Wooldridge (2013), only a VIF greater than 10 may suggest that multicollinearity is an issue.

25 The adjusted coefficient of determination of 12.04 percent is roughly similar to the adjusted R^2s reported by previous studies (e.g., Clement (1999), Herrmann and Thomas (2005), Keskek et al. (2017)). If I exclude analysts' industry-specific prior accuracy from the regression equation, the adjusted R^2 decreases to 11.96 percent (unreported).

Second, I examine whether the influence of analysts' industry-specific prior accuracy on their current performance diminishes after the enactment of Reg FD. The regulation was implemented on the 23rd of October in 2000 by the U.S. Securities and Exchange Commission and prohibits the dissemination of private information from management to single analysts or to other market participants (Gintschel and Markov (2004)). Keskek et al. (2017) question if Reg FD as well as other regulations introduced between 2000 and 2003 affect the ability of several analyst and forecast characteristics to explain relative accuracy. In support of their conjecture, the authors find that the influence of forecast horizon, broker size, experience, task complexity, effort and All-Star status on analysts' performance decreases post-regulation.[26] Thus, I check whether the implementation of Reg FD also impacts the effect of the forecast-based measure for industry knowledge on relative accuracy. In particular, I define a pre- and a post-Reg FD phase and separately run the regression in both time periods. While the pre-Reg FD phase spans from 1990 to 1999, the post-Reg FD phase runs from 2001 to 2011. I exclude fiscal year 2000 in order to mitigate any confounding effects caused by a transition period.[27]

The results for the pre- and the post-Reg FD period are shown in Panel A and Panel B of Table 5, respectively. As it can be seen, the introduction of Reg FD did not influence the dominant effect of analysts' industry-specific prior accuracy on their current relative performance. That is, the coefficient estimates in both periods are highly significant at the 1 percent level and almost identical in value (0.045 in the pre-regulation phase vs. 0.044 in the post-regulation phase). Moreover, an unreported test shows that the difference is not statistically significant at conventional levels.

Table 5. Regression results by Reg FD

Table 5 shows the regression results separately for the pre-Regulation FD period spanning from 1990 to 1999 (Panel A) and the post-regulation FD period running from 2001 to 2011 (Panel B). Since Regulation FD was introduced on the 23rd of October in 2000, fiscal year 2000 is excluded from the analysis to reduce confounding effects due to a transition period. Precise definitions of the range-adjusted regression variables can be found in Appendix Table A1. Two-sided p-values in parentheses indicate the statistical significances of the coefficients. *, **, *** denote a significance level at the 10%, 5%, 1% level (heteroscedasticity-consistent standard errors), respectively. See Table 4 for the regression equation.

			Panel A: Pre-Reg FD period (1990–1999)
		Exp.	n = 72,042
Intercept	β_0	N/A	0.644^{***}
			(<0.001)
FOR_HORIZON	β_1	-	-0.242^{***}
			(<0.001)
LAG_ACCURACY	β_2	+	0.056^{***}
			(<0.001)
BROKER_SIZE	β_3	+	-0.007^{*}
			(0.088)
EXPERIENCE	β_4	+	0.032^{***}
			(<0.001)
COMPANIES	β_5	-	-0.036^{***}
			(<0.001)
INDUSTRIES	β_6	-	-0.035^{***}
			(<0.001)
FOR_FREQUENCY	β_7	+	0.027^{***}
			(<0.001)
BOLDNES	β_8	+	0.058^{***}
			(<0.001)
ALLSTAR	β_9	+	0.014^{**}
			(0.010)
ILAG_ACCURACY	β_{10}	+	0.045^{***}
			(<0.001)
Adj. R^2			8.07%

Table 5. Regression results by Reg FD (continued)

			Panel B: Post-Reg FD period (2001–2011)
		Exp.	n = 100,322
Intercept	β_0	N/A	0.712^{***}
			(<0.001)
FOR_HORIZON	β_1	-	-0.361^{***}
			(<0.001)
LAG_ACCURACY	β_2	+	0.037^{***}
			(<0.001)
BROKER_SIZE	β_3	+	-0.014^{***}
			(<0.001)
EXPERIENCE	β_4	+	0.024^{***}
			(<0.001)
COMPANIES	β_5	-	-0.011^{***}
			(0.007)
INDUSTRIES	β_6	-	-0.013^{***}
			(<0.001)
FOR_FREQUENCY	β_7	+	-0.001
			(0.836)
BOLDNES	β_8	+	0.064^{***}
			(<0.001)
ALLSTAR	β_9	+	0.005
			(0.303)
ILAG_ACCURACY	β_{10}	+	0.044^{***}
			(<0.001)
Adj. R^2			15.17%

This is generally consistent with Keskek et al. (2017) who show that the importance of analysts' firm-specific prior

26 Correspondingly, Findlay and Mathew (2006) find that the coefficient on the size of the brokerage house as well as the one on firm-specific experience lose influence post-Reg FD. This is because these two variables proxy for the flow of private information from management to analysts.

