Before an analyst becomes an analyst: Does industry experience matter?

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Abstract

Using hand-collected biographical information on financial analysts from 1983 to 2011, we exploit their employment history and find that analysts with pre-analyst industry experience have significantly better forecast accuracy resulting in stronger market reactions when they forecast firms in industries similar to their previous industry experience. We also document that previous industry experience is positively related to favorable career outcomes—analysts possessing such experience are more likely to be named as *Institutional Investor* all-stars. This result is persistent pre- and post-Reg FD suggesting that industry expertise as opposed to social connections from previous employment is a more likely channel to explain our findings.

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Does knowledge matter? Industry experience and analyst performance

1. Introduction

What makes a good sell-side financial analyst? A large body of academic research has been devoted to this question since sell-side analysts are one of the most important information agents in capital markets. The literature generally indicates that certain innate characteristics and external factors such as analysts' general forecasting experience, political views, portfolio complexity, and their brokerage house are related to analysts' performance (Clement, 1999; Gilson et al., 2001; Clement, Rees, and Swanson, 2003; Jiang, Kumar, and Law, 2013; etc.).

Practitioners indicate that industry knowledge is perhaps the most important trait an analyst can possess. Each October, *Institutional Investor* (*II*) releases its annual all-star analyst rankings, which polls buy-side institutions and ranks the top sell-side analysts in each industry. In addition to a list of top analysts, the survey also reveals the qualities that respondents view as the most important. Industry knowledge has consistently been ranked the number one trait. Corroborating *II*'s poll, Brown, Call, Clement, and Sharpe (2013) survey sell-side *analysts* and they too believe that industry knowledge is the most important characteristic related to their performance and career concerns. Despite the overwhelming view that industry knowledge is critical to an analyst's job, there is surprisingly very little systematic evidence examining the relation between industry knowledge and analyst performance—most likely because it is inherently difficult to measure.

A few papers have attempted to empirically address the link between analyst performance and industry specialization. Boni and Womack (2006) find that analysts have superior ability in ranking individual stocks within industries. Kadan, Madureira, Wang, and Zach (2012) examine industry recommendations made by strategy analysts that take a macroeconomic top-down view of the overall industry. They find that a portfolio of optimistic industry recommendations earns significant positive abnormal returns while portfolios created based on negative industry recommendations earn negative abnormal returns.

In this paper, we aim to fill the void on the relation between industry knowledge and analyst performance by exploiting the pre-analyst employment experience of sell-side analysts using a novel hand-collected biographical dataset and examine whether this is related to forecasting performance. Specifically, we extrapolate pre-analyst industry experience from their previous employment history and match this with analysts' coverage portfolios. This allows us to discern if a covered firm is related or unrelated to the analyst's pre-analyst industry work experience. We conjecture that industry knowledge acquired from pre-analyst industry work experience can provide sell-side analysts a competitive advantage by enabling them to better interpret the factors that have an economic impact on the operations, financial condition, and industry of the firms in their coverage portfolio above and beyond factors that have been previously found in the literature to be related to analyst performance. This should not only aid their forecasting performance, but also lead to favorable career outcomes.

To illustrate our empirical design, take one analyst in our sample. Before becoming an analyst, he worked at CBS Group for 7 years as a Director of Strategic Planning. In a given year, he was an analyst at Bear Stearns and the sample firms in his coverage portfolio included Cablevision Systems, Comcast Corporation, Cox Communications, Cox Radio, Young Broadcast, Walt Disney Corporation, and Adelphia Communications. These firms are in the entertainment/broadcasting industry and are related to his previous work experience at CBS Group. He also covers Hertz Corporation, The Learning Company, and Avis Rent A Car among others. These firms are unrelated to his previous work experience. To avoid confusion with analysts' general and firm-specific forecasting experience, we refer to *pre-analyst work experience* related to the industry of a covered firm as *related experience*. When these industry-experienced analysts make forecasts on firms operating in an industry that is unrelated to their pre-analyst industry experience, we refer to this experience as *unrelated experience*. Analysts without industry experience are called *inexperienced* or *no experience analysts*.

In our 1983 to 2011 sample of 112,973 earnings forecasts on 5,581 firms, we find that the relative earnings accuracy of forecasts issued by analysts with related experience is significantly higher than analysts with unrelated experience or no previous work experience. Specifically, the mean relative forecast accuracy of analysts with related industry experience is 3.58% higher compared to forecasts issued by other analysts after controlling for intertemporal variations in task difficulty, general and firm specific forecasting experience, and other factors shown in the analyst literature to explain cross-sectional differences in earnings forecast accuracy. Furthermore, related-industry experience has at least as large of an economic impact on forecast accuracy as any other documented analyst characteristic. On the other hand, the relative accuracy of forecasts issued by industry experienced analysts on unrelated firms is not different than those of inexperienced analysts.

We separate bold forecasts from herding forecasts using a similar method as in Clement and Tse (2005) to examine the types of forecasts for which the effect of related industry experience is most important. We find that related industry experience is associated with more accurate forecasts for both bold and herding forecasts. This result holds in subsamples sorted on *Institutional Investor* all-star status, the length of general forecast experience, brokerage house prestige, and analysts' affiliation with the firm. We also investigate *improvements* in firm-specific forecast accuracy across experienced and inexperienced analysts motivated by learning-by-doing models (Mikhail et al., 1997; Jacob et al., 1999; Clement and Tse, 2005). We find significantly larger improvements in the forecast accuracy of experienced analysts on related firms than for unrelated firms or forecasts of inexperienced analysts. This finding suggests that sell-side analysts might have a steeper learning curve as a result of their superior industry knowledge gained from pre-analyst industry experience. These results further support the view that industry knowledge is persistent, similar to other analyst characteristics found in previous work (e.g. Clement, 1999; Clement and Tse, 2003; and Malloy, 2005).

Given the evidence of higher relative forecast accuracy, our next set of tests examine the extent to which pre-analyst work experience for sell-side analysts leads to favorable career outcomes. Several papers show that accuracy is related to analysts' career concerns (Hong, Kubik and Solomon, 2000; Hong and Kubik, 2003). Our evidence also supports this conjecture. We find that previous work experience incrementally increases the likelihood of becoming an *Institutional Investor* all-star analyst, but only when the analyst covers stocks related to her pre-analyst industry work experience.

Finally, we consider the variation in the market's assessment to earnings forecast revisions from industry experienced and inexperienced analysts. We consider not only the direction of forecast revisions, but also their magnitudes (Ivkovic and Jegadeesh, 2004). We find that experienced analysts' upward and downward forecast revisions on related firms yield stronger market reactions relative to those of inexperienced analysts after controlling for various firm and analyst-level attributes. For instance, a one-standard deviation increase in the average upward (downward) earnings forecast revision by an analyst with related experience results in a 0.19% (0.29%) greater (lower) abnormal market reaction compared to forecasts of analyst with unrelated industry experience. By contrast, the short-term market reaction to forecast revisions of experienced analysts on unrelated firms is not different from those of inexperienced analysts. These findings are in line with the evidence regarding the pattern of relative forecast accuracy and show that analysts' industry knowledge brings valuable information to the capital markets through their earnings forecasts.

There are two likely channels through which industry knowledge can manifest itself in analysts' superior forecasting abilities. First, industry knowledge can be disseminated through a deep understanding of industry fundamentals, such as the impact of both macroeconomic and microeconomic factors such as changes in fiscal and monetary policy, political risk, and how each firm is positioned within the industry. Alternatively, an analyst might use his previous industry connections to gather private information. Cohen, Frazinni, and Malloy (2010) find that analysts with educational links to senior executives perform better than non-connected analysts, implying that these connections foster the transfer of private information. They further show that this effect vanished after Regulation FD (Reg FD), which prohibited selective disclosure by firm management to analysts. To determine which is a more likely conduit, we separate our sample into pre- and post-Reg FD periods. If industry connections vis-à-vis sharing private information is dominant, we would likely find the benefit of connections to be much weaker after post-Reg FD. However, we find that industry experience matters in both periods and the passage of Reg FD has not diminished the marginal impact of industry experience on forecast performance. This suggests that a fundamental understanding of the industry is a more likely explanation of value creation than industry connections. This result is also consistent with the strong emphasis buy-side institutions and sell-side analysts put on industry knowledge for forecasting performance in the post-Reg FD era (e.g. Brown, Call, Clement, and Sharpe, 2013).

A potential concern with our analysis is that analysts that post information on *LinkedIn.com*, our main employment data source, might be systematically different from analysts that do not subscribe to this service. To deal with this issue, using the universe of *I/B/E/S* coverage, we test for systematic differences in forecast accuracy between both types of analysts (those that subscribe versus those that do not). We find no significant difference. Another plausible explanation for our results is that analysts simply exert more effort on their coverage of firms in which they possess related industry experience. To gauge effort, we investigate the number of earnings revisions made on portfolio firms (Jacob, Lys and Neale, 1999). We find no differences between the number of forecast revisions made for firms where the analyst has related industry experience compared to that of firms where she does not. Finally, we eliminate all forecasts except those issued by analysts on industry-related firms. We find that the number of years of industry experience is also related to forecast accuracy.

Our paper illustrates the importance of industry knowledge and how this knowledge is disseminated through analysts' earnings forecasts. Our paper bridges the gap between what practitioners (i.e., buy-side institutions) claim is the most important analyst attribute and what we empirically find.

The rest of the paper proceeds as follows. Section 2 provides the motivation and relevant literature while section 3 describes the data and provides descriptive statistics. Sections 4 through 6 present the main empirical results. Section 4 reports evidence on forecast accuracy, section 5 provides results on career concerns, and section 6 presents market reaction results. Section 7 provides a discussion and robustness tests and section 8 concludes.

2. Motivation and literature review

A voluminous literature indicates that analysts bring valuable information to individual and institutional investors through their earnings forecasts, forecast revisions, and recommendations. This value can be observed by investigating average market reactions to analysts' earnings and recommendation revision announcements (i.e., Womack, 1996; Gleason and Lee, 2003; Ivkovic and Jegadeesh, 2004; Livnat and Mendenhall, 2006; Bradley, Clarke, Lee and Orthanalai, 2013). While the average analyst tends to provide valuable information to market participants, several papers show that not all sell-side analysts are equally skilled. Characteristics like brokerage house prestige, portfolio complexity, and political views have all been linked to analyst performance (Mikhail, Walther, and Willis, 1997; Clement, 1999; Gilson et al., 2001; Clement and Tse, 2003; Clement, Rees, and Swanson, 2003; Jiang, Kumar, and Law, 2013). Several papers suggest that experience matters in the context of analyst forecasting performance. For instance, Mikhail et al. (1997) finds that analysts that cover a firm longer produce better forecasts implying a learning curve. Other papers suggest that general analyst experience translates into more accurate forecasts (Clement, 1999; Clement et al., 2007). A related strand of literature indicates that geographical proximity to firms influences analysts' coverage decisions and results in better accuracy (Malloy, 2005; Bae, Stulz, and Tan, 2008; Tan and O'brien, 2012). Du, Yu, and Yu (2013) find that cultural proximity, which is distinct from geographical proximity, improves processing of financial information and forecasting performance.

