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 find that analysts making forecasts on firms in industries related to their pre-analyst experience have better forecast accuracy, evoke stronger market reactions to earning revisions, and are more likely to be named *Institutional Investor* all-stars. Exogenous losses of analysts with related industry experience have real financial market implications—changes in firms' information asymmetry and price reactions are significantly larger than those of other analysts. Overall, industry expertise acquired from pre-analyst work experience is valuable to analysts, consistent with the emphasis placed on their industry knowledge by institutional investors.

Keywords: Analyst forecasts, industry knowledge, all-star analysts, analyst coverage terminations, information asymmetry, price impact

JEL classifications: G14, G20, G23, G24

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We appreciate comments from John Banko, Jonathan Clarke, Diego Garcia, Andy Fodor, Jacquelyn Humphrey, Ryan Huston, Russell Jame, Chris James, Avner Kalay, Andy Naranjo, Jacob Oded, Sugata Ray, Jay Ritter, Dahlia Robinson, John Stowe, Geoff Warren, Fei Xie, Xiaoyun Yu, Qiaoqiao Zhu, two anonymous referees, an anonymous Associate Editor, the Editor (Kenneth Singleton), and seminar participants at the Australian National University, Ohio University, Tel Aviv University, University of Florida, 2014 Western Finance Association, and 2014 Financial Management Association meetings. The authors do not have any potential conflicts of interest, as identified in the JF Disclosure Policy. We are solely responsible for any errors or omissions.

Sell-side analysts are among the most important information agents in capital markets. As a result, a large body of academic research has been devoted to the question of what makes a good sell-side analyst. The literature shows that a number of innate characteristics and external factors such as analysts' forecasting experience, political views, portfolio complexity and the prestige of their brokerage house are related to analysts' performance (Clement (1999), Gilson et al. (2001), Malloy (2005), Jiang, Kumar, and Law, (2014)). Of these factors, practitioners indicate that industry knowledge is perhaps the most important quality 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, *II* provides information on the qualities that respondents view as most important. Industry knowledge has been consistently ranked the most important trait. Corroborating *II*'s survey results, Brown et al. (2014) find that sell-side analysts also believe that industry knowledge is the most important characteristic related to their performance and career concerns.

However, despite the widespread view that industry knowledge is critical to an analyst's job, there is little systematic evidence on the relation between industry knowledge and analyst performance, likely because industry knowledge is inherently difficult to measure. In one attempt 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. In more recent work Kadan et al. (2012) examine industry recommendations made by strategy analysts that take a macroeconomic top-down view of the overall industry and 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 shed new light on the relation between analysts' industry knowledge and forecasting performance. Specifically, using a novel hand-collected biographical data set, we extrapolate sell-side analysts' pre-analyst industry experience from their previous employment history and match this with their coverage portfolios to determine whether a covered firm is related to the analyst's pre-analyst industry work experience. We then examine whether industry knowledge acquired from pre-analyst industry work experience provides sell-side analysts a competitive advantage by enabling them to better interpret the factors that affect the operations, financial condition, and industries of the firms in their coverage portfolios above and beyond the factors previously shown in the literature to be related to analyst performance.

To illustrate our empirical design, consider an analyst in our sample. Before becoming an analyst, he worked at CBS Group for seven years as Director of Strategic Planning. As an analyst at Bear Stearns, his coverage portfolio included both firms that are in the entertainment/broadcasting industry that are related to his previous work experience at CBS Group such as Comcast Corporation, Cox Communications, Cox Radio, Young Broadcast, Walt Disney Corporation, and Adelphia Communications and firms not in this industry and hence unrelated to his previous work experience such as Hertz Corporation, The Learning Company, and Avis Rent A Car among others. To distinguish 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 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 any prior industry experience are called *inexperienced analysts*.[1]

For a sample of 112,973 earnings forecasts on 5,581 firms over the period 1983 to 2011, we find that the relative earnings accuracy of forecasts by analysts with related experience is significantly better than that of analysts with unrelated experience or of inexperienced analysts. Specifically, the mean relative forecast accuracy of analysts with related industry experience is 3.6% higher than that of other analysts after controlling for intertemporal variation in task difficulty, general and firm specific forecasting experience, and other factors shown to explain cross-sectional differences in earnings forecast accuracy. To put this in perspective, the forecast performance of a sell-side analyst with nine years of general forecasting experience (the 90th experience percentile) is 2.1% more accurate than that of an analyst with three years of such experience (10th percentile). The relative accuracy of forecasts issued by industry-experienced analysts on unrelated firms is not different, however, than that of forecasts issued by inexperienced analysts.[2]

We next examine the impact of Regulation FD (Reg FD) on our analysis. Cohen, Frazinni, and Malloy (2010) find that analysts with educational links to senior executives at covered firms performed better than nonconnected analysts pre-FD, but this effect vanished after Reg FD when selective disclosure to analysts was prohibited, implying that these connections foster the transfer of private information. Accordingly, one plausible mechanism driving our results may be that industry work experience cultivates industry connections and the

[1] Throughout the paper, we refer to analysts with related pre-analyst industry experience as industry expert analysts and analysts without related pre-analyst industry experience as nonexpert analysts.

[2] To ensure our results are not sensitive to how analysts' forecast performance is measured (i.e., the proportional mean absolute forecast error (PMAFE)) or the choice of econometric specification, we rerun regressions with the unadjusted absolute forecast error (AFE) and include firm-year and broker fixed effects. We further use Hong and Kubik's (2003) relative performance metric, and we also perform tests using the subsample of experienced analysts that make forecasts on both industry-related and industry-unrelated firms and include analyst-year paired fixed effects. The results remain unchanged.

flow of private information. We find, however, that related industry experience matters in both periods and the passage of Reg FD has not weakened the economic or statistical impact of industry experience on forecast performance. Therefore, while we cannot completely rule out the possibility that information flow from social connections with industry networks may contribute to our results, private information flow is unlikely to be a primary explanation. Rather, our evidence is in line with the view that pre-analyst industry work experience provides analysts with an understanding of the industry. This result is also consistent with the strong emphasis that buy-side institutions and sell-side analysts continue to place on industry knowledge in the post-Reg FD era (Brown (2014)).[3]

Given the evidence of higher relative forecast accuracy, we also examine the extent to which sell-side analysts' pre-analyst work experience leads to favorable career outcomes. We find that previous work experience incrementally increases the likelihood of becoming an *II* all-star analyst, but only when the analyst covers stocks related to her pre-analyst industry work experience. In particular, the odds of being elected to the all-star team are 75% higher for analysts with related industry experience compared to analysts with unrelated industry experience after controlling for factors previously documented in the literature. We further investigate variation in the market's response to earnings forecast revisions from industry-experienced and -inexperienced analysts. Here we consider not only the direction of the forecast revisions, but also their magnitudes (Gleason and Lee (2003)). We find that related-experienced analysts' upward and downward forecast revisions on related firms leads to stronger market reactions than the revisions of inexperienced analysts after controlling for various firm and analyst-level attributes. For instance, upward (downward) earnings revisions issued by related-experience analysts are associated with 0.43% (0.45%) higher (lower) abnormal market reactions compared to forecasts revisions issued by inexperienced analysts. By contrast, the short-term market reaction to forecast revisions of experienced analysts on unrelated firms is not different from those to revisions of inexperienced analysts. These findings suggest that capital market participants place greater emphasis on research produced by industry expert analysts.

Our evidence paints a clear picture that industry experience matters for analysts' performance and career outcomes, as well as market participants' reactions to analyst research,

[3] In separate analyses, we also examine the investment value of analysts' buy and sell recommendations. Using a calendar time portfolio approach following Barber, Lehavy and Trueman (2005), we find that buy and sell recommendations issued by industry expert analysts yield superior abnormal returns compared to those issued by other analysts.

and this supports the conventional view among practitioners. But this raises the question of why banks would allocate analysts to firms in which they do not possess related industry experience, especially given the fact that sell-side research on U.S. firms is structured mostly along sector lines (Sonney (2009)). To address this question, we examine the determinants of analyst-firm pairings at the brokerage house level and consider the allocation of analysts to covered firms given the resources that brokers have available for use. We find that the likelihood of nonexpert analysts being allocated to covered firms is negatively related to the number of industry-expert analysts employed by the brokerage house. We further consider the workload of industry-expert analysts and find that coverage from analysts lacking related industry experience is more likely when industry-expert analysts become busier, as captured by the size of their coverage portfolios. Our results, therefore imply that a misallocation of non-expert analysts to coverage firms likely occurs because of scarcity in the supply of industry-expert analysts. These results contribute to our understanding of the factors affecting analyst-firm pairings within brokerage houses.

Our final set of tests focus on the real effects of industry expert analysts on the functioning of financial markets. To this end, we first identify exogenous terminations of analyst coverage stemming from brokerage house closures in similar spirit to Kelly and Ljungqvist (2012) (KL) and others. Using a difference-in-difference (DiD) approach, we confirm the finding in KL that a loss of analyst coverage increases treatment firms' information asymmetry as proxied by an extensive set of measures including bid-ask spread, illiquidity, stale returns, stock volatility around earnings announcements, and earnings surprises. When we examine coverage terminations based on analysts' industry work experience, we find that the results are economically and statistically more pronounced for coverage terminations of industry-expert analysts compared to those loss of nonindustry expert analysts.

We next expand this analysis to investigate the price impact arising from coverage terminations. The mean cumulative abnormal return DiD over the [-1,+1]-day window of exogenous terminations of analyst coverage is 0.77% lower for firms associated with a loss of industry-expert analysts than for firms that lose other types of analysts. This difference is both economically large and highly statistically significant and does not reverse during the remainder of the trading month, suggesting that expert analyst coverage terminations have more meaningful price effects than coverage terminations of other analysts.

Our paper highlights the importance of industry knowledge for analysts' earnings forecasts and career outcomes, as well as for market participants' reactions to analyst research.