27 The results remain qualitatively unchanged when I do not exclude fiscal year 2000 or when I extend the transition period to fiscal years 2001, 2002 and 2003, respectively (unreported).

accuracy increases after the implementation of Reg FD. Likewise, the finding is consistent with Bradley, Gokkaya and Liu (2017) who report that the positive influence of preanalyst industry working experience on accuracy is not reduced post-regulation. Furthermore, the explanatory power of some of the control variables is somewhat weakened in the post-Reg FD phase which is also in line with Keskek et al. (2017). For example, the coefficients on analysts' forecast frequency and All-Star status, respectively, lose their significance after the introduction of Reg FD.[28] On the other hand, the signs and significances of the remaining coefficients are roughly comparable across two time periods.

Third, I check if industry-specific prior accuracy is more useful to explain relative performance differences when uncertainty is high. Following Blümke, Hess and Stolz (2017) and Keskek et al. (2017), I argue that it is more valuable to distinguish between analysts when their forecasts diverge. For instance, to explain the variation in the relative accuracy of five analysts is more promising when their earnings per share forecasts range between \$0.30 and \$3.00 than when their earnings estimates are within \$0.30 and \$0.33. Therefore, I divide the firms in my sample into two groups based on the standard deviation of the last price-scaled forecasts of all analysts following a company in a given fiscal year. While firms with a standard deviation lower than the median in a fiscal year are sorted into the low dispersion group (Panel A of Table 6), companies with an above median standard deviation are sorted into the high dispersion group (Panel B of Table 6). The results indicate that superior industry knowledge is more helpful to explain analysts' relative accuracy when forecast dispersion is high. Even though the coefficient estimate on industry-specific prior accuracy is significant at the 1 percent level for both groups, its value is more than 41.7 percent higher for the high dispersion companies (0.036 vs. 0.051). Besides, the difference is significant at the 5 percent level with a p-value of 0.0281 (unreported).

Table 6. Regression results by forecast dispersion

Table 6 shows the regression results separately for low forecast dispersion companies (Panel A) and for high forecast dispersion companies (Panel B). Forecast dispersion is the standard deviation of the last price-scaled forecasts of all analysts covering a given company in a given fiscal year. Companies with a forecast dispersion lower (higher) than the median in a fiscal year are sorted into the low (high) dispersion group. Precise definitions of the range-adjusted regression variables can be found in Appendix Table A1. Two-sided p-values in parentheses indicate the statistical significances of the coefficients. *, **, *** denote a significance level at the 10%, 5%, 1% level (heteroscedasticity-consistent standard errors), respectively. See Table 4 for the regression equation.

			Panel A: Low forecast dispersion (1990–2011)
		Exp.	n = 90,293
Intercept	β_0	N/A	0.660***
			(<0.001)
FOR_HORIZON	β_1	-	-0.209***
			(<0.001)
LAG_ACCURACY	β_2	+	0.041***
			(<0.001)
BROKER_SIZE	β_3	+	0.000
			(0.948)
EXPERIENCE	β_4	+	0.031***
			(<0.001)
COMPANIES	β_5	-	-0.017***
			(<0.001)
INDUSTRIES	β_6	-	-0.031***
			(<0.001)
FOR_FREQUENCY	β_7	+	-0.004
			(0.296)
BOLDNES	β_8	+	0.049***
			(<0.001)
ALLSTAR	β_9	+	0.008
			(0.129)
ILAG_ACCURACY	β_{10}	+	0.036***
			(<0.001)
Adj. R^2			5.51%

Table 6. Regression results by forecast dispersion (continued)

			Panel B: High forecast dispersion (1990–2011)
		Exp.	n = 88,543
Intercept	β_0	N/A	0.720***
			(<0.001)
FOR_HORIZON	β_1	-	-0.433***
			(<0.001)
LAG_ACCURACY	β_2	+	0.046***
			(<0.001)
BROKER_SIZE	β_3	+	-0.012***
			(<0.001)
EXPERIENCE	β_4	+	0.017***
			(<0.001)
COMPANIES	β_5	-	-0.021***
			(<0.001)
INDUSTRIES	β_6	-	-0.009**
			(0.015)
FOR_FREQUENCY	β_7	+	0.017***
			(<0.001)
BOLDNES	β_8	+	0.067***
			(<0.001)
ALLSTAR	β_9	+	0.010**
			(0.036)
ILAG_ACCURACY	β_{10}	+	0.051***
			(<0.001)
Adj. R^2			20.88%

[28] The adjusted coefficient of determination, however, increases in the post Reg-FD period.

To provide further evidence on this result, I test whether industry-specific prior accuracy is better able to explain analysts' relative performance in periods of uncertainty. In this context, Bloom (2014) notes that uncertainty increases in recessions. Thus, I obtain monthly business cycle data from the Federal Reserve Bank of St. Louis.[29] For each month, the data lists whether the business cycle expands (recession indicator variable equal to zero) or contracts (recession indicator variable equal to one), respectively. My methodology is straight-forward. In particular, I classify a given fiscal year as a contraction period when the recession indicator variable is equal to one for six or more months of that fiscal year. Based on this approach, fiscal years 2001 (dot-com bubble), 2008 and 2009 (financial crisis) correspond to contraction periods. The remaining fiscal years are classified as expansion periods. Panel A and Panel B of Table 7 show the results for the expansion and contraction periods, respectively. In support of the previous findings, the coefficient on analysts' industry-specific prior accuracy is highly significant is both expansion and contraction periods but the value is about 47.6 percent larger in contraction periods, that is, when uncertainty is high (0.042 vs. 0.062). Again, the difference is statistically significant at the 5 percent level (unreported).