Perhaps to gauge the skills that are deemed the most important of financial analysts one should consider their primary customers, that is, the buy-side clients that they produce research for. Each year, *Institutional Investor* (*II*) does just that. *II* polls buy-side institutions on who they believe are the top analysts in each industry. They also publish a list of qualities that buy-side clients believe makes a top analyst. In Appendix A, we supplement Table 1 of Bagnoli, Watts, and Zhang (2008) by providing the survey results of *II*'s poll regarding the qualities top analysts should possess.[1] Over the 1999 to 2009 time period, there is considerable variation in the qualities that buy-siders value with one exception—industry knowledge is consistently ranked the most important quality.

[1] They provide survey results over 1998-2003. For illustrative purposes, we provide the survey results from 1999 to 2009. To conserve space, we report the results of the survey every other year.

While it is generally known that analysts tend to specialize in particular industries, there is surprisingly very little empirical research focusing on the industry aspect of analyst performance. Boni and Womack (2006) find that analysts have superior ability in ranking individual stocks within industries. Kadan, Madureira, Wang, and Zach (2013) come to similar conclusions. They argue that analysts have stock selection abilities within an industry, but do not have superior market timing abilities. Kadan, Madureira, Wang, and Zach (2012) take a different approach by examining industry recommendations made by strategy analysts that take a macroeconomic top-down view of the overall industry. They find that an industry portfolio of optimistic recommendations earns significant positive abnormal returns while industry portfolios created with a negative industry outlook earn negative abnormal returns. Interestingly, Brown, Call, Clement, and Sharpe (2013) survey sell-side analysts and they also indicate that industry knowledge is the most important component of their forecasting performance and compensation.

Unlike the existing work on industry expertise or general analyst-related experience, our paper expands on the role of industry knowledge by considering analysts' pre-analyst work experience. We use a large novel hand-collected dataset of pre-analyst employment information and relate this information to analysts' coverage portfolios. We conjecture that previous work experience can aid sell-side analysts in interpreting the factors that have an economic impact on the operations, earnings and industry of the firms in their coverage portfolio, or social connections made through their previous employment can facilitate information flow therefore leading to better forecast performance. If buy-side clients view industry knowledge as valuable, assuming that previous industry experience gives analysts a competitive advantage over their inexperienced counterparts, then two other hypotheses can be advanced and empirically tested. First, if industry knowledge learned through previous employment aids in analysts' performance, then it should be related to favorable career outcomes. Previous studies find analyst forecast accuracy is related with job turnover and career prospects (Hong, Kubik, and Solomon, 2000; Mikhail, Walther, and Willis, 2003; Hong and Kubik, 2003). In general, these studies find that analysts are more likely to be promoted or less likely to lose their job if their forecasts are more accurate. In particular, since buy-side managers suggest industry knowledge is the most important analyst quality and presumably vote on the top analysts in each industry with this in mind, then industry experience should be related to becoming an *II* all-star analyst. Using analyst compensation data from an anonymous high status investment bank, Groysberg, Healy, and Maber (2011) suggest that *II* all-star analysts earn 61%

higher compensation than their unrated peers. Thus, there are strong monetary incentives for analysts to be included in the rankings.

Finally, studies by Stickel (1995), Ivkovic and Jegadeesh (2004) and others indicate that market participants systematically differentiate between analyst characteristics that proxy for analysts' skill. If buy-side clients are more likely to listen to what analysts with industry knowledge say, then earnings revisions from industry experienced analysts should result in more prominent market reactions.

3. Data and descriptive statistics

The data used in this study is constructed from several sources. Appendix B describes the data screening and collection process. We start by merging Institutional Broker Estimate System (*I/B/E/S*) detail history tape with CRSP/COMPUSTAT, and then identify sell-side analysts who provided at least one annual earnings forecast with a horizon of at least 1 month between 1983 and 2011. We retain the most recent forecast. This provides us with 14,458 analysts making 470,137 forecasts. For each analyst, *I/B/E/S* provides only the analyst's last name and the initial of his/her first name. We remove observations with missing analyst names or brokerage id's and forecasts made by analyst teams (those analyst names recorded as "research department" or contain two analyst last names). We also delete observations if we find multiple analysts sharing the same first initial and last name at the same brokerage firm. These initial filtering criteria results in 9,305 analysts issuing 398,919 annual earnings forecasts.

Next, for each *I/B/E/S* analyst in our sample, we search *Zoominfo.com*, a search engine that specializes in indexing employment data to capture the analyst's full first name. The last name, first initial, and brokerage house where the analyst is employed must match the forecast date to be included in the sample. In a few rare cases, we perform Google searches to capture this information. We follow a very conservative approach in building our final sample and remove any observations where there is ambiguity as to whether or not we have the correct analyst.[2] This leaves us with 253,983 forecasts issued by 4,849 analysts.

[2] We acknowledge that name changes may occur through marriage or divorce. If the *I/B/E/S* name does not match the employment indexing sites, they are removed from our sample. However, there is no reason to believe that analysts that change their names because of marital reasons or other reasons would systematically bias our results. In a few cases, we manually match names such as 'Michael' for 'Mike' if and only if, the last name and brokerage house are an exact match and we cannot find another employee at the brokerage house with a similar name.

For each analyst remaining in the sample, we collect information on their pre-analyst employment. Our employment data source is *LinkedIN.com*, the world's largest professional network with more than 225 million members worldwide. We capture the names of all firms listed in their employment background, regardless if they are public or private firms. An analyst must have at least a year of non-analyst experience to be considered an experienced analyst. We then decompose the analysts' work experience into "related" and "unrelated" at the firm-level based on the analyst's experience relative to the firm followed. Specifically, we define experience as related if a previous employer and the followed firm shares 1 of 5 similar Fama-French industry classification codes, else we define previous experience as unrelated.[3, 4]

Panel A of table 1 provides summary statistics of our sample by time period. We report the number of firms, earnings forecasts and a breakdown of the percentage of forecasts from experienced and inexperienced analysts. Experience is further decomposed into 'related' and 'unrelated' experience. We also report the percentage of firms, forecasts, and market capitalization of our sample relative to the 'cleaned' $I/B/E/S$ universe. Our sample contains a total of 112,973 earnings forecasts on 5,581 unique firms (Appendix B). If we average across years, 53% of earnings forecasts are made by analysts with experience. Conditional on having industry experience, we find that close to half of earnings forecasts are made on firms by analysts with related industry experience. Taking the time series average of our sample relative to the clean sample on $I/B/E/S$, our sample represents 61% of firms, 19% of forecasts, and 79% of market capitalization.

Table 1 here

We note two evident time series patterns shown in panel A. First, our ability to find reliable employment data for analysts is much lower in the early part of our sample and increases through time. For instance, before the 1993-1997 time period, we are able to use less than 10% of analyst earnings forecasts, but this rises to close to 50% in the last year of our sample. Second, the

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[3] In order to identify the industry group of the firms listed in the comprehensive analyst employment background data, we first merge the names of pre-analyst employers with CRSP/COMPUSTAT based on the firm name. For those matched firms, we assign each firm into one of the 5 Fama-French industry classification groups based on their 4-digit SIC code. For the unmatched public or private firms, we conduct a thorough web search and manually assign each firm to one of these industry groups based on either the business description from Securities and Exchange Commission (SEC)'s website, firm's official website or other business news websites such as Bloomberg and BusinessWeek.

[4] We recognize that we are broadly defining related industry experience by using only 5 Fama-French industry classifications. Because the majority of employers in our analyst employment background data are private firms, it is difficult to assign analysts to finer industries. However, if anything, this introduces noise and biases any results against us. To deal with this concern, we rerun our analysis using the subset of analysts that worked for publicly-traded firms. In this analysis, we are able to assign previous employment using the Global Industry Classification Standard (GICS). Boni and Womack (2006) suggest that the GICS system matches well with analyst industries. The results are robust and discussion of this analysis is presented in section 7.

percentage of forecasts issued by analysts that have previous employment experience also rises through time (from about 1/3 to 3/4 of analysts). These time series patterns are likely due to the sharp increase in the use of online employment networks particularly among investment professionals in recent years.

Panel B of table 1 provides summary statistics on the main variables used throughout this paper. We follow the literature and construct our primary performance measure for relative earnings forecast accuracy as the proportional mean absolute forecast error ($PMAFE_{i,j,t}$) developed by Clement (1999) and widely adopted in the literature (i.e, Malloy, 2005; Clement et al., 2007; De Franco and Zhou, 2009; Horton and Serafeim, 2012; etc.). Specifically, $PMAFE_{i,j,t}$ is defined as the difference between the absolute forecast error ($AFE_{i,j,t}$) of analyst *i* for firm *j* in time *t* and the mean absolute forecast error for firm *j* at time *t*. This difference is then scaled by the mean absolute forecast error for firm *j* at time *t* to reduce heteroskedasticity. PMAFE is the relative forecast accuracy for all analysts covering the same firm and thus controls for differences across companies, time and industry (Ke and Yu, 2006). As constructed, negative values of $PMAFE_{i,j,t}$ represent better than average performance, while positive values indicate worse than average performance. Formally, the proportional mean absolute forecast error is defined as:

$$AFE_{ijt} = \text{Absolute (Forecast EPS}_{ijt} - \text{Actual EPS}_{ijt}) \quad (1)$$

$$PMAFE_{ijt} = (AFE_{ijt} - MAFE_{jt})/MAFE_{jt} \quad (2)$$

where AFE_{ijt} is the absolute forecast error for analyst *i*'s forecast of firm *j* for year *t*, and $MAFE_{jt}$ is the mean absolute forecast error for firm *j* for year *t*. The lower the PMAFE value the more accurate the forecast.[5]

Following Clement (1999) and others, we include several proxies for analyst ability and experience. We report general and firm-specific forecasting experience, which are calculated as the total number of years that analyst *i* appeared in *I/B/E/S* (*Gexp*) and the total number of years since analyst *i* first provided an earnings forecast for firm *j* (*Fexp*), respectively. Clement (1999) shows that relative forecast errors are positively associated with the number of days between the forecast and announcement of actual earnings date, emphasizing the need to control for timeliness. Therefore, age is the number of days between the forecast and earnings date (*Age*). Portfolio complexity is

[5] To account for outliers, we winsorize PMAFE at the 0.5% tails. The results are robust with or without winsorizing.

measured by the size of analyst's *i's* coverage portfolio (*PortSize*) and the number of 2 digit SICs followed by analyst *i* (*SIC2*). Resources available to analysts is controlled for by employment at large brokerage houses, which takes the value of 1 if analyst *i* works at a top decile brokerage house (*Top10)*, zero otherwise. The left-hand columns in panel B present these unadjusted mean values. The average absolute forecast error is 0.12, which is consistent with existing studies. The average analyst in our sample has been providing forecasts for 6.7 years, and covering the average firm in our sample for 2.8 years. The average number of days between forecasts and earnings announcements is 85.6. The average analyst covers 12.4 firms each year, which represents 3.5 distinct 2-digit SIC codes. Approximately 60% of forecasts are issued by analysts working for a top decile brokerage house. These values are in line with those reported in other studies (e.g. Clement et al., 2007; De Franco and Zhou, 2009).