Our paper also sheds light on analyst allocation decisions in brokerage houses, as well as on the real economic implications of analyst industry knowledge for covered firms' information environments. Our research thus bridges the gap between what practitioners (i.e., buy-side institutions and sell-side analysts) claim is the most important analyst attribute and what we empirically find.

The rest of the paper proceeds as follows. Section I discusses our motivation and relevant literature while Section II describes the data and provides descriptive statistics. Section III reports empirical results on forecast accuracy, career outcomes, and market reactions to forecast revisions. Section IV focuses on the allocation of analysts to firms within brokerage houses and the real effects on firms' information environments. Section V reports results of robustness tests and additional analyses. Section VI concludes.

I. Motivation and Previous Work

A voluminous literature shows that analysts' earnings forecasts, forecast revisions, and recommendations provide information that is of value to individual and institutional investors. This value can be observed by investigating average market reactions to analysts' earnings and recommendation revision announcements or by examining the impact of analyst coverage on a firm's information environment (i.e., Brennan, Jegadeesh and Swaminathan (1993), Brennan and Subrahmanyam (1995), Womack (1996), Hong, Lim and Stein (2000), Gleason and Lee (2003), Ivkovic and Jegadeesh (2004), Livnat and Mendenhall (2006), Kelly and Ljungqvist (2012), Bradley, Clarke, Lee and Orthanalai (2014)). However, while the average analyst provides valuable information to market participants, not all sell-side analysts are equally skilled. Characteristics like brokerage house prestige, portfolio complexity, and the analyst's own political views have been linked to analyst performance (Mikhail, Walther, and Willis (1997), Clement (1999), Gilson, Healy, Noe and Palepu (2001), Clement and Tse (2003), Clement, Rees, and Swanson (2003), Jiang, Kumar, and Law (2014)). Experience also matters for analyst forecasting performance. For instance, Mikhail, Walther, and Willis (1997) find that analysts that cover a firm longer produce better forecasts, which implies that there is a learning curve. Other papers suggest that general analyst forecasting experience translates into more accurate forecasts (Clement (1999), Clement, Koonce, and Lopez (2007)). A related strand of literature shows that geographical proximity to firms influences analysts' coverage decisions and results in better accuracy (Malloy (2005), Bae, Stulz, and Tan (2008), O'Brien and Tan (2014)). Du, Yu, and Yu

(2014) find that cultural proximity, which is distinct from geographical proximity, improves the processing of financial information and forecasting performance.

To access the skills believed to be the most important for financial analysts, *II* surveys the buy-side clients that analysts produce research for. Specifically, *II* asks buy-side institutions who they believe are the top analysts in each industry. *II* also collects information on the qualities that buy-side clients believe makes a top analyst. In Appendix A we supplement Table 1 of Bagnoli, Watts, and Zhang (2008) by listing *II*'s survey results on the qualities top analysts should possess.[4] Over the 1999 to 2009 period, there is considerable variation in the qualities that buy-side institutions value with one exception—industry knowledge is consistently ranked the most important attribute. Interestingly, in a Brown et al. (2014) survey of sell-side analysts, they find that analysts themselves also believe that industry knowledge is the most important component of their forecasting performance and compensation.

While it is well known that domestic analysts tend to specialize by industry, there is little empirical evidence on the relation between industry specialization and analyst performance. Boni and Womack (2006) find that analysts have superior ability in ranking individual stocks within industries. Kadan et al. (2013) similarly find that analysts have stock selection ability within an industry, but do not have superior market timing ability. Kadan et al. (2012) examine industry recommendations made by strategy analysts that take a top-down view of the overall industry and find that these analysts have some predictive ability at the industry level.

Our paper examines the role of industry knowledge by considering analysts' pre-analyst work experience. Using a large hand-collected data set that contains pre-analyst employment information, we relate this information to analysts' coverage portfolios. We conjecture that previous industry work experience can help sell-side analysts interpret the factors that affect firms' operations and/or the social connections made through their previous employment can facilitate the flow of information and thus lead to better forecast performance. If previous industry experience gives analysts a competitive advantage over their inexperienced counterparts, then several other hypotheses can be advanced and empirically tested. First, if buy-side investors regard industry knowledge as the most important analyst quality and rank analysts accordingly, then industry experience should be also related to whether one becomes an *II* all-star analyst. Using analyst compensation data from an anonymous high status investment bank, Groysberg,

[4] Bagnoli, Watts, and Zhang (2008) report the survey results for the 1998 to 2003 period. For illustrative purposes, we report the survey results for the 1999 to 2009 period, although to conserve space, we report the results for every other year.

Healy, and Maber (2011) find that *II* all-star analysts earn 61% higher compensation than their unrated peers. Analysts therefore have strong monetary incentives to be included in these rankings.

Second, 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 superior industry knowledge say, then earnings revisions from industry experienced analysts should result in more prominent market reactions.

Third, Kelly and Ljungqvist (2012) exploit exogenous terminations in analyst coverage arising from brokerage house mergers and closures and document that sell-side analysts have real effects on firms' information environment. Better analysts should be more capable of alleviating information asymmetries between investors and insiders. Thus, assuming industry expert analysts provide more precise signals to financial market participants through superior research output, we posit they should have more profound effects on coverage firms' information environments compared to their peers lacking such industry work experience.

II. Data and Descriptive Statistics

The data used in this study come from several sources. Appendix B describes the data collection process. We start by merging the Institutional Broker Estimate System (*I/B/E/S*) detail history tape with CRSP/COMPUSTAT to identify sell-side analysts who issued at least one annual earnings forecast with a horizon between one and 12 months between 1983 and 2011. We retain the most recent forecast. This provides us with a sample of 14,458 analysts making 470,137 forecasts. For each analyst, *I/B/E/S* provides only their last name and the initial of their first name. We remove observations with missing analyst names or brokerage id's and forecasts made by analyst teams (those for which the analyst name is recorded as "research department" or contains two analyst last names). We also delete observations for which multiple analysts share the same first initial and last name at the same brokerage firm. These initial filtering criteria results in a sample of 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 obtain this information. We follow a very conservative approach in building our final sample and remove any observations for which there is ambiguity as to whether or not we have the correct analyst.[5] This leaves us with a final sample of 253,983 forecasts issued by 4,849 analysts.

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 332 million members worldwide. We capture the names of all firms listed in analysts' employment background, regardless of whether they are public or private firms. An analyst must have at least one year of nonanalyst experience to be considered an experienced analyst. We then classify an analyst's work experience as related or unrelated at the covered firm level based on the analyst's experience relative to the firm followed. More specifically, we define experience as related if a previous employer and the followed firm shares one of five similar Fama-French industry classification codes, otherwise we define previous experience as unrelated.[6, 7]

Panel A of Table I provides summary statistics for our sample by subperiod. We report the number of firms, the number of earnings forecasts, and the percentage of forecasts from experienced analysts. We further decompose the percentage of forecasts from experienced analysts into the percentage of these forecasts that are related and unrelated at the covered firm level. We also report the percentage of firms, analysts, forecasts, and market capitalization of our sample relative to the "clean" $I/B/E/S$ universe. Our final sample contains a total of 112,973 earnings forecasts on 5,581 unique firms (see Appendix B). If we average across periods, 53% of earnings forecasts are made by analysts with industry experience. Conditional on having industry

[5] We note that name changes may occur through marriage or divorce. If the $I/B/E/S$ name does not match the employment indexing sites, the analyst is removed from our sample. However, there is no reason to believe that analysts that change their names due to marriage or divorce would systematically bias our results. In a few cases, we manually match names such as "Michael" for "Mike" 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.
[6] To identify the industry group of the firms listed in the 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 five Fama-French industry classification groups based on their four-digit SIC code. For the unmatched public or private firms, we manually assign each firm to one of these industry groups based on the business description from the Securities and Exchange Commission's (SEC) website, firm's official website, or other business news websites such as Bloomberg and BusinessWeek.
[7] We recognize that we are broadly defining related industry experience by using five industry classifications. Because the majority of employers in our analyst employment background data are private firms, it is difficult to assign firms to finer industries. However, if anything, this introduces noise and biases against finding results. Nevertheless, to address this concern, we rerun our analysis using the subset of analysts that worked for either publicly traded firms or private firms for which we are able to assign previous employment to the Global Industry Classification Standard (GICS). Boni and Womack (2006) suggest that the GICS system well matches well analyst industries. The results are unchanged. Discussion of this analysis is presented in Section V.

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, 20% of analysts, 19% of forecasts, and 79% of market capitalization.

Table I here

Two time-series patterns are evident in panel A. First, our ability to obtain reliable employment data for analysts is much lower in the early part of our sample and increases over time. For instance, we are able to use less than 10% of the analyst earnings forecasts before the 1993 to 1997 period, but this rises to nearly 50% in the last year of our sample. Second, the percentage of forecasts issued by analysts that have previous employment experience also rises over time (from about 1/3 to 3/4 of analysts). These time-series patterns are most likely due to the sharp increase in the use of online employment networks, particularly among investment professionals, in recent years.

Panel B of Table I provides summary statistics on the main variables used in our analyses. Appendix C provides detailed information on variable construction. To facilitate comparison with a vast body of prior work examining analyst forecasting performance, our primary performance measure is relative earnings forecast accuracy, constructed as the proportional mean absolute forecast error ($PMAFE_{i,j,t}$) developed by Clement (1999) (e.g., Malloy (2005), De Franco and Zhou (2009), Green, Jame, Markov and Subasi (2014)). Specifically, $PMAFE_{i,j,t}$ is 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. This gives an analyst's forecast accuracy relative to all analysts covering a given firm and thus controls for differences across companies, time, and industries (Ke and Yu (2006)). We use the full I/B/E/S sample to compute PMAFE. As constructed, negative values of $PMAFE_{i,j,t}$ represent above-average performance. Formally, PMAFE 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* excluding analyst's *i*'s forecast. The lower the value of PMAFE, the more accurate the forecast.[8]

Following Clement (1999) and others, we include several proxies for analyst ability and forecasting experience. We first include 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. Next, motivated by Clement (1999), who shows that relative forecast errors are positively associated with the number of days between the forecast and actual announcement earnings date and thus emphasizes the need to control for timeliness, we include the number of days between the forecast and earnings announcement date (*Age*). We also account for portfolio complexity, measured as the size of analyst *i*'s coverage portfolio (*Portsize*), the number of two digit SICs that analyst *i* follows (*SIC2*), and the resources available to analysts, which we capture using a dummy that takes a value of one if analyst *i* works at a top-decile brokerage house (*Top10)*, and zero otherwise. The left-hand columns in Table I, Panel B present the unadjusted mean values. The average AFE is 0.10 dollars, consistent with existing studies. The average analyst in our sample has provided forecasts for 6.7 years and has covered 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 corresponds to 3.5 distinct two-digit SIC codes. Finally, approximately 60% of forecasts are issued by analysts working for a top-decile brokerage house. All of these values are in line with prior studies (e.g., Clement, Koonce, and Lopez (2007), De Franco and Zhou (2009)).