Table 7. Regression results by business cycle

Table 7 shows the regression results separately for business cycle expansions (Panel A) and for business cycle contractions (Panel B). Fiscal years are classified as contraction periods when the recession indicator variable obtained from the Federal Reserve Bank of St. Louis is equal to one for six or more months of a fiscal year. Otherwise, fiscal years are classified as expansion periods. Fiscal years 2001 (dot-com bubble), 2008 and 2009 (financial crisis) correspond to contraction periods. The remaining fiscal years are expansion periods. Precise definitions of the range-adjusted regression variables can be found in Appendix Table A1. Two-sided p-values in parentheses indicate the statistical significances of the coefficients. *, **, *** denote a significance level at the 10%, 5%, 1% level (heteroscedasticity-consistent standard errors), respectively. See Table 4 for the regression equation.

		Exp.	*Panel A*: Expansions (1990–2000, 2002–2007, 2010–2011) n = 154,418
Intercept	β_0	N/A	0.683***
			(<0.001)
FOR_HORIZON	β_1	-	-0.313***
			(<0.001)
LAG_ACCURACY	β_2	+	0.048***
			(<0.001)
BROKER_SIZE	β_3	+	-0.006**
			(0.029)
EXPERIENCE	β_4	+	0.024***
			(<0.001)
COMPANIES	β_5	-	-0.021***
			(<0.001)
INDUSTRIES	β_6	-	-0.022***
			(<0.001)
FOR_FREQUENCY	β_7	+	0.011***
			(<0.001)
BOLDNES	β_8	+	0.061***
			(<0.001)
ALLSTAR	β_9	+	0.010***
			(0.008)
ILAG_ACCURACY	β_{10}	+	0.042***
			(<0.001)
Adj. R^2			11.60%

Table 7. Regression results by business cycle (continued)

		Exp.	*Panel B*: Contractions (2001, 2008, 2009) n = 24,418
Intercept	β_0	N/A	0.703***
			(<0.001)
FOR_HORIZON	β_1	-	-0.354***
			(<0.001)
LAG_ACCURACY	β_2	+	0.025***
			(<0.001)
BROKER_SIZE	β_3	+	-0.016**
			(0.016)
EXPERIENCE	β_4	+	0.033***
			(<0.001)
COMPANIES	β_5	-	-0.013
			(0.110)
INDUSTRIES	β_6	-	-0.016**
			(0.016)
FOR_FREQUENCY	β_7	+	0.004
			(0.571)
BOLDNES	β_8	+	0.061***
			(<0.001)
ALLSTAR	β_9	+	0.000
			(0.974)
ILAG_ACCURACY	β_{10}	+	0.062***
			(<0.001)
Adj. R^2			14.89%

In sum, the previous analyses suggest that analysts' industry-specific prior accuracy is an important determinant of their relative performance and functions as a measure for industry knowledge. Furthermore, the influence is not reduced after the introduction of Reg FD. Likewise, the forecast-based proxy for industry knowledge appears to contribute more to the explanation of differences in analysts' accuracy when the identification of these differences is most interesting, that is, when uncertainty is high.

[29] The data are publicly available (cf. https://fred.stlouisfed.org/series/USREC) and were originally published by the National Bureau of Economic Research (cf. http://www.nber.org/cycles/cyclesmain.html).

The effect of forecast-based industry knowledge on boldness, all-star status and career outcomes

The following three analyses examine whether forecast-based industry knowledge also influences the informativeness of analysts' forecasts, their reputation and their career outcomes, respectively. Specifically, I estimate three logistic regressions in which I explain an analyst's boldness, her membership on the All-America Research Team and a third indicator variable equal to one if she works at a prestigious brokerage house in the future by industry-specific prior accuracy and the set of controls.

First, I follow Clement and Tse (2005) and regress the forecast-based proxy for industry knowledge on boldness, controlling for the remaining analyst and forecast characteristics.[30] Boldness is an indicator variable which is equal to one when an analyst's forecast exceeds (or falls below) both her previous forecast as well as the outstanding consensus. Otherwise, the variable is set to zero.[31] I choose an analyst's boldness as a measure for the informativeness of her forecast since Clement and Tse (2005) find that bold forecasts are issued by analysts with superior private information. The results in Table 8 show that the likelihood to issue a bold forecast increases sharply with the forecast-based measure for industry knowledge, as indicated by the significantly positive coefficient. Specifically, it is 1.072 times more likely to observe a bold forecast from an analyst with the highest level of industry-specific prior accuracy as compared to an analyst with the lowest level of industry-specific prior accuracy.[32] In other respects, the results are broadly consistent with Clement and Tse (2005). For instance, the likelihood of an analyst to issue a forecast that deviates from her previous forecast and the consensus increases with forecast horizon, firm-specific prior accuracy, broker size, experience, forecast frequency and All-Star status. In contrast, bold forecasts are less likely issued by analysts who follow more companies. The coefficients are significant at the 1 percent level except for the ones on All-Star status, the number of covered companies and the number of covered industries. While the former two coefficients are significant at the 5 percent and 10 percent level, respectively, the coefficient estimate on the number of covered industries is insignificant.[33] Summed up, industry-specific prior accuracy does not only increase analysts' current relative performance but also the likelihood to issue more informative forecasts.