The right-hand columns in panel B present mean-adjusted values. Clement (1998) finds that controlling for firm-year effects in dependent and independent variables improves the likelihood of identifying performance differences across sell-side analysts compared to a model that includes firm and year fixed effects. This is due to a firm's predictability of earnings changing over time. Therefore, we follow the literature and adjust these variables by their related firm-year means in order to control for firm-year effects (Clement, 1999; Clement et al., 2007). Appendix C provides a detailed discussion of how we compute these variables. Of course, subtracting mean values from raw values will drive the averages closer to zero, which is what we find.

4. Relative forecast accuracy and industry experience

In this section, we examine the forecast accuracy made by analysts with related industry experience compared to other analysts. We test the hypothesis that forecasts issued by these analysts are more accurate. As a starting point for our analysis, we examine univariate differences between earnings forecasts from analysts with related industry experience and forecasts by analysts with either unrelated experience or with no pre-analyst experience at all. In untabulated tests, the average PMAFE for related forecasts is -0.16 compared to unrelated forecasts or forecasts of inexperienced analysts at -0.09 and -0.12, respectively. A *t*-test assuming equal variances indicates that these differences are statistically significant indicating that analysts with related industry experience are more accurate forecasters.

Insert Table 2 here

Table 2 reports Pearson correlation coefficients between the main variables in the forecasting models. Each value is multiplied by 100. Earnings forecast errors are negatively correlated with pre-analyst work experience, however only when the forecast is made on a firm operating in an industry related to the analysts' previous work experience. Conversely, unrelated experience is positively correlated with forecast errors. Related and unrelated work experience are negatively correlated with analyst general and firm specific forecasting experience and portfolio complexity, and also positively correlated with brokerage size. With the exception of the correlation between general and firm-specific experience, the correlations are not exceptionally worrisome, particularly since they are mean-adjusted. These correlations are consistent with Clement (1999).

4.1 Baseline regression model for forecast accuracy

We employ a multivariate OLS regression model to formally test our first hypothesis that related industry experience will result in better forecast accuracy. The primary variables of interest are binary variables representing previous work experience, overall experience (*Experience*), related experience and unrelated experience. In addition to the variables presented in table 2, we also control for firm-level characteristics. Specifically, we include controls for size, book-to-market, stock momentum and the number of analysts covering each firm. The dependent variable in each model is the proportional mean absolute forecast error (PMAFE). Standard errors are heteroskedastic-consistent and clustered at the firm and analyst level. Formally, our model is as follows:

$$PMAFE_{i,j,t} = \beta_0 + \beta_1(Experience)/\beta_2(Related\ experience) + \beta_3(Unrelated\ experience) + \beta_4(DGExp) + \beta_5(DAge) + \beta_6(DFExp) + \beta_7(DPortsize) + \beta_8(DSIC2) + \beta_9(DTop10) + \beta_{10}(Size) + \beta_{11}(BM) + \beta_{12}(Past\ Ret) + \beta_{13}(No\ of\ analysts) + \varepsilon \quad (3)$$

Insert Table 3 here

Table 3 reports the regression results. Models 1-2 use the full sample of earnings forecasts. Model 1 indicates that earnings forecasts issued by experienced analysts are relatively more accurate compared to those of analysts without pre-analyst work experience. Economically, analysts with previous employment experience issue earnings forecasts that are on average 1.55% more accurate. Consistent with previous studies, analyst experience as measured by both analyst general and firm-specific forecasting experience results in more accurate forecasts, while busier analysts that cover more firms have poorer earnings forecasts. Analysts that work for more prestigious banks have better forecasts consistent with the view that have more resources available to them. The more analysts that cover a firm the more accurate are the earnings forecasts, which is likely due to a lower degree of asymmetric information for these more followed firms. In general, the coefficients on the control variables are consistent with the analyst earnings forecast literature.

In model 2 we decompose experience into its related and unrelated experience components. The results suggest that only forecasts made by analysts with related industry experience produce more accurate forecasts. The coefficient on *Related experience* indicates that relative annual earnings forecast errors of experienced analysts on related firms are 3.58% (t=-6.76) more accurate compared to that of inexperienced analysts. On the other hand, experienced analysts' forecasts on unrelated firms are not more accurate than inexperienced analysts. Other control variables have generally similar coefficients as estimated in model 1.

In model 3, we restrict the sample to only experienced analysts that provide both related and unrelated forecasts. Thus, this particular estimation examines the ability of analysts with previous employment experience to forecast on companies in both related and unrelated industries. That is, analyst i makes forecasts on firms R and U, where R is related to her previous work experience and U is unrelated. The findings indicate that forecasts by analysts on related firms are 4.3% more accurate compared to forecasts on unrelated firms, on average. Taken together, these results are consistent with the hypothesis that industry experience improves forecasting performance of sell-side analysts.

In models 4-9 we investigate the impact of previous analyst experience on bold versus herding forecasts. Several papers suggest that bold forecasts are more likely to reflect sell-side analysts' private information compared to herding forecasts (Hong, Kubik and Solomon, 2000; Clement and Tse, 2005). Therefore, the impact of analyst work experience on earnings forecast accuracy might be more pronounced for bold forecasts if analysts use industry knowledge to their advantage. Bold forecasts are defined as earnings forecast revisions that are above/below both the consensus and the previous earnings forecast issued by the same analyst on the same firm (Gleason and Lee, 2003). Herding forecasts are the complement to bold forecasts.

Similar to the results for the full sample in models 1-3, analysts with related industry experience produce more accurate earnings forecasts. These results provide further evidence that previous industry experience improves forecast performance regardless of boldness behavior.

4.2 Sorts by analysts characteristics

In this subsection, we sort on several analyst characteristics that have been shown to impact forecast accuracy to determine if industry expertise is a general effect or only impacts a subset of analysts. In particular, we focus on *II* all-stars (yes/no), overall analyst forecasting experience (above/below median), brokerage house prestige (yes/no), affiliation status (Affiliated/Unaffiliated), and two proxies for industry complexity (analyst has a PhD and firm is in a high-tech industry).[6] We estimate equation (3), but to conserve space, we only report the key experience coefficients. The results are presented in Table 4.

Insert Table 4 here

Panel A reports coefficient values and *t*-statistics for related industry experience across subsamples of analyst traits. To facilitate comparison, we also report the coefficient from the full sample as in table 3. For all earnings forecasts in row 1, we find that having previous industry experience results in better forecast accuracy across all other analyst characteristics. Coefficient estimates range from -2.68% to -6.85%. Thus, previous work experience is an independent effect from all-star status, general forecasting experience, brokerage house prestige, analyst affiliation, industry complexity and has a lasting impact throughout an analyst's career.

When we separate bold from herding forecasts, we generally find similar results. For bold forecasts, industry experience matters for all categories of analyst attributes. While the coefficient is negative in all of the herding regressions, it is not significant for all-stars, analysts with less general experience, analysts that work for more prestigious brokerage houses, affiliated analysts, analysts with PhDs, and non-tech firms.

Panel B reports coefficient estimates for *Unrelated Experience*. Some interesting results emerge. We find that unrelated experience leads to worse forecast accuracy for presumably more skilled analysts (all-stars, more experienced, and top 10 broker). This may imply that more skilled analysts with prior success become overconfident in their abilities when making forecasts on firms in industries unrelated to their own experience (Hilary and Menzly, 2006). These are generally consistent for bold and herding forecasts. Analysts that work at lower ranked brokerage houses seem to benefit from unrelated work experience, but only when they herd.

[6] Close to 4% of our sample of analysts have a PhD. Of these analysts, close to half cover the biotechnology industry while another 20% cover software and semiconductor equipment. Thus, analysts with PhDs tend to cover complicated industries. Along with educational traits, we also consider if the analyst has an MBA degree. For the 46% of analysts that have an MBA, we find they do not provide more accurate forecasts than analysts without an MBA.

4.3 Analyst experience and learning curves

Learning-by-doing models suggest a positive relation between experience and task performance improvement. A number of studies have applied this model in the context of sell-side analysts and document that company-specific forecast experience yields improvements in forecast accuracy. In these models, the starting point of analysts' accumulation of experience is measured by general and company-specific experience (Mikhael et. al, 1997, 2003; Jacob et al. 1999; Clement et al., 2007). In our context, we examine if analysts' previous employment experience results in a steeper learning curve. In a similar fashion to Clement and Tse (2005), we measure the improvement in forecast accuracy as the difference between PMAFE for analyst *i* for firm *j* between year *t* and *t-1*. All independent variables are measured as changes between *t* and *t-1* as well. If experienced analysts increase their relative forecast accuracy at a faster rate relative to their non-experienced counterparts, the coefficient on *Experience* should be significantly negative. Like our previous analysis, we differentiate between related and unrelated experience and include similar control variables as in table 3.

Insert Table 5 here

The findings in Table 5 reveal a significant negative coefficient on related experience, suggesting that analysts with pre-analyst work experience show more improvement in their forecasting performance relative to inexperienced analysts. Results are robust for the full sample, and also for bold and herding forecasts. Other analyst characteristics are also associated with expected signs. For example, analysts with lower initial forecast performance, higher company-specific forecasting experience, and analysts working for high-status brokerage houses are associated with larger improvements in forecasting performance.

Overall, the results in section 4 paint a very clear picture. Analysts with pre-analyst work experience in a related industry as firms in their coverage portfolio make more accurate earnings forecasts and have a steeper learning curve, on average. This effect is pervasive. It is present in earnings forecasts that are considered bold or herding and holds after controlling for other known analyst characteristics previously shown to influence analyst forecasting accuracy. Economically, it is just as large as these other known important influences.