The right-hand columns in Table I, 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 earnings predictability changing over time. Accordingly, we adjust the above variables by their firm-year means to control for firm-year effects (Clement (1999), Malloy, (2005), Clement, Koonce, and Lopez (2007)). Of course, subtracting mean values from raw values drives the average closer to zero, which is what we find. Summary statistics for the other variables used in the paper can be found

[8] To account for outliers, we winsorize AFE and PMAFE at the 0.5% tails. The results are also robust to winsorizing both measures at the 1% tails and to not using winsorization.

in the Internet Appendix, Table IA.I. The Internet Appendix is available in the online version of the article on the Journal of Finance website.

III. Industry Experience, Relative Forecast Accuracy, Career Outcomes and Market Reactions to Analyst Forecasts

In this section, we first examine the forecast performance of analysts with related industry experience compared to other analysts. We test the hypothesis that forecasts issued by these expert analysts are more accurate. As a starting point for our analysis, we examine univariate differences between earnings forecasts issued by analysts with related industry experience and those issued by analysts with either unrelated experience or with no pre-analyst work experience. The average PMAFE for related industry forecasts is -0.16 compared to unrelated industry forecasts or forecasts of inexperienced analysts of -0.09 and -0.12, respectively (untabulated). A *t*-test assuming equal variances indicates that these differences are statistically significant, which suggests that analysts with related industry experience are more accurate forecasters. We perform a more rigorous multivariate test below and then examine plausible channels through which industry experience improves analysts' forecasting ability, followed by the impact of industry knowledge on analyst career outcomes, and the stock market's perception of analysts' forecast revisions.

A. Baseline Regression Model for Forecast Accuracy

We employ a multivariate OLS regression model to formally test our first hypothesis that related industry experience results in better forecast accuracy. The primary variables of interest are binary variables representing previous overall work experience, related experience, and unrelated experience. In addition to the mean-adjusted variables presented in Panel B of Table I, we also control for several 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 heteroskedasticity-consistent and double-clustered at the firm and analyst levels (Peterson (2009)). 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 II here

Table II reports the regression results. Models 1 and 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 by 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 forecasting experience as measured by both general and firm-specific forecasting experience results in more accurate forecasts, while busier analysts (i.e., those that cover more firms) have inferior earnings forecasts. Analysts who work for more prestigious banks have more accurate forecasts, consistent with the view that these analysts have more resources available to them. The more analysts that cover a firm, the more accurate are their earnings forecasts, which is likely due to a lower degree of asymmetric information for firms with greater coverage. In general, the coefficients on the control variables are consistent with prior analyst earnings forecast literature.

In model 2 we decompose analyst experience into its related and unrelated experience components at the firm level. The results suggest that only forecasts made by analysts with related industry experience are more accurate. The coefficient on *Related experience* indicates that the annual earnings forecasts of experienced analysts on related firms are 3.58% (t=-6.76) more accurate than those of inexperienced analysts. On the other hand, experienced analysts' forecasts on unrelated firms are not more accurate than those of inexperienced analysts. The coefficients on the control variables are generally similar to those estimated in model 1.[9]

In model 3, we restrict the sample to only experienced analysts that provide both related and unrelated forecasts. This more restrictive model examines the forecast ability of analysts with previous employment experience with respect to companies in both related and unrelated industries. The findings indicate that forecasts on related firms are 4.3% more accurate compared to forecasts on unrelated firms, on average. Taken together, these results are consistent with the view that pre-analyst related industry work experience improves the forecasting performance of sell-side analysts.

[9] As an alternative way to assess the economic significance of related industry experience on earnings forecast accuracy, we also estimate regressions using the unadjusted absolute forecast error (AFE) as the dependent variable and include firm-year and broker fixed effects. The coefficient on related experience is statistically significant and ranges between -0.76 and -0.98. These estimates are also economically meaningful relative to the average AFE of 10 cents. These results and a corresponding discussion can be found in Section V.

B. Channels through which Industry Experience Affects Performance

Given the results in models 1-3 that industry-related forecasts are superior to non-industry related forecasts, we are interested in the mechanisms through which previous industry experience improves analysts' superior forecasting ability. There are two likely potential channels. First, previous industry employment may give an analyst a competitive advantage in her ability to analyze covered firms' industry trends, competitive threats, positioning within the industry, the impact of regulatory risk, etc. Second, analysts with previous industry experience are likely to have contacts in the industry as well as supply chain or with former customers if they had interactions outside of their firm in which case they may be privy to soft or private information about the covered firm as well as its suppliers/customers. Cohen, Frazzini, and Malloy (2010) find that analysts with school ties to senior executives at covered firms perform better than nonconnected analysts, which implies that such social connections promote the transfer of private information, but that this result disappears after Reg FD. Reg FD prohibits selective disclosure of information to sell-side analysts and thus reduces the benefit of having social connections to management. Similarly, Tang (2013) finds that analysts who later switch to the buyside outperform in stocks they used to cover, but that this result becomes significantly weaker post-Reg FD. It is important to note, however, that while these papers establish a direct link between analysts/mutual fund managers and covered/portfolio firms, we do not. Thus, in our analysis any social connection that may facilitate the flow of private information is loosely defined and our results should be interpreted with this caveat in mind.

To evaluate the role of the two proposed channels, we follow Cohen, Frazzini, and Malloy (2010) and estimate separate regressions before and after Reg FD. If the social connection explanation of industry experience holds, the impact of related industry experience should weaken or disappear in the post-Reg FD era. However, if the effect of industry experience effect on forecast performance is present both before and after the passage of Reg FD, then superior industry knowledge is a more likely explanation behind our results.

Models 4 to 6 and 7 to 9 rerun the analyses in models 1 to 3 for the pre- and post-Reg FD periods, respectively. We find that experience, particularly that driven by related industry experience, is significantly related to forecast accuracy in both periods. The magnitude of the estimates on *Related experience* for the post-Reg FD period is not economically or statistically different from the magnitude of the estimates for the pre-Reg FD era. The social connection explanation is thus not likely to be behind our main results (with the caveat noted above in mind). Rather, a better understanding of industry dynamics that reflect covered firms' operations is a more likely channel through which industry experience improves analyst performance. This finding is consistent with *II*'s survey results (Appendix A) indicating that industry knowledge continues to be an important factor influencing analyst performance.

C. Industry Experience and Analyst Career Outcomes

Having demonstrated that previous industry experience augments analysts' ability to forecast earnings we next explore whether this 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.[10]

We first estimate a logistic regression and explore the likelihood of becoming an *II* all-star analyst using similar analyst characteristic variables as in our other models. Here we are interested in the relation between related industry experience and all-star status.[11] We include year fixed effects, adjust *t*-statistics for heteroskedasticity and within-analyst correlation using heteroskedasticity-consistent standard errors clustered at the analyst level. To mitigate reverse causality concerns, we lag all control variables in addition to *Lag (All-star)* by one year. The logit model takes the following form:

$$(All\text{-}star=1)_{i,t} = \beta_1(Experience)\ /\ \beta_2(Related\ experience)_{t-1} + \beta_3(Unrelated\ experience)_{t-1}\ /\ \beta_4(Percentage\ related\ firms)_{t-1} + \beta_5(GExp)_{t-1} + \beta_6(Portfolio\ size)_{t-1} + \beta_7(SIC2)_{t-1} + \beta_8(Brokerage\ size)_{t-1} + \beta_9(Average\ PMAFE)_{t-1} + \beta_{10}(Average\ firm\ size)_{t-1} + \beta_{11}Lag\ (All\text{-}star) + Year\ fixed\ effects + \varepsilon. \quad (4)$$

Insert Table III here

The first column in Table III suggests that analysts with industry work experience are more likely to become all-star analysts compared to inexperienced analysts. The odds ratio is

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10 One reason for the disparity in compensation between star and nonstar analysts is that all-star analysts are instrumental in attracting investment banking deal flow (Clarke et al. (2007)). However, in 2003 the Global Research Settlement prohibited analyst compensation being directly tied to investment banking business.

11 Previous work shows that analysts working for larger and more reputable banks are more likely to become all-star analysts (Emery and Li (2009), Cohen, Frazzini, and Malloy (2010)). We therefore match each experienced analyst to a portfolio of inexperienced analysts based on the size quintile of their respective brokerage houses. Results are qualitatively similar with or without this matching as well as when we use quartile matching.

1.43, which implies that the odds of becoming an all-star analyst are 43% higher for analysts with previous industry experience. All of the other control variables behave as expected and are consistent with the literature. For example, analysts employed by higher-status brokerage houses and analysts following larger firms are more likely to become all-stars. It is important to note that we also find that past forecast accuracy is related to becoming an all-star, but industry experience is still statistically and economically relevant. This suggests that the buyside clients participating in the *II* annual survey view industry knowledge as distinct from the quality of past earnings estimates. Finally, we find that the likelihood of becoming an all-star in year *t* is correlated with whether an analyst is an all-star in year *t*-1 *(Lag (All-Star))*.