Table 8. The effect of forecast-based industry knowledge on boldness

Table 8 shows the results of a pooled logit regression. The dependent variable is the indicator variable boldness which is equal to one when an analyst's forecast is either above or below both her previous forecast and the 90 day mean consensus one day before the forecast is issued, and zero otherwise. The explanatory variables are forecast horizon, firms-specific prior accuracy, broker size, experience, number of covered companies and industries, forecast frequency, All-Star status and industry-specific prior accuracy. Precise definitions of the range-adjusted regression variables can be found in Appendix Table A1. *, **, *** denote a significance level at the 10%, 5%, 1% level.

Dependent variable: BOLDNESS					
		Final sample (1990–2011)			
		n = 178,836			
		Parameter	Odds Ratio Estimates		
			Point Estimate	95% CI	
Intercept	δ_0	0.722*** (<0.001)			
FOR_HORIZON	δ_1	0.423*** (<0.001)	1.526	1.474	1.581
LAG_ACCURACY	δ_2	0.055*** (<0.001)	1.057	1.025	1.089
BROKER_SIZE	δ_3	0.202*** (<0.001)	1.223	1.180	1.269
EXPERIENCE	δ_4	0.051** (0.010)	1.053	1.012	1.095
COMPANIES	δ_5	-0.039* (0.066)	0.962	0.923	1.002
INDUSTRIES	δ_6	-0.011 (0.561)	0.989	0.952	1.027
FOR_FREQUENCY	δ_7	0.200*** (<0.001)	1.221	1.177	1.268
ALLSTAR	δ_8	0.056** (0.047)	1.057	1.001	1.117
ILAG_ACCURACY	δ_9	0.070*** (0.006)	1.072	1.020	1.127

Second, I investigate the association between forecast-based industry knowledge and an analyst's reputation as approximated by her All-Star status. An analyst is classified as an All-Star if she is a member of the Institutional Investor (II) All-America Research Team. In particular, each year in October, the II Magazine publishes the results of a large survey of institutional investors based on which sell-side analysts are voted into the team (Green,

30 Consistent with Clement and Tse (2005), I exclude analysts' current relative accuracy as an explanatory variable.

31 In line with Clement and Tse (2005), I use the 90 day mean consensus forecast. Following Blümke, Hess and Stolz (2017), I further set the indicator variable boldness equal to zero for an analyst's first forecast in a given fiscal year as there is no previous forecast in these instances.

32 Note that the regression variables are adjusted and range from zero to one. Thereby, a value of zero (one) indicates the lowest (highest) level of a variable among all analysts in a given firm-year. For instance, an analyst with a range-adjusted broker size of zero (one) works at the smallest (largest) broker, relative to all analysts issuing forecasts in the firm-year. The odds ratio for an independent variable in the logistic regression is the change in odds if the that variable changes by one unit (that is, increases from the lowest to highest level), holding constant the remaining independent variables (Clement and Tse (2005); cf. University of California, Los Angeles, Institute for Digital Research and Education, https://stats.idre.ucla.edu/sas/output/proc-logistic/).

33 Clement and Tse (2005) find a significant influence of the number of covered industries on boldness. Their coefficient estimate on the number of covered companies, however, is not significant. This might be due to the high correlation between these two explanatory variables.

Jegadeesh and Tang (2009)). Existing literature finds that All-Star analysts possess different characteristics than their non-All-Star peers. For example, Stickel (1992) shows that accuracy and forecast frequency are positively related with an analyst's All-Star status. Likewise, Groysberg, Healy and Maber (2011) find that members of the All-America Research team earn higher salaries than non-members. To check if industry-specific prior accuracy influences the likelihood of an analyst to be an All-Star, I follow the methodology of Kumar (2010). Specifically, I estimate a logistic regression in which the dependent variable All-Star status is explained by the forecast-based proxy of industry knowledge while controlling for the other analyst and forecast characteristics.[34] The results can be found in Table 9. Consistent with previous research, the positive coefficient on industry-specific prior accuracy indicates that the likelihood of an analyst to be an All-Star significantly increases with industry knowledge (Bradley, Gokkaya and Liu (2017)). Besides, the chance of being a member of the All-America Research Team is positively associated with analysts' (prior) accuracy, the size of the brokerage house, general experience, the number of companies followed, forecast frequency and boldness. In turn, there is a negative relation with the forecast horizon and the number of industries followed.[35] All coefficients are significant at the 1 percent level, except for the ones on forecast frequency and boldness (significant at the 5 percent and 10 percent level, respectively).