5. Experience and career concerns

We have demonstrated that previous industry experience aids in analysts' abilities to forecast earnings. As Hong and Kubik (2003) and others have found, forecast accuracy is related to analyst career concerns. And as discussed previously and shown in Appendix A, industry knowledge is the most important quality that buy-side institutions value in analysts. In this section, we explore whether this previous experience leads to favorable career outcomes after controlling for forecast accuracy.

Data limitations prevent us from directly examining the link between analyst compensation and industry experience. However, as Groysberg, Healy and Maber (2011) report, holding brokerage firm prestige constant, *II* all-stars earn 61% more than non-star analysts.[7]

We first estimate a probit regression and explore the likelihood of becoming an *II* all-star analyst using similar analyst characteristic variables in our other models. Our primary interest is in the relation between analyst industry experience and all-star status in the following year.[8] We include year fixed effects with standard errors that are heteroskedastic-consistent and clustered at the analyst level. The probit model takes the following form:

$$Probit\ (All\text{-}star\ next\ year=1)_{i,t+1} = \beta_1(Experience) / \beta_2(Related\ experience) + \beta_3(Unrelated\ experience) + \beta_4(GExp) + \beta_5(Port\ size) + \beta_6(SIC2) + \beta_7(Brokerage\ size) + \beta_8(Average\ PMAFE) + \beta_9(Average\ firm\ size) + \beta_{10}(All\text{-}star) + Year\ dummies + \varepsilon \quad (4)$$

Insert Table 6 here

The first column in Table 6 suggests that analysts with industry work experience are more likely to become all-star analysts compared to inexperienced analysts from similar brokerage houses. The odds ratio is 1.63, which implies that the odds of being elected an all-star analyst among analysts with previous industry experience is 63% higher than the odds among analysts without industry experience. All of the other control variables behave as expected and are consistent with the literature. For example, analysts with greater skill (i.e., more general experience, employed by higher-status brokerage houses) and following larger firms are more likely to be selected all-stars. It is important to note that we also find that forecast accuracy is related to becoming an all-star, but industry experience is still statistically and economically relevant. Finally, the likelihood of becoming an all-star in year *t+1*, is correlated with being an all-star in year *t*.

[7] One reason for the disparity in compensation between star and non-star analysts is because all-star analysts are instrumental in attracting investment banking deal flow (Clarke, Khorana, Patel, and Rau, 2007). However, in 2003, the Global Research Settlement prohibited analyst compensation being tied to investment banking business.

[8] Previous work has shown analysts working for larger and more reputable banks are more likely to be selected all-star members (Emery and Li, 2009; Cohen, Frazzini, and Malloy, 2010). Therefore, we match each experienced analyst to a portfolio of inexperienced analysts based on the size quintile of their brokerage houses. Results are qualitatively similar with or without matching and when we use quartile matching.

We next decompose experienced analysts into related and unrelated based on the composition of their portfolios. Specifically, we define an experienced analyst if they follow at least 1 firm operating in a related industry, else they are unrelated. In model 2, we document that experienced analysts following related firms are more likely to become all-stars compared to inexperienced analysts or experienced analysts following only unrelated firms. Finally, in model 3 we include only analysts with experience. Again, *Related Experience* is positive and significant.[9]

As an additional way to assess the impact of industry work experience on career outcomes, we also examine the probability of moving up to a more prestigious brokerage house. We reestimate equation 4, but the dependent variable is a binary variable that takes a value of one if the analyst is promoted to a more prestigious brokerage house, zero otherwise. In untabulated results, we find industry experience is important for movement to a top decile brokerage, but the result for related industry experience is weak.[10]

6. Stock price impact of experience on forecast revisions

Given our evidence of higher forecast accuracy for industry experienced analysts and a higher likelihood of being included in the *II* rankings, we next investigate the market reactions to forecast revisions issued by these analysts. If buy-side institutions value industry knowledge because they perceive it leads to superior forecasting skills, then it is plausible that institutions and other market participants are more likely to listen to analysts with previous industry experience. If so, the market reaction to these forecasts should be more pronounced.

Similar to the framework developed in Ivkovic and Jegadeesh (2004), we consider the direction as well as the magnitude of forecast revisions (*FR*) when examining the implications of pre-analyst experience for market reactions. We regress cumulative abnormal 3-day CRSP VW-Index adjusted returns on the interactions between the magnitude of forecast revisions and experienced binary variables, and then we compare the coefficients across these interactions. Our regression model also controls for a wide array of analyst and firm characteristics in equation (3) and

[9] In model 3, we also restrict the sample to analysts that cover at least one firm related to their previous experience and compute the proportion of the analyst's coverage portfolio that is related to their industry experience. We continue to find a positive and significant relationship.

[10] As pointed out to us, a junior research analyst at a top brokerage house moving down to a lower-level brokerage in a senior position may be considered a favorable career move thus making this test problematic. On the other hand, being included in the annual *II* all-star poll is unambiguously favorable.

includes year fixed effects with heteroskedasticity-robust and standard errors clustered at the firm and analyst level. Our model is as follows:

$$CAR_{i,j,t} = \beta_1(FR*Experience)/\beta_2(FR*Related\ experience) + \beta_3(FR*Unrelated\ experience) + \beta_4(FR*Inexperience) + \beta_5(DGExp) + \beta_6(DAge) + \beta_7(DFExp) + \beta_8(Dportsize) + \beta_9(DSIC2) + \beta_{10}(DTop10) + \beta_{11}(Size) + \beta_{12}(BM) + \beta_{13}(Past\ ret) + \beta_{14}(No\ of\ analysts) + Year\ dummies + \varepsilon \quad (5)$$

Insert Table 7 here

Table 7 presents the regression results. Models 1-3 report results for upward revisions and models 4-6 report downward revision estimates. In model 1, the main variables *Experience* and *Inexperience* interacted with the forecast revision are reported. The coefficients on *FR*Experience* and *FR*Inexperience* are 5.70 and 4.20, respectively, both of which independently are highly significant. However, this is not surprising since they are interacted with forecast revisions. The important question is whether or not the coefficients are significantly different from each other. We find they are (p-value = .001). To interpret, a 1 standard deviation in forecast revision for upward revisions is approximately 0.12, multiplied by the difference in coefficients (5.7 – 4.2 = 1.5%) results in approximately 0.18% larger market reaction for experienced analysts.[11]

In model 2, we separate experience into its related and unrelated components. The coefficients on *FR*Related experience, FR*Unrelated experience* and *FR*Inexperience* are 6.60, 4.99, and 4.20, respectively. Thus, a 1 standard deviation in relative analyst forecast revisions implies a 0.19% and 0.29% larger market reaction to forecasts from analysts with industry experience compared to analysts with unrelated experience or no experience, respectively. The difference in market reactions between related analyst experience and unrelated or inexperienced forecasts are highly statistically significant at conventional levels. However, the difference in market reactions between experienced analysts in unrelated industries and inexperienced analysts is not (p-value = 0.26).

Model 3 is conditional on experienced analysts that provide both related and unrelated industry forecasts similar to table 3, model 3. Holding previous industry experience constant, market reactions are stronger for upward earnings forecasts when they coincide with an analyst's previous employment experience. On average, given a 1 standard deviation in forecast revisions, the market reaction is 0.20% higher for revisions made by an analyst on a firm that has previous related industry

[11] Note that because we have all four types of analyst categories in the specification, we do not include *FR* alone (Ivkovic and Jegadeesh, 2004).

experience compared to forecast revisions by the same analysts that provide earnings forecasts on unrelated companies.

Models 4-6 present results for downward revisions. Similar to the results for upward revisions, previous industry experience is important. In model 1, a 1 standard deviation change in downward revisions results in a -0.21% lower reaction (for downward revisions, 1 standard deviation from the mean equals 0.15). When we examine related and unrelated industries, we observe larger differences for downward revisions than upward revisions. For instance, in the conditional regression in model 6, the market reaction is -0.39% greater when an analyst provides a downward forecast on a related industry compared to when the same analyst provides a downward forecast on an unrelated industry.[12]

7. Discussion and robustness tests

We have documented that previous industry experience aids analysts in providing more accurate forecasts, is related to favorable career outcomes, and market reactions are higher for analysts possessing such experience. In this section, we explore potential channels through which industry experience manifests itself and provide additional robustness tests.

7.1 Channel through which industry experience is transmitted

We are interested in the channel through which previous industry experience permeates analysts' superior forecasting skills. There are two likely potential channels. First, analysts with previous industry experience likely have industry or social connections to management and other employees at their former job. Additionally, similar connections may exist up and down the supply chain and/or with former customers if the analyst had interactions outside of their firm. Through these social connections, analysts may be privy to soft or private information that is not easily accessible through normal channels. This may be the source of the analyst's superior forecasts. Cohen, Frazinni, and Malloy (2010) find that analysts with school ties to senior executives perform better than non-connected analysts. They suggest that these connections promote the transfer of private information. In our context, the social connections made while working in the industry would foster these relationships.

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[12] We also separate bold and herding forecast revisions. For bold revisions, the results are qualitatively similar to the full sample results for both upward and downward revisions. For herding revisions, only the coefficient on related industry experience is statistically (and economically) significant for both revision types. These results are available upon request.

Alternatively, previous industry employment may give an analyst a competitive advantage in their ability to analyze industry fundamentals such as industry trends, competitive threats and positioning within the industry, impact of regulation, etc. To determine which of the two influences are the most dominant, we employ a test similar to Cohen et al. (2010) where we estimate separate regressions before and after Regulation Fair Disclosure (Reg FD). Reg FD prohibited selective disclosure of information to sell-side analysts and thus lessened the benefit of having social connections. Cohen et al. (2010) find that the competitive advantage of educational ties disappeared after Reg FD implying that the transfer of private information from these connections stopped (or at least was not embedded in analysts' recommendations). If the social connection explanation of industry experience dominates, we would observe the impact of related industry experience to diminish in the post-Reg FD era. However, if industry experience is present before and after Reg FD, industry expertise is a more likely explanation.

Insert Table 8 here

Table 8 presents the estimation of equation 3 pre- and post-Reg FD. We find that experience, driven by related industry experience is significantly related to forecast accuracy in both periods. This implies that industry knowledge through social connections is an unlikely explanation for our results. Rather, the channel through which industry knowledge is reflected in analyst forecasting is more likely related to a fundamental understanding of industry dynamics. It is worth noting that according to Appendix A, industry knowledge is just as important to buy-side institutions after as before Reg FD. Our results are at least consistent with this view.[13]

7.2 Industry classification

A legitimate concern with our analysis is that our industry classifications are based on broad Fama-French industry classifications. These concerns should be mitigated because our conditional models examine differences in forecasts by experienced analysts that provide forecasts on firms both related and unrelated to their previous employment experience. Further, misclassification will introduce noise and bias the results against us finding differences between analysts with and without industry experience. Nonetheless, we acknowledge this still may be a reasonable concern. To deal with this potential issue, we limit our sample to the 458 analysts that worked at publicly-traded firms before becoming an analyst. We then use the Global Industry Classification System (GICS) that

[13] We also examine market reactions to analyst forecast revisions in the pre- and post-Reg FD periods. We find that related industry experience is significant in both periods consistent with the forecast accuracy results.

classifies firms into 68 industries. Boni and Womack (2006) argue that the GICS system matches well with analyst industries. GICS classifications are also used in Kadan, Madureira, Wang and Zach (2012).