We next decompose experienced analysts into related and unrelated based on the composition of their coverage portfolios. Specifically, we define experienced analysts as Related if they follow at least one firm operating in a related industry otherwise we regard them as 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. The economic magnitude implies that the odds of being elected to the all-star team are 75% higher for analysts with related industry experience compared to analysts that possess no related industry experience. In model 3 we focus attention on those analysts with experience. We again find that *Related experience* is positive and significant. In model 4, where we also restrict the sample to experienced analysts, we compute the proportion of the analyst's coverage portfolio that is related to their industry experience (*Percentage related firms*). We continue to find a positive and significant relationship.[12]

D. Stock Price Impact of Industry Experience on Forecast Revisions

Given our evidence of greater forecast accuracy for industry-experienced analysts, and as a result a higher likelihood of being included in the *II* all-star list, we next investigate market reactions to forecast revisions issued by all-star analysts. If buyside institutions value the industry

[12] As an alternative way to assess the impact of industry work experience on career outcomes, we examine the probability of moving to a more prestigious brokerage house. Specifically, we reestimate equation (4) but use as the dependent variable a binary variable that takes the value of one if the analyst is promoted to a more prestigious brokerage house and zero otherwise. In untabulated results, we find that industry experience is important for movement from a non-top-decile brokerage house to a top-decile brokerage house, but the result for related industry experience is statistically weak. As was pointed out to us, a junior research analyst at a top brokerage house moving to a more senior position at a lower-level brokerage may be considered as making a favorable career move, which would work against our finding results. On the other hand, being included in the annual *II* all-star list is unambiguously favorable.

knowledge of sell-side analysts, then the reactions of institutions and other capital market participants to the revisions of analysts with previous industry experience related to covered firms. should be more pronounced.

Similar to Gleason and Lee (2003) and 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 stock market reactions. Following Malloy (2005), we first classify a forecast revision as positive (negative) news if the revision is above (below) both the analyst's prior forecast *and* the prior consensus forecast. Then, for the positive and negative news samples, we regress cumulative abnormal CRSP VW-Index adjusted returns ([0,+2]-day) on binary variables for revising analysts' industry work experience (*Experience*, *Related experience, Unrelated experience*) and the absolute value of forecast revisions (*Abs(FR)*). The regression model also controls for the analyst and firm characteristics in equation (3) and includes year fixed effects with heteroskedasticity-robust standard errors double-clustered at the firm and analyst level. Our model is as follows:

$$CAR_{i,j,t} = \beta_1(Experience)/\beta_2(Related\ experience) + \beta_3(Unrelated\ experience) + \beta_4(Abs(FR)) + \beta_5(DGExp) + \beta_6(DAge) + \beta_7(DFExp) + \beta_8(DPortsize) + \beta_9(DSIC2) + \beta_{10}(DTop10) + \beta_{11}(Size) + \beta_{12}(BM) + \beta_{13}(Past\ ret) + \beta_{14}(No\ of\ analysts) + \beta_{15}(Lag\ PMAFE) + Year\ fixed\ effects + \varepsilon. \quad (5)$$

Insert Table IV here

Table IV presents the regression results. Models 1 to 3 report results for earnings upgrades. Model 1 shows that market reactions to experienced analysts' upward revisions are indeed more pronounced (0.25%, *t*-statistic=3.23). Separating industry work experience into its related and unrelated experience components, we find that *Related experience* is positive and significant while *Unrelated experience* is not significantly different from zero. The coefficient of 0.43 on *Related experience* implies that market reactions to upward revisions issued by analysts with related industry expertise are 0.43% greater than those to upward revisions issued by analysts with no industry experience. The controls variables generally take the expected signs. For instance, market reactions are positively related to the absolute change in the forecast revision and the size of the forecasting analyst's brokerage firm. In model 3 where we restrict attention to analysts with related industry experience, we find similar results.

Models 4 to 6 repeat the above analyses for earnings downgrades. Our findings indicate that the market reaction is -0.45% when an analyst with related industry experience revises their estimate downwards relative to an analyst without industry work experience. Likewise, abnormal returns surrounding unrelated industry-experienced analysts' forecast revisions are not statistically different from those issued by analysts lacking experience. Overall, the evidence in Table IV is consistent with the notion that stock market participants place greater emphasis on industry expert analysts' positive and negative forecast revisions.[13]

V. The Allocation of Analysts and the Real Effects of Analysts' Industry Experience on Covered Firms' Information Environment

Thus far, we have documented that previous industry experience allows analysts to make more accurate forecasts, leads to favorable career outcomes, and induces stronger market reactions to forecast revisions. Since industry experience is regarded as the most important attribute of sell-side analysts, and since analyst research is structured along sector lines in the U.S., it is not clear why brokerage houses would allocate inexperienced analysts or analysts with unrelated experience analysts to covered firms. In this section, we first address this question we then turn our attention to the real economic effects of analyst industry expertise on covered firms' information environments.

A. The Allocation of Analysts to Firms

It is widely known that analyst decisions to follow a particular set of firms are driven by institutional investor demand (Frankel, Kothari, and Weber (2006), Maber, Groysberg, and Healy (2014)) or the client firm itself (Kirk (2011)). It is also commonly accepted that sell-side research on U.S. firms is mostly segmented across industry sectors (i.e., Boni and Womack (2006), Sonney (2009)). However, while analysts may concentrate on a specific industry, our paper (and others) illustrate that the average analyst covers other industries as well. Given that practitioners and analysts both view industry knowledge as the most valuable analyst attribute, why do brokerage houses allocate analysts to firms outside their area of expertise? Put differently, why do we not observe that banks only hire analysts with pre-analyst industry work experience and assign them to firms operating in industries related to their area of expertise?

We posed this question to several Directors of Research as well as analysts on the buy and sellsides. The most common explanation we received related to a lack of supply of industry-

[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. These results are available upon request.

experienced analysts. And even for brokers that do employ analysts with related industry experience, there is a threshold to the number of firms these analysts can reasonably cover. In our sample, the average analyst covers 12 firms. As the number of firms in an analyst's portfolio increases, the amount of time devoted to each individual firm declines and likely so does the quality of the analyst's research (e.g., Clement (1999)). Brokerage houses may therefore be more likely to assign analysts lacking related industry experience to covered firms when the cost of allocating an industry-experienced analyst outweighs the benefit (i.e., the related industry analyst is too busy to pick up a new firm and it is not feasible to hire a new industry-experienced analyst).

Based on the above discussion, we examine whether the misallocation of analysts to covered firms is an exogenous resource issue driven by the supply of industry expert analysts as our practitioner sources indicate. If the allocation of analysts with unrelated experience or of inexperienced analysts to covered firms arises from resource scarcity, then an analyst without industry expertise is less likely to be allocated to a firm within a brokerage as the number of industry-experienced analysts employed at the same brokerage increases.

To test the likelihood of a nonindustry expert analyst (*Unrelated experienced or Inexperienced)* being allocated to covered firms, we estimate a logistic regression. The primary explanatory variable of interest, *No. of other related experienced analysts*, equals the number of other analysts with related pre-analyst industry expertise employed by the same brokerage house. We also examine the busyness of industry expert analysts (*Average other related experienced analyst portsize).* The conjecture is that we are more likely to observe coverage by nonindustry expert analysts when industry expert analysts at the same brokerage house are too busy to add a new firm to their research portfolio. In this analysis we control for the analyst's average relative forecast performance across all portfolio coverage firms *(Average PMAFE*), firm characteristics, and a set of controls that may be important for analyst coverage decisions such as the firm's expected future prospects as captured by sales growth (*Sales growth*) (McNichols and O'Brien (1997)), the frequency with which the firm raises debt or equity capital (*Issuance*) (Barth, Kasznik, and McNichols (2001)) and whether the firm has underwriting relationships with affiliated investment banks (*Affiliated*) (Bradley, Jordan, and Ritter (2003)). Broker and year fixed effects are included to mitigate concerns that time invariant brokerage characteristics are correlated with the allocation of analysts to covered firms. All control variables are lagged by one year and standard errors are heteroscedasticity-robust and clustered at the analyst level. Our model is as follows:

$$(Nonexpert\ analyst\ =1)_{i,t} = \beta_1(No.\ of\ other\ related\ experienced\ analysts)_{t-1} / \beta_2(Average\ other\ related\ experienced\ analyst\ portsize)_{t-1} + \beta_3(Average\ PMAFE)_{t-1} + \beta_4(Size)_{t-1} + \beta_5(BM)_{t-1} + \beta_6(No.\ of\ analysts)_{t-1} + \beta_7(Past\ ret)_{t-1} + \beta_8(Sales\ growth)_{t-1} + \beta_9(Issuance)_{t-1} + \beta_{10}(Affiliated)_{t-1} + Broker,\ Year\ fixed\ effects + \varepsilon. \quad (6)$$

Insert Table V here

Table V presents the results. Model 1 shows that the coefficient on *No. of other related experienced analysts* is negative and significant, suggesting that a brokerage house is less likely to allocate analysts lacking related industry experience to a firm as the number of other analysts possessing such experience increases. Economically, a one-standard-deviation increase in the number of other analysts with related industry experience decreases the likelihood of nonexpert analysts' covering a firm by 58.3%. In model 2, we control for the workload of industry expert analysts for the subsample of brokers employing at least one such analyst. The results indicate that the probability of an inexperienced or unrelated analyst covering a firm increases with the average size of related industry-experienced analysts' portfolios. The coefficient on *Average other related experienced analyst portsize* is 2.64, indicating that nonexpert analysts are 11.9% more likely to provide coverage on firms if the average portfolio size of other industry expert analysts increases by one standard deviation.[14]

The findings in this section add to our understanding of analyst-firm pairings at the brokerage house level and suggest that a misallocation of nonindustry expert analysts is more likely to occur when there are constraints in the supply of related industry-experienced analysts.