Table 9. The effect of forecast-based industry knowledge on all-star status

Table 9 shows the results of a pooled logit regression. The dependent variable is the indicator variable All-Star status which is equal to one when an analyst is listed as a member of the All-America Research Team by the Institutional Investor Magazine in October of the previous year, and zero otherwise. The explanatory variables are accuracy, forecast horizon, firms-specific prior accuracy, broker size, experience, number of covered companies and industries, forecast frequency, boldness and industry-specific prior accuracy. Precise definitions of the range-adjusted regression variables can be found in Appendix Table A1. *, **, *** denote a significance level at the 10%, 5%, 1% level.

Dependent variable: ALLSTAR				
		Final sample (1990–2011)		
		n = 178,836		
		Parameter	Odds Ratio Estimates	
			Point Estimate	95% CI
Intercept	δ_0	-6.056*** (<0.001)		
ACCURACY	δ_1	0.128*** (<0.001)	1.136	1.055 1.224
FOR_HORIZON	δ_2	-0.192*** (<0.001)	0.826	0.764 0.892
LAG_ACCURACY	δ_3	0.144*** (<0.001)	1.155	1.083 1.232
BROKER_SIZE	δ_4	1.814*** (<0.001)	6.137	5.743 6.559
EXPERIENCE	δ_5	2.212*** (<0.001)	9.132	8.21510.151
COMPANIES	δ_6	0.763*** (<0.001)	2.144	1.973 2.330
INDUSTRIES	δ_7	-0.464*** (<0.001)	0.628	0.580 0.681
FOR_FREQUENCY	δ_8	0.101** (0.011)	1.106	1.023 1.196
BOLDNESS	δ_9	0.052* (0.066)	1.053	0.997 1.114
ILAG_ACCURACY	δ_{10}	0.311*** (<0.001)	1.364	1.218 1.528

It should be noted, however, that the indicator variable All-Star status is analyst-year-specific and not analyst-firm-year-specific. In other words, whether an analyst is a member of the All-America Research Team in a given year does not differ for each of the firms she covers.[36] The same holds true for an analyst's broker size, her working experience and her task complexity. On the other hand, an analyst's (prior) accuracy, forecast horizon, forecast frequency and boldness are analyst-firm-year-specific, that is, different for each firm in each year. Thus, in contrast to Kumar (2010), other papers only explain the dependent variable All-Star status by analyst-year-specific variables and average the analyst-firm-year-specific characteristics such that they are constant for all firms in a given year (e.g., Green, Jegadeesh and Tang (2009)). For instance, instead of an analyst's firm-specific boldness, the average boldness for all covered firms in that year is included as an explanatory variable (e.g., Klettke, Homburg and Gell (2015)). To check if the results are sensitive to this issue, I run the same regression as before but replace accuracy, forecast horizon, forecast frequency, boldness and industry-specific prior accuracy by the average values for all covered firms in each year (unreported).[37] The results indicate that the coefficient on the forecast-based proxy for industry knowledge is still highly significant. Therefore, I conclude that industry-specific prior accuracy is an important determinant of the likelihood to be an All-Star.

Third, I examine if forecast-based industry-knowledge also influences analysts' career outcomes. Having established the positive relation between industry-specific prior accuracy

[34] In line with Kumar (2010), the indicator variable All-Star status is equal to one for analysts who were voted into the All-America Research Team in October of the previous year. Otherwise, the variable is set to zero.

[35] Kumar (2010) reports results which are generally similar. Two exceptions are the non-significant coefficients on accuracy and on forecast horizon in his regression. My results remain robust when I exclude accuracy from the regression equation (unreported).

[36] See Klettke, Homburg and Gell (2015) for a similar argument.

[37] This implies that analysts' industry-specific prior accuracy is measured slightly different here as it includes firm-specific prior accuracy. Thus, the latter variable is dropped from the regression equation and industry-specific prior accuracy functions as a proxy for overall prior performance. To ensure that the measure still approximates industry knowledge, I restrict the sample to analysts who only cover firms from a single industry in a given fiscal year, retaining 58.6 percent of the initial observations in this robustness check.

and All-star status, I hypothesize that the former might also affect the likelihood that an analyst works at a prestigious brokerage house in the future. The status of a brokerage house is approximated by its size (Hong and Kubik (2003). Since analysts employed by larger brokerages also earn a higher compensation, working at a larger broker is associated with a more favorable career outcome (Hong and Kubik (2003)). Similar to Clement (1999), I compute the indicator variable $Top10_{t+1}$ which is equal to one when an analyst works at a brokerage house in the top size decile in the subsequent year. Otherwise, the variable is equal to zero. The size deciles are calculated based on the number of analysts issuing forecasts for the broker in a given year.[38] I then use $Top10_{t+1}$ as the dependent variable in a logistic regression and explain it by forecast-based industry knowledge as well as by the set of controls (Keskek at al. (2017)). Table 10 reports the results. Most importantly, I find that an analyst’s chance of working at a prestigious brokerage house increases significantly with industry-specific prior accuracy.[39] Thus, forecast-based industry knowledge is associated with a higher relative performance, more informative forecasts, a higher likelihood to be an All-Star and additionally has a positive influence on analysts’ career outcomes.[40]

Table 10. The effect of forecast-based industry knowledge on career outcomes

Table 10 shows the results of a pooled logit regression. The dependent variable is the indicator variable $Top10_{t+1}$ which is equal to one when an analyst works at a brokerage house in the top size decile in terms of the number of analysts working at the broker in the subsequent year, and zero otherwise. The explanatory variables are accuracy, forecast horizon, firms-specific prior accuracy, experience, number of covered companies and industries, forecast frequency, boldness, All-Star status and industry-specific prior accuracy. Precise definitions of the range-adjusted regression variables can be found in Appendix Table A1. *, **, *** denote a significance level at the 10%, 5%, 1% level.