Insert Table 9 here

Table 9 estimates equation 3 with the sample of publicly-traded firms that can easily be assigned to GIC industries. We find the results are robust in this more restricted sample. Comparing the coefficients on *Related experience* from table 3 (model 3) to model 1, table 9, the economic magnitude is larger for this more restricted sample of publicly-available firms (-5.04 versus -4.33). Thus, our classification system based on broad industries does not pose a problem for our analysis.

7.3 Self-selection and measurement of related industry experience

Another reasonable concern with our analysis is that analysts self-select to subscribe to *Linkedin.com*. This may be a particular concern in the early part of our sample as our match rate with these sources is low. To deal with this concern, we perform two additional tests. First, we estimate equation (3) for each of the 6 time periods in panel A of table 1. In 5 of the 6 time periods, we find our results are statistically and economically robust. Second, we consider the universe of $I/B/E/S$ coverage and create a variable *Linkedin Dummy*, which equals one if we captured the analyst's employment information, zero otherwise. We are interested if self-reported analysts (those that subscribe to *Linkedin*) are systematically different than analysts that do not subscribe to this service. Model 1 of table 10 reports this result. We find that the coefficient on *Linkedin Dummy* is negative, but statistically insignificant.

Insert Table 10 here

We have interpreted the results of our findings being consistent with the view that industry experience aids in analysts' performance because it provides them with a competitive advantage over their inexperienced peers. An alternative explanation is that analysts simply exert more effort on these firms because they believe they can forecast them better. With an asymmetric level of effort, it might explain why they forecast industry-related firms better. To gauge effort, we consider the number of revisions made on portfolio firms within a given year (Jacob, Lys and Neale, 1999). The number of revisions provides a reasonable proxy for effort as more revisions reflect more information production. Model 2 provides the results of this analysis. The variable of interest is

Related experience, which is positive, but statistically insignificant. This implies that analysts' level of effort for industry-related and unrelated forecasted firms is not different.[14]

In most of our tests we use a dummy variable to capture related industry experience primarily because of the ease of economic interpretation and the ability to separate the impact of accuracy on related and unrelated forecasts. Rather than using a dummy variable, in model 3 of table 10, we instead use a continuous variable of related experience. Specifically, for each forecasted firm, we substitute the natural logarithm of 1 plus the number of years of industry-related experience. The coefficient is -0.8 and highly statistically significant. Economically, this suggests a 1 year increase in analyst related industry experience will lead to about 0.16% improvement in forecast accuracy. Thus, it does not matter whether we use the actual length of industry experience or a dummy—our results remain robust.

Model 4 is conditional on analysts forecasting industry-related firms only. The coefficient is -3.1, which implies a 0.63% improvement in relative forecast accuracy given a one year increase in related experience. This also confirms that our results are not driven by potential self-selection of analysts exerting more effort on companies related to their previous experience.

7.4 Alternative proxy for forecast accuracy

Throughout our paper, we adopt the widely-accepted measure of analyst forecast accuracy developed in Clement (1999). To ensure our results are robust, we also use the performance metric in Hong and Kubik (2003). In this method, forecast errors are computed for each firm covered by an analyst. Analysts are then ranked based on this performance and a score between 0 and 100 is assigned to each analyst (see Table IV, page 322 in Hong and Kubik (2003) for a hypothetical example). Relative forecast accuracy is the average of all analyst *i*'s scores over year *t, t-1* and *t-2*. As Hong and Kubik argue, this long 3-year average horizon should reduce noise and might be a more appropriate test for performance persistence.[15]

In untabulated analyses, we reestimate equation 3 substituting this new measure of relative forecast accuracy in place of PMAFE. Year, firm, and industry fixed effects are included in these models. Similar to the results found in Table 3, we continue to find that analysts with related experience have significantly better forecast accuracy. Further, we also find that unrelated industry

[14] We also consider if analysts with related industry experience are more likely to provide bold forecasts on their set of industry-related firms. We do not find evidence supporting this conjecture.
[15] We also compute this measure over only year *t* and find similar results.

experience does not aid performance. Thus, our results are robust to this alternative measure of forecast accuracy.

7.5 Industry forecasting experience

It is known that analysts tend to specialize in industries, so it is likely that an analyst's industry forecasting experience is highly correlated with general experience (we find the correlation is 0.85). Nonetheless, we control for an analyst's industry forecasting experience by computing the number of years that each analyst provided forecasts in the same 2-digit industry as the forecasted firm. We estimate equation (3) and in untabulated results, we find that related pre-analyst experience is still highly significant (coefficient = -3.93, t-stat = -9.23).

8. Conclusion

Practitioners indicate that industry knowledge is consistently the most important quality a sell-side analyst can possess. Despite this anecdotal observation, surprisingly little empirical evidence has addressed how industry knowledge impacts analyst performance and career concerns. This paper attempts to fill this gap. Using novel biographical data on sell-side analysts, we exploit their previous employment history and examine how previous employment in related and unrelated industries influence earnings forecasts, career concerns, and market responses to earnings revisions.

In our sample of earnings forecasts from 1983 to 2011, we find that analyst forecasts are more accurate for analysts with previous industry experience. However, this is only true for analysts with experience in industries related to the firms they cover. Likewise, experienced analysts have a steeper learning curve. That is, their forecast accuracy improves at a faster rate compared to inexperienced analysts or analysts with unrelated experience. These results are robust after holding constant other known analyst characteristics linked to skill such as general and firm-specific forecasting experience, portfolio complexity, and working for a top brokerage house. We test if this superior performance is driven by social connections or fundamental knowledge of industry dynamics. Our results suggest that the latter is a more likely explanation.

In subsequent analyses we examine if industry experience influences analysts' career concerns. Analysts with related industry experience are more likely to be named to *II* annual all-star poll. Finally, we document that analysts' previous industry experience is positively related to the market reaction of analyst forecast revisions. Thus, given that buy-side institutions rank industry knowledge as the most important analyst trait, this suggests that they are more likely to listen to analysts’ forecast revisions if they have previous industry experience to acquire this superior knowledge.

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Table 1. Summary statistics

This table reports summary statistics of the sample. Panel A presents summary statistics by period. % Forecasts Experienced, % Related Forecasts, and % Unrelated Forecasts are the percentage of forecasts made by analysts that have any previous work experience (Experienced) and work experience in a related industry (Related) or unrelated industry (Unrelated) to the analyst's forecast on a firm. % Firm, % Forecasts, and % Market Capitalization is the percentage of firms, forecasts, and market capitalization representing the 'clean' *I/B/E/S* universe of US firms. Panel B presents descriptive statistics of analyst characteristics of our main variables used throughout this paper. See Appendix B for a detailed description of the data screening and collection process and Appendix C for a description of control variables. Analyst data are from *I/B/E/S* from 1983 to 2011, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Employment history is collected from *LinkedIn.com* and supplemented with *Zoominfo.com*.

Panel A: Summary statistics by period

Year	*N* Firms	*N* Forecasts	% Forecasts Experienced	% Related Forecasts	% Unrelated Forecasts	% Firms	% Forecasts	% Market Capitalization
1983-1987	866	1,240	29%	13%	16%	24%	2%	48%
1988-1992	2,330	4,083	42%	20%	22%	38%	6%	68%
1993-1997	4,638	10,055	48%	23%	25%	51%	10%	79%
1998-2002	6,796	22,736	61%	32%	29%	73%	22%	89%
2003-2007	8,723	42,249	67%	36%	31%	89%	36%	95%
2008-2011	5,712	32,610	73%	37%	36%	95%	44%	99%
Sum/Avg.	29,065	112,973	53%	27%	26%	61%	19%	79%

Panel B: Unadjusted and mean-adjusted analyst characteristics

	Unadjusted				Mean-adjusted		
	Mean	Median	Std. Dev.		Mean	Median	Std. Dev.
AFE	0.12	0.04	1.81	*PMAFE*	-0.13	-0.26	0.72
GExp	6.70	6.00	5.24	*DGExp*	-0.16	-0.89	4.93
FExp	2.83	2.00	3.12	*DFExp*	0.00	-0.17	2.69
Age	85.62	67.00	51.51	*DAge*	-15.42	-23.71	49.95
Portsize	12.40	12.00	6.16	*DPortsize*	0.11	-0.30	5.49
SIC2	3.53	3.00	2.36	*DSIC2*	-0.06	-0.25	1.83
Top10	0.60	1.00	0.49	*DTop10*	0.04	0.24	0.45

Table 2. Pearson correlation coefficients between main variables

This table presents correlation coefficients between our main explanatory variables. All values are multiplied by 100. See Appendix C for a description of control variables. Analyst data are from *I/B/E/S* from 1983 to 2011, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Employment history is collected from *LinkedIn.com* and supplemented with *Zoominfo.com*.