B. The Real Economic Effects of Analyst Industry Experience on Firms' Information Environment

We next examine whether these exogenous misallocations documented above have real effects on covered firms' information environment. Several recent papers exploit the loss of analyst coverage stemming from brokerage house mergers and closures as quasi-natural experiments to examine the impact of analysts on financial markets (e.g., Hong and Kacperczyk (2010), KL, Derrien and Kecskes, (2013), Derrien, Kecskes, and Mansi (2014)). Analyst

[14] This result indicates that the busyness of industry expert analysts explain why brokers may misallocate analysts to firms. However, if busyness lowers the quality of analyst research, why do banks not load up industry-expert analysts to the point where their accuracy is equivalent to that of nonexpert analysts? This is unlikely to occur because forcing analysts to increase their workload at the expense of their research quality and reputation is not optimal for the brokers, their buyside clients, and/or the analysts.

terminations arising from these shocks are plausibly exogenous because they are independent of covered firm characteristics and thus provide an appealing identification strategy. In our setting, however, the brokerage house must choose which analysts to retain and which to let go in the case of mergers (industry versus nonindustry expert), in which case termination decisions are endogenous. Accordingly, in this analysis we focus on brokerage closures and the impact of industry-expert analyst coverage terminations on the information environment of followed firms.

We identify 12 brokerage closures over the 1994 and 2009 period. We employ a difference-in-differences (DiD) approach to eliminate common influences that affect similar firms at the same time and to minimize the impact of cross-sectional and time-series effects of brokerage closures on real financial market effects. Specifically, we compare *changes* in the information environments of treatment firms (treatment difference) and control firms (control difference), focusing on the difference between treatment and control firms (DiD). Control firms are matched using the Daniel et al. (1997) algorithm based on the Fama and French (1993) pricing factors and analyst coverage (KL). Specifically, we require that candidate control firms to be in the same size and book-to-market quintile in the preceding June, be covered by one or more sell-side analysts in the year before the broker event, and not experience a coverage termination in the year before or after the brokerage closure. We retain control firms that have the smallest difference in the number of analysts compared to corresponding treatment firms affected by broker closures.

Insert Table VI here

In Table VI, we report the mean DiD for the firm-level information asymmetry measures. We compute the effect of coverage terminations on changes in three- and six-month bid-ask spreads, Amihud's (2002) illiquidity measure, Lesmond, Ogden, and Trzcinka's (1999) stale returns measure (% of days with missing or zero returns), volatility of stock returns around earnings announcements, and absolute earnings surprises.

The first column "Lost analyst" provides the results for the full sample of treatment firms affected by the loss of analyst coverage. For three of the eight information asymmetry measures presented, a loss of analyst coverage increases firm-level information asymmetry, which is broadly consistent with the findings of KL. In the next two columns, we separate the sample of treatment firms into two groups based on the exogenous termination of coverage by related industry-experienced analysts (*Lost related experienced analyst)* and all other analysts (*Lost other analyst*). We find that all measures of information asymmetry presented are statistically and economically significant for the firms affected by a loss of related experienced analyst research coverage. In comparison only one measure of information asymmetry is statistically significant for the control sample. The last column in Table VI computes the difference in DiD between the two groups and suggests that for all proxies of information asymmetry, a loss of related experienced analyst coverage leads to increased information asymmetry relative to a loss of other types of analysts.

Insert Table VII here

We next consider the price impact following a loss of analyst coverage on treatment and non-treatment firms. In Table VII, we employ the price impact measures of KL. Similar to Table VI, we first present the results for the full sample. Consistent with KL, on average we find that a loss of analyst coverage results in a significant decline in stock prices. For instance, the [-1,+1]-day ([-1,+3]-day) mean DiD cumulative abnormal return (CAR) around an analyst coverage termination is -0.58% (-0.74%). These returns are not transitory over the first trading month as the [+5,+22]-day CAR is not statistically different from zero. More importantly, the price decline is again more pronounced for firms that lose industry expert analysts. For instance, average CARs over the [-1,+1]-day period are an economically and statistically significant -1.12% for terminations of related experienced analysts compared to -0.35% for other analysts. The difference in mean DiD of -0.77% is highly significant as shown in the last column.

Taken together, the results in this section suggest that a loss of analysts with related pre-analyst industry experience has more pronounced effects on covered firms' level of information asymmetry and stock prices relative to loss of nonindustry expert analysts.

V. Robustness Tests

In this section we discuss additional analyses and results presented in the Internet Appendix that accompanies this paper. In particular, we consider finer industry classifications of analyst industry experience and alternative definitions of forecast performance. We also address potential sample selection issues, investigate whether the effect of related industry-experienced analysts exhibits cross-sectional variation across pre-analyst experience characteristics, examine the investment value of stock recommendations, and perform additional robustness tests.

A. Industry Classifications

A legitimate concern with our analysis above is that our industry classifications are based on broad Fama-French industry classifications. This concern should be mitigated, however, because our conditional models examine differences in forecasts by experienced analysts who provide forecasts on both firms related and firms unrelated to their previous employment experience. Further, any misclassification will introduce noise and thus bias the results against finding differences between analysts with and without industry experience. Nonetheless, to further address this concern, we limit our sample to analysts who worked at publicly traded firms or private firms that we are able to classify into one of with the Global Industry Classification System (GICS) industries.[15] Boni and Womack (2006) suggest that the GICS system well matches analyst industries, and these classifications are used in other analyst studies such as Kadan et al. (2012).

Insert Table VIII here

Table VIII reestimates equation (3) for the sample of pre-analyst experience firms that can be assigned to a GICS industry. We find the results are robust to using this more restricted sample. Comparing the coefficients on *Related experience* between Table II and model 1 of Table VIII, the economic magnitude of related experience is -4.61 for this more restricted sample of firms assigned to GICS industries. Models 2 and 3 present the results for the pre- and post-Reg FD periods, respectively. Our baseline results continue to hold. We therefore conclude that our classification system based on broad industries does not pose a problem for our analysis.

B. Alternative Forecast Performance Measures and Fixed Effects

Throughout the paper, we employ the widely accepted measure of analyst forecast accuracy developed by Clement (1999) to facilitate comparison with related work in the area. To ensure our results are not sensitive to how we measure forecast performance, we consider two alternative ways of capturing analyst forecast accuracy.

First, we estimate regressions with the unadjusted absolute forecast error and include firm-year paired fixed effects. In this setting, we compare each analyst's absolute forecast error relative to the average AFE of other analysts covering the same firm at the same point in time. In addition, we add broker fixed effects to control for time-invariant brokerage characteristics that might be correlated with analyst performance. Similar to the results in model 2 of Table II,

[15] We are able to obtain 4-digit SIC codes for a subset of 436 (out of 1,892) private pre-analyst employment firms from Compustat and Thomson Financial's Securities Data Company (SDC) database.

model 1 of Table IX shows that analysts with related industry experience have significantly better forecast accuracy, while unrelated industry experience does not improve performance. Tables IA.II and IA.III of the Internet Appendix replicate the analyses of Tables II and VIII using the unadjusted absolute forecast error. The results are robust to using this alternative measure of forecast accuracy.

Insert Table IX here

We next repeat our analysis using the subsample of experienced analysts who make forecasts on industry related and unrelated firms, include fixed effects for each analyst-year pair, and measure relative forecast performance with *PMAFE*. In this estimation, we compare the relative forecast accuracy issued by the same analyst at the same time across firms for which she possesses pre-analyst related industry work experience and firms for which she lacks such experience. The results, findings are reported in Model 2 of Table IX, indicate that the forecasts of experienced analysts are, on average, 6.58% more accurate for related firms. Table IA.IV of the Internet Appendix, provides the results for the full sample, the pre-Reg FD period and the post-Reg FD period, as well as estimation using GICS industry classifications.[16]

C. Self-Selection, Analyst Effort, and Additional Analysis

Another reasonable concern with our analysis is that analysts self-select to subscribe to *LinkedIn.com*. This concern may be particularly relevant in the early part of our sample, when our match rate based on this source is lower. To address this concern, we perform two additional tests. First, we estimate equation (3) for each of the six subperiods in Panel A of Table I. In five of the six periods, we find that our results continue to be statistically and economically significant. Second, we consider the universe of *I/B/E/S* coverage and create the variable *LinkedIn dummy*, which equals one if we obtain employment information for the analyst and zero otherwise. Here, we are interested in whether self-reported analysts (those that subscribe to *LinkedIn*) are systematically different from analysts who do not subscribe to this service. Model 3

[16] We also consider the performance metric of Hong and Kubik (2003). Under their approach, 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 analyst *i*'s scores over years *t*, *t*-1, and *t*-2. As Hong and Kubik argue, this three-year average horizon should reduce noise and might be a more appropriate test for performance persistence. We reestimate equation (3) using this new measure of relative forecast accuracy in place of *PMAFE* and include year, firm, and industry fixed effects. Our results are robust to this measure as well.

of Table IX reports the test results. We find that the coefficient on *LinkedIn dummy* is negative but statistically insignificant.

Next, we consider the possibility that some analysts may selectively disclose their industry experience on *LinkedIn*, leading to an increase in the fraction of inexperienced analysts in our sample. While there is little reason to believe that such a pattern might systematically bias the results, we attempt to address this concern by considering the time between college graduation and the start of employment at the brokerage house for inexperienced analysts. For the 46% of inexperienced analysts in our sample for which we can determine the graduation year, the median gap is only one year, suggesting that the majority of inexperienced analysts are indeed hired directly from college. In further analysis we also examine whether these "fresh out of college" analysts have different forecasting abilities compared to their older counterparts lacking industry experience according to their *LinkedIn* profiles. In model 4 of Table IX, we employ the indicator variable *Within 1 year gap*, which equals one if the employment/graduation gap is one year or less and zero otherwise. We find that the coefficient on *Within 1 year gap* is positive but statistically insignificant. Thus, selective disclosure is unlikely to be a major concern for our analysts.