Dependent variable: $Top10_{t+1}$				
		Final sample (1990–2011)		
		n = 178,836		
		Parameter	Odds Ratio Estimates	
			Point Estimate	95% CI
Intercept	δ_0	-0.137^{***} (<0.001)		
ACCURACY	δ_1	0.117^{***} (<0.001)	1.124	1.088 1.160
FOR_HORIZON	δ_2	0.192^{***} (<0.001)	1.211	1.172 1.252
LAG_ACCURACY	δ_3	0.114^{***} (<0.001)	1.121	1.090 1.152
EXPERIENCE	δ_4	0.187^{***} (<0.001)	1.205	1.163 1.249
COMPANIES	δ_5	0.454^{***} (<0.001)	1.574	1.515 1.636
INDUSTRIES	δ_6	-0.848^{***} (<0.001)	0.428	0.414 0.443
FOR_FREQUENCY	δ_7	0.396^{***} (<0.001)	1.486	1.437 1.538
BOLDNESS	δ_8	0.131^{***} (<0.001)	1.140	1.114 1.167
ALLSTAR	δ_9	2.306^{***} (<0.001)	10.037	9.04611.137
ILAG_ACCURACY	δ_{10}	0.352^{***} (<0.001)	1.422	1.359 1.488

Robustness checks

I check the robustness of my findings with respect to three issues (unreported). First, previous literature generally uses two methods to standardize analysts’ absolute forecast errors such that the errors are comparable across firms and years. In this context, I follow Clement and Tse (2003) as well as Clement and Tse (2005) and range-adjust analysts’ absolute forecast errors. Other studies, however, use the so-called Proportional Mean Absolute Forecast Error (PMAFE) as the dependent variable in their accuracy regressions (e.g., Clement (1999), Brown (2001)). This relative accuracy measure is computed by subtracting the mean absolute forecast error of all analysts covering company j in fiscal year t ($\overline{AFE_{jt}}$) from analyst i’s absolute forecast error (AFE_{ijt}). The demeaned absolute forecast error is then scaled by the mean absolute forecast error and multiplied by minus one.[41]

$$\mathrm{PMAFE}_{ijt} = \frac{\mathrm{AFE}_{ijt} - \overline{\mathrm{AFE}}_{jt}}{\overline{\mathrm{AFE}}_{jt}} \cdot (-1) \tag{4}$$

To ensure that my results are robust with regard to the standardization method applied, I re-estimate my analyses using the PMAFE as the relative accuracy measure. The results remain unchanged. Most importantly, the coefficient estimate on analysts’ industry-specific prior accuracy is still positive and highly significant (p-value < 0.001), both pre- and post-regulation as well as for low and high dispersion firms and in expansion and contraction periods,

38 In other words, an analyst’s career outcome is defined as favorable when she stays at or moves to a top size decile brokerage house in the subsequent year (Hong and Kubik (2003)).

39 The other analyst and forecast characteristics are significant at the 1 percent level as well. The likelihood to work at a high status brokerage increases with analysts’ (prior) accuracy, forecast horizon, experience, number of covered companies, forecast effort, boldness and All-Star status but decreases with the number of industries followed.

40 As with an analyst’s All-Star status, it can be argued that $Top10_{t+1}$ is an analyst-year-specific and not an analyst-firm-year-specific variable. In particular, whether an analyst works at a prestigious broker is constant for all firms covered in a given year. Therefore, I again re-estimate the regression but replace analysts’ accuracy, forecast horizon, forecast frequency, boldness and industry-specific prior accuracy by the respective average values for all companies covered in each year and restrict the sample to analysts who solely follow firms from one industry. The results remain unchanged. The same holds true when I do not lead $Top10_{t+1}$ by one year and when I exclude accuracy from the regression equation (unreported).

41 The explanatory variables are demeaned as well. Thus, the PMAFE also accounts for firm-year-specific influences.

respectively.[42] Furthermore, forecast-based industry knowledge is still a significant determinant of the informativeness of analysts' forecasts, their All-Star status and their career outcomes, respectively.

Second, Brown and Mohammad (2010) separately examine the effects of firm-specific lagged accuracy and general lagged accuracy for all other covered firms on relative performance. The authors find that general lagged accuracy is incremental to firm-specific lagged accuracy in explaining analysts' relative performance. As the former is closely related to the forecast-based proxy for industry knowledge, I check the robustness of my results when I additionally control for analysts' general prior performance. I define general prior performance as the average range-adjusted prior accuracy for all firms not operating in firm j's industry. In the regression, I then separately include this measure for general prior accuracy, industry-specific prior accuracy (excluding firm j) as well as firm-specific prior accuracy.