	Experience	*Related experience*	*Unrelated experience*	*PMAFE*	*DGExp*	*DFExp*	*DAge*	*DPortsize*	*DSIC2*	*DTop10*
PMAFE	-0.71***	-3.52***	2.87***	100						
DGExp	-26.58***	-11.66***	-15.51***	0.11	100					
DFExp	-10.42***	-0.18	-10.50***	0.13	53.55***	100				
DAge	-0.27	-2.45***	2.25***	42.68***	3.77***	4.04***	100			
DPortsize	-7.22***	-5.35***	-2.13***	1.03***	26.38***	13.70***	-0.22	100		
DSIC2	-4.43***	-3.35***	-1.19***	2.48***	11.27***	4.90***	2.58***	61.36***	100	
DTop10	6.05***	1.82***	4.32***	-2.54***	-2.90***	-1.68***	-1.85***	-1.78***	-11.92***	100

Table 3. Regression of analyst forecast accuracy and previous work experience

This table presents OLS regression results for analyst earnings forecasts for the full sample and bold and herding forecasts. The dependent variable is the proportional mean absolute forecast error (PMAFE) defined as the difference between the absolute forecast error for analyst *i* for firm *j* and the mean absolute forecast error at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. Bold forecasts are defined as earnings forecast revisions that are above/below both the consensus and previous earnings forecast issued by the same analyst on the same firm. Herding forecasts are the complement of bold forecasts. The primary variables of interest are *Experience*, *Related experience*, and *Unrelated experience*, which represent analysts' previous overall employment and previous employment in an industry related or unrelated to the firms forecast, respectively. See Appendix C for a description of control variables. Analyst data are from *I/B/E/S* from 1983 to 2011, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Employment history is collected from *LinkedIn.com* and supplemented with *Zoominfo.com*. *t*-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	All Forecasts			Bold Forecasts			Herding Forecasts		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	5.45***	5.07***	5.38***	1.47	0.99	1.53	17.73***	17.45***	17.75***
	(4.734)	(4.40)	(3.86)	(1.15)	(0.78)	(0.99)	(7.26)	(7.13)	(5.86)
Experience	-1.55***			-1.57***			-0.87		
	(-3.28)			(-3.07)			(-0.87)		
Related experience		-3.58***	-4.33***		-3.77***	-4.70***		-2.94***	-4.44***
		(-6.76)	(-8.05)		(-6.54)	(-8.19)		(-2.68)	(-3.76)
Unrelated experience		0.76			0.91			1.53	
		(1.36)			(1.53)			(1.26)	
DGExp	-0.16***	-0.16***	-0.15*	-0.15**	-0.15**	-0.09	-0.16	-0.17	-0.33*
	(-2.95)	(-2.96)	(-1.90)	(-2.53)	(-2.49)	(-1.06)	(-1.32)	(-1.37)	(-1.94)
DAge	0.51***	0.51***	0.52***	0.51***	0.50***	0.52***	0.54***	0.54***	0.54***
	(93.50)	(93.27)	(76.28)	(78.98)	(78.79)	(64.51)	(52.06)	(51.91)	(41.88)
DFExp	-0.26***	-0.22**	-0.21	-0.18*	-0.14	-0.16	-0.51**	-0.47**	-0.32
	(-2.77)	(-2.31)	(-1.61)	(-1.78)	-0.14	(-1.20)	(-2.54)	(-2.31)	(-1.14)
DPortsize	0.11**	0.10*	-0.01	0.02	0.01	-0.06	0.31***	0.31***	0.12
	(2.02)	(1.88)	(-0.22)	0.02	(0.14)	-0.06	(3.00)	(2.94)	(0.88)

DSIC2	0.21	0.21	0.39**	0.16	0.15	0.29	0.29	0.30	0.63
	(1.38)	(1.39)	(2.05)	(0.95)	(0.93)	(1.36)	(0.92)	(0.95)	(1.55)
DTop10	-2.04***	-2.11***	-0.73	-1.73***	-1.80***	-0.94	-2.01**	-2.10**	0.52
	(-4.38)	(-4.53)	(-1.27)	(-3.44)	(-3.56)	(-1.51)	(-2.00)	(-2.09)	(0.42)
Size	-0.27	-0.22	-0.15	-0.22	-0.16	-0.11	-0.59	-0.55	-0.34
	(-1.54)	(-1.25)	(-0.66)	(-1.13)	(-0.82)	(-0.47)	(-1.58)	(-1.47)	(-0.71)
BM	-0.02***	-0.02***	-0.02***	-0.01	0.01	0.16	-0.03***	-0.03***	-0.02***
	(-4.26)	(-4.16)	(-5.75)	(-0.06)	(0.03)	(0.55)	(-6.65)	(-6.39)	(-7.44)
Past Ret	7.43*	7.74**	3.94	-7.18*	-6.94	-10.00*	67.86***	68.67***	65.11***
	(1.94)	(2.02)	(0.84)	(-1.68)	(-1.63)	(-1.91)	(7.95)	(8.04)	(6.15)
No of Analysts	-0.45***	-0.46***	-0.46***	-0.46***	-0.47***	-0.46***	-0.33***	-0.34***	-0.37***
	(-15.26)	(-15.38)	(-12.29)	(-14.50)	(-14.63)	(-11.50)	(-5.05)	(-5.09)	(-4.45)
R^2	13.10%	13.15%	13.53%	13.06%	13.13%	13.56%	14.08%	14.13%	14.34%
n	112,479	112,479	75,810	85,612	85,612	55,984	26,867	26,867	17,322

Table 4. Regression of analyst forecast accuracy sorted by analyst characteristics

This table reports coefficient estimates for previous analyst industry experience. Panel A reports the coefficient estimate for related experience and panel B reports the coefficient estimate for unrelated experience. All other explanatory variables from equation 3 are suppressed. The dependent variable is the proportional mean absolute forecast error (PMAFE). We report coefficient values for the overall sample, all-star and non-star analysts, long and short general analyst experience separated by the median value of general experience, and brokerage house status (Top 10 decile, non-top 10 decile). See Appendix C for a description of control variables. Analyst data are from *I/B/E/S* from 1983 to 2011, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Employment history is collected from *LinkedIn.com* and supplemented with *Zoominfo.com*. *t*-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Related Experience Coefficients by Analyst Characteristics

	Overall	All-Star	Non-Star	Long-Exp	Short-Exp	Top 10	Non-Top 10	Affiliated	Unaffiliated	Ph.D	Non-Ph.D	High Tech	Non-Tech
All	-3.57***	-3.33***	-3.74***	-3.25***	-3.85***	-2.68***	-4.55***	-4.39**	-3.53***	-6.85**	-3.46***	-5.53***	-3.00***
	(-7.16)	(-2.68)	(-6.86)	(-4.60)	(-4.84)	(-4.13)	(-5.78)	(-2.32)	(-6.75)	(-2.37)	(-6.80)	(-5.22)	(-5.29)
Bold	-3.76***	-3.88**	-3.85***	-2.87***	-4.86***	-3.33***	-4.16***	-5.61***	-3.65***	-9.67***	-3.55***	-4.41***	-3.57***
	(-6.79)	(-2.80)	(-6.36)	(-3.66)	(-5.48)	(-4.72)	(-4.71)	(-2.67)	(-6.29)	(-3.05)	(-6.30)	(-3.84)	(-5.63)
Herding	-2.94**	-1.65	-3.33***	-4.34***	-0.58	-0.55	-5.39***	-0.94	-3.07***	-3.35	-3.18***	-9.24***	-1.16
	(-2.68)	(-0.60)	(-2.81)	(-2.75)	(-0.34)	(-0.38)	(-3.21)	(-0.22)	(-2.67)	(0.52)	(-2.85)	(-3.72)	(-0.95)

Panel B: Unrelated Experience Coefficients by Analyst Characteristics

	Overall	All-Star	Non-Star	Long-Exp	Short-Exp	Top 10	Non-Top 10	Affiliated	Unaffiliated	Ph.D	Non-Ph.D	High Tech	Non-Tech
All	0.75	3.30**	0.29	2.20***	-0.12	2.89***	-2.24***	-0.22	0.82	0.83	0.70	1.82*	1.06*
	(1.48)	(2.38)	(0.52)	(2.93)	(-0.15)	(4.36)	(-2.78)	(-0.11)	(1.52)	(0.28)	(1.35)	(1.87)	(1.73)
Bold	0.90	2.53*	0.59	3.05***	-0.80	2.38***	-1.31	-0.14	0.89	-2.34	0.98*	2.24	1.18*
	(1.61)	(1.76)	(0.97)	(3.69)	(-0.92)	(3.28)	(-1.46)	(-0.07)	(1.50)	(-0.73)	(1.70)	(2.12)	(1.74)
Herding	1.53	6.05**	0.60	0.84	3.37*	5.33***	-3.16*	-0.43	1.91	14.49**	1.02	1.20**	1.77
	(1.34)	(2.08)	(0.49)	(0.49)	(1.94)	(3.54)	(-1.79)	(-0.10)	(1.60)	(2.18)	(0.88)	(0.52)	(1.33)

Table 5. Regression of analyst forecast accuracy and previous work experience

Table 5 displays the OLS regression results for the accuracy of forecasts issued by experienced and inexperienced analysts for 112,973 forecasts for 5,581 firms between 1983 and 2011. The dependent variable is the *difference* in proportional mean absolute forecast error (*PMAFE*) for analyst *i* on firm *j* between year *t* and *t-1*. All independent variables are measured as changes between *t* and *t-1*. *Lag (PMAFE)* is the proportional mean absolute forecast error for analyst *i* on firm *j* at year *t-1*. Coefficient values are reported as percentages with *t*-statistics in parenthesis. See Appendix C for a description of control variables. Analyst data are from *I/B/E/S* from 1983 to 2011, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Employment history is collected from *LinkedIn.com* and supplemented with *Zoominfo.com*. *t*-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-12.80***	-12.84***	-10.75***	-16.49***	-16.55***	-14.03***	-1.39	-1.36	0.44
	(-23.475)	(-23.53)	(-16.97)	(-27.27)	(-27.36)	(-20.41)	(-1.15)	(-1.13)	(0.30)
Experience	-0.43			-0.09			-1.10		
	(-0.77)			(-0.15)			(-0.88)		
Related experience		-2.78***	-5.20***		-2.53***	-5.43***		-3.70***	-5.61***
		(-4.46)	(-7.78)		(-3.69)	(-7.46)		(-2.70)	(-3.68)
Unrelated experience		2.44***			2.88***			2.12	
		(3.62)			(3.93)			(1.36)	
Δ*DGExp*	-0.04	-0.04	-0.01	0.00	0.00	-0.16	-0.19	-0.19	0.32
	(-0.16)	(-0.15)	(-0.03)	(0.00)	(0.01)	(-0.42)	(-0.31)	(-0.31)	(0.41)
Δ*DAge*	0.34***	0.34***	0.35***	0.33***	0.33***	0.34***	0.37***	0.37***	0.38***
	(58.92)	(58.85)	(48.11)	(49.91)	(49.83)	(40.59)	(33.33)	(33.30)	(27.00)
Δ*DFExp*	-2.38***	-2.34***	-1.98***	-2.51***	-2.46***	-2.01***	-2.04*	-2.02*	-2.04
	(-4.62)	(-4.55)	(-3.08)	(-4.37)	-2.46***	(-2.79)	(-1.79)	(-1.77)	(-1.42)
Δ*DPortsize*	-0.45***	-0.45***	-0.45***	-0.41***	-0.41***	-0.38***	-0.58***	-0.57***	-0.69**
	(-4.38)	(-4.37)	(-3.52)	-0.41***	(-3.60)	-0.38***	(-2.72)	(-2.70)	(-2.54)
Δ*DSIC2*	0.14	0.14	0.34	0.20	0.19	0.35	0.10	0.11	0.64
	(0.48)	(0.45)	(0.89)	(0.60)	(0.56)	(0.84)	(0.15)	(0.16)	(0.73)
Δ*DTop10*	-3.10***	-3.10***	-3.86***	-2.83***	-2.80***	-3.55***	-4.22**	-4.30**	-5.02**