In most of our tests, we use a dummy variable to capture related industry experience because of the ease of economic interpretation and the ability to separate the impact of accuracy on related and unrelated forecasts. In model 5 of Table IX, we instead use a continuous measure of related experience. Specifically, for each forecasted firm, we employ the natural logarithm of one plus the number of years of related industry experience (*Ln(Related exp length))*. The coefficient is -0.8 and highly significant. Economically, this suggests that a one year increase in related industry experience leads to about a 0.16% improvement in relative forecast accuracy. Our results are therefore robust to using either the actual length of industry experience or a dummy for industry experience. In model 6, we rerun this analysis on the subsample of analysts who possess industry experience. The coefficient is -3.07, which implies a 0.63% improvement in relative forecast accuracy given a one-year increase in the length of related experience.

As we note earlier, it is well known that analysts tend to specialize in industries. As a result, it is likely that an analyst's industry forecasting experience is highly correlated with their general forecasting experience (indeed, we find that the correlation is 0.85). Nonetheless, we also reestimate equation (3), controlling for an analyst's industry forecasting experience by computing the number of years that each analyst provided forecasts in the same two-digit industry as the forecasted firm. We find that related pre-analyst experience is still highly significant (coefficient = -3.93, *t*-statistic = -9.23).

To better understand the mechanisms through which industry work experience affects forecasting performance, we further investigate how related experience varies with the nature and source of such experience. We first differentiate between related industry experience obtained at private and public firms. We conjecture that public firm experience should be more relevant in improving analysts' ability to understand covered firms' fundamentals. Next, we consider the revenue synchronicity between pre-analyst employment and covered firms. Covered firms whose revenues are highly synchronous with their corresponding industries may result in more industry knowledge transfer from pre-analyst employment firms to firms followed by related industry-experienced analysts (Hutton, Lee, and Shu (2012)). Finally, we consider the implications of information complementariness obtained through work experience in supplier-customer firms' industry (Guan, Wong, and Zhang (2014)). Accordingly, we partition *Related experience* into two new explanatory variables based on the public status of pre-analyst employment firms (*Public/Private firm*), revenue synchronicity (*High/Low synchronicity*), and experience along the customer-supply chain (*CS industry/No CS industry*) at the median value of these variables. We then reestimate model 2 in Table II. Columns 1 through 3 of Table IA.V in the Internet Appendix present the coefficient estimates for each variable of interest; for brevity, we do not report results for the controls. We find that the marginal impact of related industry experience is higher for analysts previously employed at public, high synchronicity, and customer-supplier industry firms. In all cases presented in Table IA.V, the coefficients are statistically significantly different from each other at the 1% level.

We interpret the results of our main findings as consistent with the view that industry experience improves analyst performance by providing them with a competitive advantage over their inexperienced peers. A potential alternative explanation may be that analysts simply exert more effort in forecasting related industry firms, leading to more accurate forecasts. The analysis above on the real effects on firms' information environment would not support this view unless market participants were able to systematically infer effort. Nevertheless, in Table IA.VI of the Internet Appendix, we consider the role of asymmetric effort using the the frequency with which an analyst issues the first forecast on a firm (Chen and Matsumoto (2006)), analyst portfolio turnover, the issuance of no forecasts over the following fiscal year (Chen and Matsumoto (2006)), and the number of firms followed within a given year (Barth, Kasznik, and McNichols

(2001)) as dependent variables in models 1 through 4, respectively. Our results suggest that experienced analysts' level of effort on related firms is not statistically different from that of other analysts.

Finally, we explore the stock return performance of buy and sell recommendations issued by industry-expert and nonindustry-expert analysts. We use a calendar time portfolio approach following prior work (e.g. Barber, Lehavy, and Trueman (2005), Cohen, Frazzini, and Malloy (2010)). We construct "Buy" and "Sell" portfolios based on analysts' recommendations. To be included in the Buy (Sell) portfolio, a stock is required to be upgraded (downgraded) relative to a previous recommendation, or reiterated/resumed/initiated with a I/B/E/S numeric ratings of 1 or 2 (3, 4, or 5) corresponding to "Strong buy" and "Buy" ("Hold", "Sell", "Strong Sell") recommendations. Stocks are dropped or added from portfolios when an analyst revises their recommendation or when the recommendation becomes stale (no activity for one year). To compute abnormal returns, we use Daniel et al. (1997) (DGTW) characteristic-adjusted excess stock returns.[17]

In Panel A of Table X, we find that related industry-experienced analysts' buy recommendations provide 0.67% monthly abnormal returns compared to 0.30% (0.35%) for inexperienced (unrelated experience) analysts. The difference in monthly returns between related analysts and other analysts is highly significant. In Panel B, we find a similar pattern for sell recommendations.[18]

Insert Table X here

VI. Conclusion

[17] DGTW returns are defined as the compounded raw stock returns minus the value-weighted returns of the matching characteristic-sorted benchmark portfolio. In particular, we sort the universe of firms listed on NYSE/AMEX and Nasdaq into quintiles by equity market capitalization in June of each year using breakpoints for NYSE quintiles. Firms are further placed into quintiles based on the industry-adjusted book-to-market ratios within each market capitalization quintile, yielding 25 portfolios (5×5). Finally, the firms in each of the 25 size/book-to-market portfolios are sorted into quintiles according to their 12-month buy-and-hold raw returns at the end of May of each year, yielding 125 (25x5) size/book-to-market/momentum portfolios every June. To account for the rating scale change that many banks adopted in 2002 (i.e., from a 5-point to 3-point scale), we remove revisions that were mechanically revised as a result of this change.

[18] We also estimate regressions with the DGTW return as the dependent variable and nondemeaned controls as in Table II. The regressions are run daily, but we convert reported coefficients into abnormal monthly returns. We find that the coefficient on *Related experience* is positive and significant in all specifications. Economically, our results indicate that industry-expert analysts' buy recommendations outperform those issued by analysts without pre-analyst experience by 0.38% per month, or 4.6% annually. Likewise, industry-experienced sell recommendations perform -0.28% monthly (-3.30% annually) compared to those by inexperienced analysts.

Practitioners consistently indicate that industry knowledge is the most important quality a sell-side analyst can possess. Despite this anecdotal observation, there is surprisingly little empirical evidence on how industry knowledge impacts analyst performance, career outcomes, and covered firms' information environment. This paper attempts to fill this gap. Using novel biographical data on sell-side analysts, we exploit their previous employment history to examine how pre-analyst employment in related and unrelated industries influences earnings forecasts, career outcomes, and market responses to earnings revisions. Further, we analyze the real economic effects of exogenous analyst coverage terminations on covered firms' information environments.

For a sample of analyst earnings forecasts from 1983 to 2011, we find that forecasts are more accurate for analysts with previous work experience. However, this is only true for forecasts issued in industries related to analysts' previous work experience. These results are robust to holding constant other known analyst characteristics linked to skill such as general and firm-specific forecasting experience, portfolio complexity, and brokerage house prestige.

When we examine whether industry experience influences analysts' career outcomes, we find that analysts with related industry experience are more likely to be named to *II* annual all-star list. We also find that analysts' previous industry experience is positively related to market reactions to analyst forecast revisions and that a portfolio of industry expert analysts' buy and sell recommendations outperforms a similar portfolio consisting of nonexpert analyst recommendations.

Finally, in our tests on the effect of a loss of analyst coverage resulting from exogenous brokerage house closures on firms' information environments, we find economically and statistically more pronounced information asymmetry information and stock price effects when covered firms lose coverage by analysts with related industry experience.

Initial Submission: 2/4/2014; Accepted: 10/1/2015

Editor: Kenneth Singleton

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Table I Summary Statistics

This table reports sample summary statistics. Panel A presents summary statistics by subperiod. % Forecasts experienced, % Related forecasts, and % Unrelated forecasts are the percentage of forecasts made by analysts that have pre-analyst industry work experience, work experience in a related industry, and work experience in an unrelated industry relative to the industry of the covered firm. %Firm, % Analysts, %Forecasts, and %Market capitalization are the percentage of firms, analysts, forecasts, and market capitalization relative to the clean $I/B/E/S$ universe of firms. Panel B presents descriptive statistics for the main analyst characteristics used in our analyses. Appendix B provides a detailed description of the data screening and collection process. See Appendix C for variable definitions. 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 Subperiod

Year	*N* Firms	*N* Forecasts	% Forecasts experienced	% Related forecasts	% Unrelated forecas	% Firms	% Analysts	% Forecasts	% Market capitalization
1983-1987	387	1,240	29%	13%	16%	24%	2.24%	2%	48%
1988-1992	922	4,083	42%	20%	22%	38%	5.75%	6%	68%
1993-1997	2,052	10,055	48%	23%	25%	51%	12.56%	10%	79%
1998-2002	2,952	22,736	61%	32%	29%	73%	21.11%	22%	89%
2003-2007	3,013	42,249	67%	36%	31%	89%	32.34%	36%	95%
2008-2011	2,469	32,610	73%	37%	36%	95%	37.78%	44%	99%
Sum/Avg.	5,581	112,973	53%	27%	26%	61%	20.42%	19%	79%

Panel B: Unadjusted and Mean-Adjusted Analyst Characteristics

	Unadjusted				Mean-Adjusted		
	Mean	Median	Std. Dev.		Mean	Median	Std. Dev.
AFE	0.10	0.04	0.16	*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*	-0.13	-0.26	0.72

Table II Baseline Regression of Analyst Forecast Accuracy and Previous Industry Work Experience

This table presents OLS regression results for analyst earnings forecasts. The dependent variable is the proportional mean absolute forecast error (*PMAFE*) defined as the difference between the absolute forecast error of 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*. Tests for the pre- (post-) Reg FD periods are in models 4 to 6 (7 to 9). 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 covered firms, respectively. See Appendix C for variable definitions. 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 doubled-clustered at the firm and analyst levels. All coefficients are multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Overall sample			Pre-Reg FD			Post-Reg FD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	5.45***	5.07***	5.38***	1.43	1.02	-0.38	6.18***	5.82***	7.13***
	(4.734	(4.40)	(3.86)	(0.67)	(0.47)	(-0.13)	(4.38)	(4.12)	(4.41)