The results show that industry-specific prior accuracy is essential for explaining analysts' relative performance even after controlling for general prior accuracy.[43] That is, the coefficient estimate is still positive and significant at the 1 percent level in the pooled regression. In addition, it is more than double the size of the coefficient on general prior accuracy, indicating that industry-specific prior accuracy is the more important characteristic.[44] Furthermore, the influence is positive and significant before and after the introduction of RegFD, when the dispersion of analysts' forecasts is low or high and when the business cycle expands or contracts, respectively. Likewise, the likelihood to issue a bold forecast, to be an All-Star analyst and to work at a large broker in the future are still significantly associated with the forecast-based proxy for industry knowledge. Similarly, the results remain robust when I compute industry-specific prior accuracy such that it includes company j.[45]

Besides, when I additionally consider the natural logarithm of the number of years of analysts' industry experience (Mikhail, Walther and Willis (1997)) the coefficient on the forecast-based industry knowledge proxy remains positive and significant in all regressions. The coefficient estimate on industry experience, however, is positive but not statistically significant in the pooled regression, for example.[46] Likewise, industry-specific prior accuracy does not lose its influence when I control for an analyst's industry specialization or the industry specialization of the broker the analyst works at (e.g., Jacob, Lys and Neale (1999)).[47]

Third, I follow Blümke, Hess and Stolz (2017) and check if the findings are affected by the number of analysts following a company in a given fiscal year. Specifically, I increase the minimum analyst coverage from two to five. Most notably, the importance of industry-specific prior accuracy is still evident when the accuracy model needs to differentiate between more analysts in a given firm-year. In particular, I find a positive and significant influence on relative accuracy in the pooled analysis that is robust pre- and post-Reg FD and which holds for both low and high dispersion companies as well as in periods of business cycle expansion and contractions, respectively.[48] Last, this positive influence extends to the informativeness of analysts' forecasts, their membership on the All-America Research Team and their career outcomes, respectively.

5. Conclusions

Previous studies have identified several analyst and forecast characteristics that determine relative accuracy such as the number of years of working experience, the size of the brokerage house or even analysts' political views (e.g., Clement (1999), Jiang, Kumar and Law (2016)). Of all these determinants, however, analysts' industry knowledge is frequently named by academics and practitioners as the most important characteristic (e.g., Bagnoli, Watts and Zhang (2008), Brown et al. (2015)). Therefore, this paper introduces analysts' industry-specific prior accuracy as an easily observable measure for industry knowledge. The results show that the forecast-based proxy for industry knowledge is positively and significantly associated with relative performance. Furthermore, the performance advantage of analysts with higher industry-specific prior accuracy is presumably caused by a superior interpretation of industry-relevant public information. In other words, it is not due to management providing analysts with private information. This is because the positive influence on relative accuracy

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42 Interestingly, the coefficient estimate on broker size in the pooled regression becomes significantly positive when the PMAFE is used as the dependent variable.

43 All-Star status, however, is now insignificant in this regression specification (pooled analysis).

44 In contrast, Brown and Mohammad (2010) compute general prior performance for analyst i in year t as the average prior accuracy for all covered firms, except firm j. The coefficient estimate on industry-specific prior accuracy even remains positive and significant at the 5 percent level when general prior accuracy as measured in Brown and Mohammad (2010) is alternatively included into the regression.

45 Firm-specific prior accuracy is excluded from the regressions in this robustness check.

46 This is probably due to the high correlation between general and industry experience of 0.896 (p-value < 0.001). When I exclude general experience from the pooled regression, the coefficient estimate on industry experience becomes significant at the 1 percent level. The coefficient on industry-specific prior accuracy, however, stays significantly positive and is about 1.8 times larger than the one on industry experience (0.025 vs. 0.045).

47 An analyst's industry specialization and broker specialization are both calculated in absolute and relative terms. That is, an analyst's absolute (relative) industry specialization is computed as the number of companies covered in each industry (relative to the total number of companies covered in a given fiscal year). The absolute (relative) broker specialization is the number of analysts covering companies from the same industry (relative to the total number of analysts working at the broker in a given fiscal year).

48 The coefficient estimates on broker size and All-Star status, in turn, are not significant at conventional levels in this pooled regression analysis.

does not diminish after the introduction of Regulation Fair Disclosure which prohibits the selective dissemination of private information from companies to analysts and other market participants (e.g., Bradley, Gokkaya and Liu (2017)). In contrast, some other well-known accuracy determinants lose statistical significance in the post-regulation period (Keskek et al. (2017)). Besides, industry-specific prior accuracy appears to be particularly helpful when the explanation of differences in analysts' performance is most interesting, that is, when uncertainty is high. Moreover, the results indicate that the acquisition of forecast-based industry knowledge has positive consequences for analysts beyond the influence on relative performance. Specifically, industry-specific prior accuracy has a significantly positive effect on the likelihood to issue a bold forecast, to be an All-Star and to work at a prestigious brokerage house in the future, respectively (e.g., Bradley, Gokkaya and Liu (2017), Keskek et al. (2017)).