	(-3.45)	(-3.45)	(-3.42)	(-2.82)	(-2.80)	(-2.82)	(-2.17)	(-2.21)	(-2.06)
Δ*Size*	0.32	0.37	0.49	-0.64	-0.60	-0.84	4.63***	4.70***	6.02***
	(0.57)	(0.66)	(0.69)	(-1.01)	(-0.93)	(-1.05)	(4.02)	(4.07)	(4.16)
Δ*BM*	0.00	0.00	0.00	0.02***	0.02***	0.02***	-0.02***	-0.02***	-0.02***
	(0.35)	(0.39)	(0.75)	(3.33)	(3.25)	(3.56)	(-8.16)	(-7.88)	(-6.24)
Δ*Past Ret*	11.75***	11.63***	8.66*	7.78*	7.60*	8.96	25.20***	25.31***	8.47
	(2.90)	(2.87)	(1.75)	(1.74)	(1.70)	(1.64)	(2.82)	(2.83)	(0.76)
Δ*No of Analysts*	0.02	0.01	0.00	-0.04	-0.05	-0.08	0.36**	0.35*	0.42*
	(0.26)	(0.15)	(-0.01)	(-0.40)	(-0.51)	(-0.70)	(1.97)	(1.93)	(1.88)
Lag PMAFE	-87.55***	-87.64***	-87.39***	-88.92***	-89.00***	-89.35***	-84.80***	-84.94***	-82.98***
	(-171.48)	(-172.16)	(-137.25)	(-162.48)	(-162.88)	(-132.11)	(-81.38)	(-81.84)	(-62.59)
R^2	45.61%	45.66%	45.56%	46.69%	46.75%	47.02%	44.08%	44.14%	42.95%
n	66,502	66,502	75,810	50,902	50,902	32,806	15,600	15,600	9,899

Table 6. Industry work experience and all-star analyst status

This table presents Probit regression results for the effect of work experience on all-star status at the analyst-year level. The dependent variable in each model is a binary variable for All-star status, which is equal to 1 if the analyst is voted American all-star analyst in the following year's October issue of *Institutional Investor* magazine. To control for year fixed effects, calendar year dummies are included in the models. See Appendix C for a description of control variables. Analyst data are from *I/B/E/S* from 1983 to 2011, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Employment history is collected from *LinkedIn.com* and supplemented with *Zoominfo.com*. *t*-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Experience	0.60***		
	(9.32)		
Related Experience		0.65***	0.57***
		(9.95)	(3.54)
Unrelated Experience		0.06	
		(0.37)	
GExp	0.06***	0.06***	0.08***
	(8.68)	(8.66)	(8.01)
Portsize	0.04***	0.04***	0.03***
	(8.01)	(7.13)	(4.48)
SIC2	0.00*	0.00**	0.00
	(-1.84)	(-2.08)	(-0.58)
Brokerage size	0.02***	0.02***	0.01***
	(18.41)	(18.78)	(12.02)
Average PMAFE	-0.10**	-0.10**	-0.14*
	(-2.06)	(-2.01)	(-1.74)
Average Firm Size	0.09***	0.09***	0.18***
	(4.14)	(4.01)	(5.08)
All-star	1.11***	1.10***	1.65***
	(19.87)	(19.51)	(22.07)
Year Fixed Effects	Y	Y	Y
n	15,907	15,907	7,952

Table 7. Regression analysis of market reactions to earnings forecast revisions

This table reports the market reaction to analysts' revisions of earnings forecasts. The dependent variable is the event (0, 2) cumulative market-adjusted abnormal return around the announcement of forecast revision by analyst *i* for firm *j* at time *t*. Forecast revision (*FR*) is the ratio of the difference between the new forecast and the old forecast to the absolute value of the old forecast. To control for year fixed effects, calendar year dummies are included. See Appendix C for a description of control variables. Analyst data are from *I/B/E/S* from 1983 to 2011, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Employment history is collected from *LinkedIn.com* and supplemented with *Zoominfo.com*. *t*-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Upward revisions			*Downward revisions*		
	(1)	(2)	(3)	(4)	(5)	(6)
*FR*Experience*	5.70***			4.77***		
	(13.96)			(9.79)		
*FR*Related experience*		6.60***	6.50***		6.14***	6.13***
		(12.42)	(11.83)		(11.17)	(10.82)
*FR*Unrelated experience*		4.99***	4.88***		3.55***	3.50***
		(9.20)	(8.67)		(4.70)	(4.55)
*FR*Inexperience*	4.20***	4.20***		3.34***	3.32***	
	(8.55)	(8.55)		(7.06)	(6.97)	
DGExp	0.00	0.00	0.00**	0.00**	0.00**	0.00***
	(1.61)	(1.64)	(2.56)	(-2.43)	(-2.54)	(-2.86)
DAge	0.01*	0.01*	0.02**	-0.02**	-0.02**	-0.02
	(1.84)	(1.83)	(2.21)	(-2.06)	(-2.11)	(-1.42)
DFExp	0.00	0.00	-0.01	0.00	0.00	-0.01
	(-0.06)	(-0.15)	(-0.61)	(0.05)	(0.20)	(-0.52)
DPortsize	-0.01	-0.01	-0.01	0.00	-0.01	0.00
	(-1.41)	(-1.38)	(-0.87)	(-0.55)	(-0.66)	(-0.43)
DSIC2	-0.02	-0.02	-0.02	0.05*	0.05*	0.04

	(-1.07)	(-1.05)	(-0.61)	(1.77)	(1.75)	(1.08)
DTop10	0.33***	0.33***	0.39***	-0.22***	-0.23***	-0.28**
	(4.96)	(4.99)	(4.63)	(-2.69)	(-2.75)	(-2.52)
Size	-0.26***	-0.26***	-0.30***	0.30***	0.30***	0.34***
	(-9.99)	(-10.01)	(-9.34)	(6.93)	(7.02)	(5.78)
BM	0.01	0.01	0.00	0.15	0.15	0.13
	(0.67)	(0.65)	(0.43)	(1.51)	(1.52)	(1.27)
Past ret	-10.10***	-10.09***	-10.07***	-7.50***	-7.47***	-7.33***
	(-9.40)	(-9.40)	(-7.39)	(-5.82)	(-5.79)	(-4.30)
No of Analysts	0.01**	0.01**	0.01**	-0.03***	-0.03***	-0.03***
	(2.15)	(2.15)	(2.34)	(-4.47)	(-4.51)	(-4.00)
R2	6.87%	6.89%	7.21%	5.29%	5.34%	5.30%
Year Fixed Effects	Y	Y	Y	Y	Y	Y
n	58,016	58,016	38,301	47,226	47,226	30,376

Table 8. Regression of analyst forecast accuracy and previous work experience: Pre- and post-Reg FD

This table presents OLS regression results for forecast accuracy by experienced and inexperienced analysts for 112,973 forecasts for 5,581 firms in the pre- and post-Reg FD era. The dependent variable is the proportional mean absolute forecast error (*PMAFE*) defined as the difference between the absolute forecast error for analyst *i* for firm *j* and the mean absolute forecast error firm firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. See Appendix C for a description of control variables. Analyst data are from *I/B/E/S* from 1983 to 2011, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Employment history is collected from *LinkedIn.com* and supplemented with *Zoominfo.com*. *t*-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

		Pre-Reg FD			Post-Reg FD	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.43	1.02	-0.38	6.18***	5.82***	7.13***
	(0.67)	(0.47)	(-0.13)	(4.38)	(4.12)	(4.41)
Experience	-1.53*			-1.21**		
	(-1.75)			(-2.12)		
Related Experience		-3.84***	-5.07***		-3.10***	-4.06***
		(-3.73)	(-4.31)		(-4.93)	(-6.72)
Unrelated Experience		0.89			1.01	
		(0.83)			(1.53)	
DGExp	-0.14	-0.15	0.07	-0.14**	-0.14**	-0.18**
	(-1.10)	(-1.13)	(0.36)	(-2.35)	(-2.34)	(-2.09)
DAge	0.41***	0.41***	0.42***	0.55***	0.55***	0.55***
	(41.19)	(41.12)	(29.42)	(85.04)	(84.81)	(70.84)
DFExp	-0.35	-0.32	-0.08	-0.26**	-0.21**	-0.25*
	(-1.59)	(-1.49)	(-0.25)	(-2.45)	(-2.01)	(-1.77)
DPortsize	0.33***	0.31***	0.15	0.02	0.02	-0.07
	(3.55)	(3.39)	(1.13)	(0.35)	(0.31)	(-0.85)

DSIC2	0.01	0.01	0.01	0.30	0.30*	0.49**
	(0.04)	(0.05)	(0.02)	(1.64)	(1.65)	(2.25)
DTop10	-7.32***	-7.29***	-7.27***	-0.41	-0.50	0.67
	(-7.91)	(-7.88)	(-5.47)	(-0.76)	(-0.93)	(1.05)
Size	0.36	0.40	0.75	-0.37*	-0.32	-0.39
	(1.01)	(1.10)	(1.54)	(-1.79)	(-1.54)	(-1.54)
BM	-0.02***	-0.02***	-0.01***	-0.28*	-0.27*	-0.22
	(-8.72)	(-8.11)	(-6.88)	(-1.83)	(-1.81)	(-1.33)
Past Ret	12.48*	12.84*	9.86	3.15	3.43	0.52
	(1.83)	(1.89)	(1.14)	(0.68)	(0.74)	(0.09)
No of Analysts	-0.52***	-0.51***	-0.51***	-0.45***	-0.46***	-0.45***
	(-8.73)	(-8.62)	(-6.16)	(-12.98)	(-13.17)	(-10.69)
R^2	11.00%	11.06%	11.18%	14.01%	14.07%	14.24%
n	27,147	27,147	75,810	85,332	85,332	59,334

Table 9. Regression of analyst forecast accuracy and previous work experience at public firms