	)								
Experience	-1.55***			-1.53*			-1.21**		
	(-3.28)			(-1.75)			(-2.12)		
Related experience		-3.58***	-4.33***		-3.84***	-5.07***		-3.10***	-4.06***
		(-6.76)	(-8.05)		(-3.73)	(-4.31)		(-4.93)	(-6.72)
Unrelated experience		0.76			0.89			1.01	
		(1.36)			(0.83)			(1.53)	
DGExp	-0.16***	-0.16***	-0.15*	-0.14	-0.15	0.07	-0.14**	-0.14**	-0.18**
	(-2.95)	(-2.96)	(-1.90)	(-1.10)	(-1.13)	(0.36)	(-2.35)	(-2.34)	(-2.09)
DAge	0.51***	0.51***	0.52***	0.41***	0.41***	0.42***	0.55***	0.55***	0.55***
	(93.50)	(93.27)	(76.28)	(41.19)	(41.12)	(29.42)	(85.04)	(84.81)	(70.84)
DFExp	-0.26***	-0.22**	-0.21	-0.35	-0.32	-0.08	-0.26**	-0.21**	-0.25*
	(-2.77)	(-2.31)	(-1.61)	(-1.59)	(-1.49)	(-0.25)	(-2.45)	(-2.01)	(-1.77)
DPortsize	0.11**	0.10*	-0.01	0.33***	0.31***	0.15	0.02	0.02	-0.07
	(2.02)	(1.88)	(-0.22)	(3.55)	(3.39)	(1.13)	(0.35)	(0.31)	(-0.85)
DSIC2	0.21	0.21	0.39**	0.01	0.01	0.01	0.30	0.30*	0.49**
	(1.38)	(1.39)	(2.05)	(0.04)	(0.05)	(0.02)	(1.64)	(1.65)	(2.25)
DTop10	-2.04***	-2.11***	-0.73	-7.32***	-7.29***	-7.27***	-0.41	-0.50	0.67
	(-4.38)	(-4.53)	(-1.27)	(-7.91)	(-7.88)	(-5.47)	(-0.76)	(-0.93)	(1.05)
Size	-0.27	-0.22	-0.15	0.36	0.40	0.75	-0.37*	-0.32	-0.39
	(-1.54)	(-1.25)	(-0.66)	(1.01)	(1.10)	(1.54)	(-1.79)	(-1.54)	(-1.54)
BM	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.01***	-0.28*	-0.27*	-0.22
	(-4.26)	(-4.16)	(-5.75)	(-8.72)	(-8.11)	(-6.88)	(-1.83)	(-1.81)	(-1.33)
Past ret	7.43*	7.74**	3.94	12.48*	12.84*	9.86	3.15	3.43	0.52
	(1.94)	(2.02)	(0.84)	(1.83)	(1.89)	(1.14)	(0.68)	(0.74)	(0.09)
No of analysts	-0.45***	-0.46***	-0.46***	-0.52***	-0.51***	-0.51***	-0.45***	-0.46***	-0.45***
	(-15.26)	(-15.38)	(-12.29)	(-8.73)	(-8.62)	(-6.16)	(-12.98)	(-13.17)	(-10.69)

R^2	13.10 %	13.15 %	13.53 %	11.00%	11.06 %	11.18 %	14.01%	14.07%	14.24%
n	112,47 9	112,47 9	73,306	27,147	27,147	13,972	85,332	85,332	59,334

Table III Industry Work Experience and All-Star Analyst Status

This table presents logistic 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 that is equal to one if the analyst is listed as an all-star analyst in the current year's October issue of *Institutional Investor* magazine. All control variables are lagged by one year. Year fixed effects are included. See Appendix C for variable definitions. 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% level, respectively.

	(1)	(2)	(3)	(4)
Experience	0.36***			
	(3.13)			
Related experience		0.56***	0.97***	
		(4.29)	(3.69)	
Unrelated experience		-0.09		
		(-0.72)		
Percentage related firms				0.49***
				(2.68)
GExp	-0.00	-0.00	-0.02	-0.01
	(-0.38)	(-0.29)	(-1.03)	(-0.86)
Portfolio size	0.04***	0.03***	0.02	0.03**
	(3.42)	(3.15)	(1.35)	(1.96)
SIC2	0.02	0.02	0.04	0.05
	(0.64)	(0.65)	(1.06)	(1.23)
Brokerage size	0.03***	0.03***	0.03***	0.03***
	(16.84)	(17.14)	(13.63)	(13.85)
Average PMAFE	-0.52***	-0.52***	-0.48**	-0.48**
	(-3.32)	(-3.29)	(-2.48)	(-2.56)
Average firm size	0.40***	0.39***	0.38***	0.37***
	(8.51)	(8.37)	(6.52)	(6.56)
Lag (All-star)	5.23***	5.22***	5.14***	5.17***
	(40.31)	(40.33)	(30.68)	(30.78)
Year fixed effects	Y	Y	Y	Y
N	12,130	12,130	8,023	8,023

Table IV Regression Analysis of Market Reactions to Earnings Forecast Revisions

This table reports results on market reactions to analysts' revisions of earnings forecasts. The dependent variable is the [0,+2]-day cumulative market-adjusted abnormal return around the announcement of a forecast revision by analyst *i* for firm *j* at time *t*. Abs (*FR*) is the absolute value of the difference between an analyst's revised forecast at time *t* and the previous forecast at time *t*-1 scaled by the absolute value of the forecast at *t*-1. Year fixed effects are included. See Appendix C for variable definitions. 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 double-clustered at the firm and analyst levels. All coefficients are multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Positive news			Negative news		
	(1)	(2)	(3)	(4)	(5)	(6)
Experience	0.25***			-0.24**		
	(3.23)			(-2.44)		
Related experience		0.43***	0.42***		-0.45***	-0.45***
		(4.94)	(4.80)		(-3.95)	(-3.77)
Unrelated experience		0.03			-0.03	
		(0.37)			(-0.22)	
Abs (FR)	6.19***	6.25***	6.54***	-4.21***	-4.25***	-4.72***
	(14.92)	(15.06)	(12.66)	(-11.11)	(-11.20)	(-9.74)
DGExp	0.01	0.01	0.02	-0.02	-0.02	-0.02
	(0.67)	(0.61)	(1.59)	(-1.39)	(-1.45)	(-0.90)
DAge	0.00**	0.00**	0.00***	-0.00***	-0.00***	-0.01***
	(2.14)	(2.23)	(3.26)	(-5.16)	(-5.23)	(-6.34)
DFExp	0.01	0.01	-0.01	-0.01	0.00	-0.02
	(0.83)	(0.51)	(-0.63)	(-0.34)	(-0.11)	(-0.71)
DPortsize	-0.01	-0.01	-0.01	-0.02*	-0.02*	-0.01
	(-1.31)	(-1.22)	(-0.93)	(-1.74)	(-1.83)	(-1.13)
DSIC2	-0.01	-0.01	-0.02	0.06**	0.06**	0.06
	(-0.65)	(-0.62)	(-0.76)	(2.03)	(2.02)	(1.47)
DTop10	0.41***	0.42***	0.52***	-0.26**	-0.26***	-0.31**
	(5.37)	(5.45)	(5.48)	(-2.57)	(-2.66)	(-2.36)
Size	-0.40***	-0.41***	-0.49***	0.37***	0.37***	0.44***
	(-13.51)	(-13.61)	(-13.20)	(8.99)	(9.06)	(8.45)
BM	-0.08*	-0.08*	-0.21***	0.12	0.13	0.11
	(-1.75)	(-1.85)	(-2.71)	(1.42)	(1.43)	(1.24)
Past ret	-11.59***	-11.60***	-11.62***	-6.96***	-6.94***	-5.71***
	(-9.93)	(-9.93)	(-8.09)	(-5.04)	(-5.01)	(-3.30)
No of analysts	0.02***	0.02***	0.02***	-0.03***	-0.03***	-0.03***
	(3.76)	(3.80)	(3.94)	(-4.14)	(-4.13)	(-3.79)
Lag PMAFE	-0.16***	-0.16***	-0.21***	0.17***	0.17***	0.22**
	(-3.42)	(-3.42)	(-3.48)	(2.63)	(2.64)	(2.56)
R^2	9.94%	9.99%	11.25%	8.57%	8.61%	9.47%
Year fixed effects	Y	Y	Y	Y	Y	Y
N	40,719	40,719	26,688	33,490	33,490	21,185

Table V Shortage and Busyness of Related Experienced Analysts

This table presents logistic regression results for the probability that an inexperienced/unrelated analyst covers a firm. The dependent variable in each model is a binary variable that equals one if the firm is covered by a nonindustry expert analyst (i.e., unrelated experience / inexperienced analyst). See Appendix C for variable definitions. 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 levels. All coefficients are multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
No of other related experienced analysts	-7.03***	
	(-9.87)	
Average other related experienced analyst portsize		2.64***
		(2.74)
Average PMAFE	1.38	-1.80
	(0.48)	(-0.47)
Size	-1.95	-4.06
	(-0.94)	(-1.44)
BM	-0.12*	-0.67
	(-1.77)	(-0.60)
No of analysts	-0.87**	0.64
	(-2.31)	(1.34)
Past ret	-2.33	1.53
	(-1.61)	(0.69)
Sales growth	1.88	-0.35
	(0.62)	(-0.11)
Issuance	4.06	5.97
	(1.08)	(1.19)
Affiliated	2.12	3.60
	(0.38)	(0.57)
Broker, Year fixed effects	Y	Y
R^2	15.23%	13.53%
N	105,574	58,099