These findings have three important theoretical and practical implications. First, more accurate consensus forecasts could be calculated by increasing the weight of analysts with superior forecast-based industry knowledge. Consequently, the more accurate consensus forecasts could be used in the context of company valuation or implied cost of capital estimation. Second, following analysts with higher industry-specific prior accuracy might enable investors to identify profitable trading strategies. This conjecture is based on the result by existing literature that earnings forecast accuracy is closely linked to stock price target accuracy and recommendation profitability, respectively (e.g., Loh and Mian (2006), Ertimur, Sunder and Sunder (2007), Gleason, Johnson and Li (2013)). Third, the findings suggest that brokerage houses should focus on employing analysts with superior industry-specific prior accuracy since these analysts achieve higher relative performance than their peers.

Appendices

Table A1. Definitions of regression variables

Table A1 shows the precise definitions of the variables used in the regressions. The definitions are, among others, based on Blümke, Hess and Stolz (2017) and Clement and Tse (2005).

$ACCURACY_{ijt}$	A measure for analyst i's annual earnings forecast accuracy. It is calculated as the maximum absolute forecast error (AFE) of all analysts following company j in fiscal year t minus the AFE of analyst i's last forecast for company j in fiscal year t, with this difference scaled by the range of AFEs of all analysts following company j in fiscal year t.
$FOR\_HORIZON_{ijt}$	A measure for analyst i's forecast horizon. It is calculated as the number of days between the forecast issuance date and the end of fiscal year t for analyst i following company j in fiscal year t minus the minimum forecast horizon of all analysts following company j in fiscal year t, with this difference scaled by the range of forecast horizons of all analysts following company j in fiscal year t.
$LAG\_ACCURACY_{ijt}$	A measure for analyst i's forecast accuracy for company j in fiscal year t-1. It is calculated as the maximum one-year lagged AFE of all analysts following company j in fiscal year t minus the one-year lagged AFE of analyst i following company j in fiscal year t, with difference scaled by the range of one-year lagged AFEs of all analysts following company j in fiscal year t.
$BROKER\_SIZE_{ijt}$ $Top10_{it+1}$	A measure for analyst i's broker size. It is calculated as the number of analysts employed by the broker employing analyst i issuing a forecast for company j in fiscal year t minus the minimum broker size of all analysts following company j in fiscal year t, with this difference scaled by the range of broker sizes of all analysts following company j in fiscal year t. The indicator variable $Top10_{t+1}$ is equal to one when analyst i is employed by a broker in the top size decile in terms of the number of analysts employed in year t+1, and zero otherwise.
$EXPERIENCE_{ijt}$	A measure for analyst i's experience. It is calculated as the natural logarithm of the number of years of experience (proxied by the number of distinct fiscal years for which analyst i issued at least one forecast) of analyst i following company j in fiscal year t minus the minimum experience of all analysts following company j in fiscal year t, with this difference scaled by the range of experience of all analysts following company j in fiscal year t.
$COMPANIES_{ijt}$	A measure for analyst i's task complexity. It is calculated as the number of companies followed by analyst i issuing a forecast for company j in fiscal year t minus the minimum companies followed by all analysts following company j in fiscal year t, with this difference scaled by the range of companies followed by all analysts following company j in fiscal year t.
$INDUSTRIES_{ijt}$	A measure for analyst i's task complexity. It is calculated as the number of distinct two-digit SIC codes followed by analyst i issuing a forecast for company j in fiscal year t minus the minimum industries followed by all analysts following company j in fiscal year t, with this difference scaled by the range of industries followed by all analysts following company j in fiscal year t.

Table A1. Definitions of regression variables (continued)

$FOR\_FREQUENCY_{ijt}$	A measure for analyst i's effort. It is calculated as the number of forecasts issued by analyst i for company j in fiscal year t (including analyst i's forecast in fiscal year t) minus the minimum forecast frequency of all analysts following company j in fiscal year t, with this difference scaled by the range of forecast frequencies of all analysts following company j in fiscal year t.
$BOLDNESS_{ijt}$	A measure indicating whether analyst i's forecast is bold. It is calculated as an indicator variable equal to one if analyst i's forecast for company j in fiscal year t is both above (below) analyst i's previous forecast for company j in fiscal year t and above (below) the 90 day mean consensus forecast for company j one day prior to the issuance date of analyst i's forecast, and zero otherwise.[i]
$ALLSTAR_{it}$	A measure indicating whether analyst i is a member of the Institutional Investor All-America Research Team. It is calculated as an indicator variable equal to one if analyst i is a member of the Institutional Investor All-America Research Team in fiscal year t.[ii]
$ILAG\_ACCURACY_{ijt}$	A measure for analyst i's forecast-based industry knowledge. It is calculated for analyst i issuing a forecast for company j in fiscal year t as the mean one-year lagged range-adjusted accuracy for all firms operating in company j's two-digit SIC code, excluding company j.

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[i] Following Blümke, Hess and Stolz (2017), I set boldness equal to zero for analyst i's first forecast for company j in fiscal year t since there is no previous forecast in these cases.

[ii] The All-America Research Team is compiled by the Institutional Investor Magazine each year in October (Green, Jegadeesh and Tang (2009)). Therefore, the indicator variable All-Star status is equal to one when forecasts are issued in between November in the year of the All-Star nomination and October in the year afterwards, and zero otherwise (Blümke, Hess and Stolz (2017)).