This table presents OLS regression results for analyst earnings forecasts for the sample of analysts that previously worked at a publicly-traded firm. The dependent variable is the proportional mean absolute forecast error (*PMAFE*) defined as the difference between the absolute forecast error for analyst *i* for firm *j* and the mean absolute forecast error at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. See Appendix C for a description of control variables. Analyst data are from *I/B/E/S* from 1983 to 2011, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Employment history is collected from *LinkedIn.com* and supplemented with *Zoominfo.com*. *t*-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	All Forecasts	Bold Forecasts	Herd Forecasts
Intercept	6.00***	1.96	18.12***
	(3.26)	(0.96)	(4.54)
Related experience	-5.04***	-4.68***	-6.43***
	(-5.20)	(-4.45)	(-3.08)
DGExp	-0.11	-0.03	-0.37
	(-1.00)	(-0.22)	(-1.49)
DAge	0.54***	0.53***	0.57***
	(58.22)	(48.75)	(32.19)
DFExp	-0.38**	-0.47**	-0.15
	(-2.14)	(-2.46)	(-0.38)
DPortsize	-0.07	-0.03	-0.13
	(-0.71)	(-0.29)	(-0.67)
DSIC2	0.34	0.16	0.85
	(1.35)	(0.58)	(1.57)
DTop10	-1.21	-1.68*	0.88
	(-1.52)	(-1.95)	(0.51)
Size	-0.55*	-0.47	-0.81
	(-1.92)	(-1.50)	(-1.28)
BM	-0.02***	0.14	-0.03***
	(-7.01)	(0.41)	(-7.66)
Past Ret	6.22	-2.43	48.52***
	(0.98)	(-0.34)	(3.42)
No of Analysts	-0.40***	-0.42***	-0.29**
	(-8.09)	(-7.86)	(-2.49)
R^2	14.06%	14.03%	15.02%
n	40,291	30,784	9,507

Table 10. Robustness Tests

This table presents OLS regression results for analyst earnings forecasts accuracy and revision frequency for different samples of analysts. In model 1, 3 and 4, the dependent variable is the proportional mean absolute forecast error (PMAFE) defined as the difference between the absolute forecast errors for analyst *i*, firm *j* at time *t* and the mean absolute forecast error scaled by the mean absolute forecast error for firm *j* at time *t*. In model 2, the dependent variable is the log transformed forecast revision frequency. See Appendix C for a description of control variables. Analyst data are from *I/B/E/S* from 1983 to 2011, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Employment history is collected from *LinkedIn.com* and supplemented with *Zoominfo.com*. *t*-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Model 1	Model 2	Model 3	Model 4
Intercept	26.55***	4.53***	5.31***	8.97*
	(19.57)	(6.92)	(4.67)	(1.75)
Linkedin Dummy	-0.70			
	(-1.16)			
Related Experience		0.29		
		(1.29)		
Ln(Related Exp Length)			-0.80***	-3.07**
			(-3.53)	(-2.51)
DGExp	-0.19***	-0.15***	-0.17***	-0.45*
	(-3.00)	(-4.88)	(-3.07)	(-1.85)
DAge	0.78***	-0.19***	0.51***	0.53***
	(129.86)	(-101.83)	(93.52)	(28.57)
DFExp	-0.67***	1.03***	-0.26***	-0.46
	(-6.45)	(18.06)	(-2.77)	(-1.12)
DPortsize	0.13***	0.07***	0.11**	0.15
	(4.22)	(2.64)	(2.01)	(1.03)
DSIC2	0.00	-0.37***	0.21	-0.75
	(0.24)	(-5.27)	(1.42)	(-1.00)
DTop10	-5.49***	2.86***	-2.06***	-0.45
	(-10.56)	(11.70)	(-4.42)	(-0.29)
Size	-0.49***	0.39***	-0.26	0.09
	(-2.61)	(3.61)	(-1.47)	(0.14)
BM	-0.01	0.12*	-0.02***	1.77
	(-1.21)	(1.69)	(-4.33)	(1.14)
Past Ret	0.85	-1.91	7.40*	4.95
	(1.09)	(-1.03)	(1.94)	(0.32)
No of Analysts	-0.63***	-0.08***	-0.46***	-0.55***
	(-19.99)	(-2.91)	(-15.29)	(-5.12)
R2	12.85%	21.23%	13.11%	14.14%
n	407,605	36,056	112,479	9,506

Appendix A: "What investors really want": Ranks of attributes by respondents to the *Institutional Investor* survey

	1999		2001		2003
Rank	Attribute	Rank	Attribute	Rank	Attribute
1	Industry Knowledge	1	Industry Knowledge	1	Industry Knowledge
2	Written Reports	2	Accessibility/Responsiveness	2	Integrity/professionalism
3	Special Services	3	Independence from Corporate Finance	3	Accessibility/Responsiveness
4	Servicing	4	Useful & timely calls & visits	4	Useful & timely calls & visits
5	Stock selection	5	Special services	5	Management Access
6	Earnings Estimates	6	Written reports	6	Special services
7	Quality of Sales Force	7	Management Access	7	Written reports
8	Market making/execution	8	Special services	8	Independence from Corporate Finance
		9	Earnings Estimates	9	Communication Skills
		10	Stock Selection	10	Financial Models
		11	Quality of Sales force	11	Stock selection
		12	Market making/execution	12	Earnings Estimates
				13	Quality of Sales Force
				14	Market making/execution
				15	Primary Market Services

	2005		2007		2009
Rank	Attribute	Rank	Attribute	Rank	Attribute
1	Industry Knowledge	1	Industry Knowledge	1	Industry Knowledge
2	Integrity/professionalism	2	Accessibility/Responsiveness	2	Integrity/professionalism
3	Accessibility/Responsiveness	3	Integrity/professionalism	3	Accessibility/Responsiveness
4	Management Access	4	Special services	4	Management Access
5	Special services	5	Management Access	5	Special services
6	Written reports	6	Written reports	6	Written reports
7	Useful & timely calls & visits	7	Useful & timely calls & visits	7	Financial Models
8	Communication Skills	8	Communication Skills	8	Useful & timely calls & visits
9	Financial Models	9	Financial Models	9	Idea generation
10	Management of conflicts on interest	10	Stock selection	10	Research delivery
11	Stock selection	11	Earnings Estimates	11	Earnings Estimates
12	Earnings Estimates	12	Management of conflicts on interest	12	Stock selection

Appendix B: Data screening and collection

	Forecasts	Firms	Analysts
All analysts annual EPS forecasts between 1983 to 2011 from *I/B/E/S*.	2,966,210	19,424	19,237
Merge with CRSP/COMPUSTAT for stock price data and firm characteristics.	2,036,023	10,563	15,531
Keep the last annual earnings forecast with a horizon between 1 month and 12 month.	470,137	6,828	14,458
Merge sample with *I/B/E/S* recommendation file to get analyst last name, first initial and brokerage firm estimid, which is used to identify the brokerage firm names. Remove analysts without first initial, last name or brokerage estimid, or analyst teams (those analyst names recorded as "research department" or contain two analyst last names). This is the 'clean' *I/B/E/S* sample.	398,919	6,793	9,305
Manually search *Zoominfo.com* for analysts' names by matching their brokerage firm, last name and first initial.	253,983	6,461	4,849
Search for analysts' employment history on *Linkedin.com*.	112,973	5,581	2,505

Appendix C: Variable definitions

Note that all variable definitions beginning with a '*D*' are adjusted by mean values. The unadjusted variable definitions are in parenthesis.

Variable	Definition
PMAFE	The proportional mean absolute forecast error calculated as the difference between the absolute forecast error (*AFE*) for analyst *i* on firm *j* and the mean absolute forecast error (*MAFE*) for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*.
Experience	Indicator variable is one if the forecast is issued by an analyst with previous industry work experience, and zero otherwise.
Related experience	Indicator variable is one if the industry of the forecasted firm is related to the analyst's prior industry work experience industry, and zero otherwise.
Unrelated experience	Indicator variable is one if the industry of the forecasted firm is unrelated to the analyst's prior industry work experience industry, and zero otherwise.
Inexperience	Indicator variable is one if the analyst making forecast has no pre-analyst industry experience, and zero otherwise.
Ln (Related Exp Length)	The length of analyst related-industry experience, measured as the natural logarithm of 1 plus the number of years of related industry experience.
Bold forecasts	Indicator variable is one if earnings forecast revision is above/below both the consensus and the previous earnings forecast issued by the same analyst on the same firm, and zero otherwise.
Herding forecasts	Indicator variable is one if earnings forecast revision is between the consensus and the previous earnings forecast issued by the same analyst on the same firm.
FR	Analyst forecast revision following Ivkovic and Jegadeesh (2004). The difference between an analyst's revised forecast at time *t* and the previous forecast at time *t-1* scaled by the absolute value forecast at *t-1*. The denominator is set to .01 if the lower. Values are multiplied by 100 and are truncated between -50% and 50%.
DGExp	The total number of years that analyst's *i* appeared in *I/B/E/S* (*GExp*) minus the average tenure of analysts supplying earnings forecasts for firm *j* at time *t*.
DFExp	The total number of years since analyst's *i* first earnings forecast for firm *j* (*FExp*) minus the average number of years *I/B/E/S* analysts supplying earnings forecasts for firm *j* at time *t*.
DAge	The age of analyst's *i* forecast (*Age*) minus the average age of forecasts issued by analysts following firm *j* at time *t*, where age is defined as the age of forecasts in days at the minimum forecast horizon date.

DPortsize	The number of firms followed by analyst *i* for firm *j* at time *t* (*Portsize*) minus the average number of firms followed by analysts supplying earnings forecasts for firm *j* at time *t*.
DSIC2	Number of 2 digit SICs followed by analyst i at time *t (SIC2*) minus the average number of 2-digit SICs followed by analysts following firm *j* at time *t*.
DTop10	Indicator variable is one if analyst works at a top decile brokerage house (*Top10*) minus the mean value of top decline brokerage house indicators for analysts following firm *j* at time *t*.
Size	The natural log of market capitalization of the covered firm (in $thousands) by the end of the month prior to the earnings forecast.
BM	Book value of equity in the fiscal year prior to the earnings forecast divided by the current market value of equity.
Past Ret	CRSP VW-index adjusted buy-and hold abnormal returns (BHARs) over six months prior to the announcement date of the earnings forecast.
No of analysts	The number of unique analysts issuing earnings forecasts for firm *j* at time *t*.
Long-Exp	Indicator variable is one if general analyst forecasting experience above median value, and zero otherwise.
Affiliated	Indicator variable is one if analyst's brokerage house was the underwriter/ advisor of the covered firm's IPO/SEO/MA deal during the past 3 years, and zero otherwise.
Ph.D	Indicator variable is one if analyst holds a Ph.D degree, and zero otherwise.
High-tech	Indicator variable is one if covered firm is in high tech industry, and zero otherwise. 4-digit SIC codes of 3570-3572, 3575, 3577-3578, 3660-3661, 3663, 3669-3672, 3674-3675, 3677-3679, 3810, 3812, 3820, 3823, 3825-3827, 3829, 3840-3841, 3845, 4812-4812, 4899, 7370-7375, or 7378-7379.
All-star	Indicator variable is one if the analyst is named to *Institutional Investor's* all-star team in current year, and zero otherwise.
Brokerage size	The total number of analysts working at a given analyst *i*'s brokerage house.
Average firm size	The mean market capitalization of firms followed by analyst *i* at time *t*.
Linkedin dummy	Indicator variable is one if the analyst is in *LinkedIn* sample, and zero otherwise.