Table VI Coverage Terminations and Information Asymmetry: Broker Closures

This table reports results on the effect of exogenous brokerage house closures on *changes* in three- and six-month bid-ask spreads, Amihud's illiquidity measure, % of days with missing or zero returns, the volatility of returns around earnings announcements, and absolute value of earnings surprises. The first column "Lost analyst" provides the cross-sectional means of difference-in-differences (DiD) for the full sample of treatment firms affected by a loss of analyst coverage. “Lost related experienced analyst” (“Lost other analyst”) provides results for sample of firms associated with exogenous terminations of coverage by related industry-experienced analysts (all other analysts). The last column reports the differences between these two groups. Control firms are matched to treatment firms using the Daniel et al. (1997) algorithm based on the Fama and French (1993) pricing factors and analyst coverage as in Kelly and Ljungqvist (2012). See Appendix C for variable definitions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Difference-in-Differences						
	Lost analyst		Lost related experienced analyst		Lost other analyst		Difference
Variable (%)	N	Mean	N	Mean	N	Mean	
Bid-ask spread (3 month window)	399	0.04*	119	0.12***	280	0.01	0.10**
Bid-ask spread (6 month window)	399	0.06**	119	0.15***	280	0.02	0.13**
Amihud illiquidity (3 month window)	399	0.37	119	1.19***	280	0.03	1.17**
Amihud illiquidity (6 month window)	399	0.44	119	1.24***	280	0.10	1.14**
Missing/zero ret days(3 month window)	399	0.23	119	0.87**	280	-0.05	0.92**
Missing/zero ret days(6 month window)	399	0.15	119	0.75**	280	-0.11	0.86**
Volatility (Earnings announcement)	399	3.99***	119	7.73***	280	2.40*	5.32**
Abs(Earnings surprise)	399	0.04	119	0.12**	280	0.00	0.12*

Table VII Coverage Terminations and Price Impact: Broker Closures

This table reports the mean difference-in-differences (DiD) market reactions to a loss of analyst coverage arising from exogenous brokerage house closures. The first column "Lost analyst" provides the cross-sectional means of DiD for the full sample of treatment firms affected by a loss of analyst coverage. "Lost related experienced analyst" ("Lost other analyst") provides results for sample of firms associated with exogenous terminations of coverage by related industry experienced analysts (all other analysts). The last column reports the differences between these two groups. Control firms are matched to treatment firms using the Daniel et al. (1997) algorithm based on the Fama and French (1993) pricing factors and analyst coverage as in Kelly and Ljungqvist (2012). See Appendix C for variable definitions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Difference-in-Differences						
	Lost analyst		Lost related experienced analyst		Lost other analyst		Difference
Variable (%)	N	Mean	N	Mean	N	Mean	Mean
CAR [-1, +1]	399	-0.58***	119	-1.12***	280	-0.35*	-0.77**
CAR [-1, +3]	399	-0.74***	119	-1.55***	280	-0.39	-1.17**
CAR [-1, +5]	399	-1.17***	119	-2.13***	280	-0.77*	-1.36**
CAR [+5, +22]	399	0.07	119	-0.67	280	0.38	-1.05
Market CAR [-1, +1]	399	-0.60***	119	-1.18***	280	-0.36*	-0.82**
Market CAR [-1, +3]	399	-0.86***	119	-1.65***	280	-0.53*	-1.12**
Market CAR [-1, +5]	399	-0.93***	119	-2.06***	280	-0.45	-1.61**
Market CAR [+5, +22]	399	-0.20	119	-0.59	280	-0.03	-0.55
FF (1993) CAR [-1, +1]	399	-0.59***	119	-1.16***	280	-0.35*	-0.81**
FF (1993) CAR [-1, +3]	399	-0.86***	119	-1.64***	280	-0.53*	-1.10**
FF (1993) CAR [-1, +5]	399	-0.74**	119	-1.80***	280	-0.29	-1.51**
FF (1993) CAR [+5, +22]	399	-0.26	119	-0.83	280	-0.01	-0.82

Table VIII Robustness of Main Results with GICS Industry Classification

This table presents OLS regression results for analyst earnings forecasts for the sample of analysts that previously worked at a publicly traded or private firm for which we can classify using the Global Industry Classification System (GICS). The dependent variable is the proportional mean absolute forecast error (*PMAFE*), defined as the difference between the absolute forecast error of 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*. Model 1 presents results for the full sample and models 2 and 3 present results for pre- and post-Reg FD periods, respectively. See Appendix C for variable definitions. 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 double-clustered at the firm and analyst levels. All coefficients are multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Overall sample	Pre-Reg FD	Post-Reg FD
Intercept	6.12***	-0.84	8.13***
	(3.43)	(-0.21)	(3.98)
Related experience	-4.61***	-3.97**	-4.66***
	(-5.57)	(-2.38)	(-4.85)
DGExp	-0.12	-0.23	-0.10
	(-1.13)	(-0.87)	(-0.82)
DAge	0.53***	0.41***	0.56***
	(59.30)	(21.75)	(55.45)
DFExp	-0.34**	-0.39	-0.36*
	(-1.97)	(-1.01)	(-1.86)
DPortsize	-0.07	0.36*	-0.17*
	(-0.79)	(1.85)	(-1.68)
DSIC2	0.36	-0.04	0.47*
	(1.47)	(-0.07)	(1.70)
DTop10	-1.84**	-7.44***	-0.51
	(-2.39)	(-4.12)	(-0.60)
Size	-0.58**	0.53	-0.87***
	(-2.10)	(0.82)	(-2.78)
BM	-0.02***	-0.02***	-0.28*
	(-6.06)	(-7.22)	(-1.79)
Past ret	7.14	11.31	4.39
	(1.18)	(0.97)	(0.62)
No of analysts	-0.39***	-0.55***	-0.36***
	(-8.11)	(-4.71)	(-6.69)
R^2	13.86%	10.86%	14.66%

N	42,509	7,879	34,630

Table IX Robustness

This table presents OLS regression results on analyst earnings forecast accuracy. The dependent variable is the absolute forecast error (*AFE*) in model 1 and the proportional mean absolute forecast error (*PMAFE*) in models 2 to 6. See Appendix C for variable definitions. 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*. All coefficients are multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept			26.55***	1.03	5.31***	8.97*
			(19.57)	(0.40)	(4.67)	(1.75)
Related experience	-0.84***	-6.58***				
	(-9.41)	(-9.81)				
Unrelated experience	0.02					
	(0.17)					
LinkedIn dummy			-0.70			
			(-1.16)			
Within 1 year gap				0.97		
				(1.04)		
Ln(Related exp length)					-0.80***	-3.07**
					(-3.53)	(-2.51)
GExp/DGExp	-0.01	-0.25	-0.19***	-0.08	-0.17***	-0.45*
	(-0.83)	(-1.39)	(-3.00)	(-0.72)	(-3.07)	(-1.85)
Age/DAge	0.06***	0.45***	0.78***	0.48***	0.51***	0.53***
	(81.41)	(72.95)	(129.86)	(40.64)	(93.52)	(28.57)
FExp/DFExp	-0.04***	-0.10	-0.67***	-0.33*	-0.26***	-0.46
	(-3.00)	(-0.74)	(-6.45)	(-1.81)	(-2.77)	(-1.12)
Portsize/DPortsize	0.02**	-0.16	0.13***	0.01	0.11**	0.15
	(2.56)	(-1.12)	(4.22)	(0.09)	(2.01)	(1.03)
SIC2/DSIC2	0.00	-0.67*	0.00	0.10	0.21	-0.75
	(0.02)	(-1.85)	(0.24)	(0.32)	(1.42)	(-1.00)
Top10/DTop10	-0.60***	-4.20**	-5.49***	-1.59	-2.06***	-0.45
	(-4.14)	(-2.51)	(-10.56)	(-1.55)	(-4.42)	(-0.29)
Size		-0.76***	-0.49***	-0.03	-0.26	0.09
		(-2.71)	(-2.61)	(-0.08)	(-1.47)	(0.14)
BM		-0.03	-0.01	0.92	-0.02***	1.77
		(-1.50)	(-1.21)	(1.56)	(-4.33)	(1.14)
Past ret		7.55	0.85	14.00	7.40*	4.95
		(1.34)	(1.09)	(1.62)	(1.94)	(0.32)
No of analysts		-0.42***	-0.63***	-0.49***	-0.46***	-0.55***
		(-8.63)	(-19.99)	(-7.61)	(-15.29)	(-5.12)
R^2	77.98%	18.15%	12.85%	12.67%	13.11%	14.14%
N	112,479	73,306	407,605	22,621	112,479	73,306
Firm-year, broker FE	Y	N	N	N	N	N
Analyst-year FE	N	Y	N	N	N	N

Table X Investment Value for Buy and Sell Recommendations

Panel A (B) presents mean DGTW-adjusted monthly stock returns for buy (sell) recommendations based on analysts' recommendations. To be included in the Buy (Sell) portfolio, a stock is required to be upgraded (downgraded) relative to a previous recommendation, or reiterated/resumed/initiated with a I/B/E/S numeric ratings of 1 or 2 (3, 4 or 5), which correspond to Strong buy and Buy (Hold, Sell, Strong Sell) recommendation. Stocks are dropped from or added to portfolios when an analyst revises their recommendation or when the recommendation becomes stale (no activity for one year). Analyst data are from I/B/E/S from 1983 to 2011, stock price data are from CRSP. Employment history is collected from LinkedIn.com and supplemented with Zoominfo.com. *t*-statistics are in parentheses with heteroskedastic-consistent standard errors double-clustered at the firm and analyst levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Buy recommendation returns (%)

Inexperienced	Experienced	Diff (Experienced-inexperienced)	Related experience	Unrelated experience	Diff (Related-unrelated)	Diff (Related-inexperienced)	Diff (Unrelated-inexperienced)
0.30***	0.52***	0.21***	0.67***	0.35***	0.32***	0.37***	0.05

Panel B: Sell recommendation returns (%)

Inexperienced	Experienced	Diff (Experienced-inexperienced)	Related experience	Unrelated experience	Diff (Related-unrelated)	Diff (Related-inexperienced)	Diff (Unrelated-inexperienced)
0.04	-0.10***	-0.14***	-0.20***	0.01	-0.20***	-0.24***	-0.03

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/Responsiven	2	Integrity/professionalism

Rank	Attribute	Rank	Attribute	Rank	Attribute
			ess		
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**
Obtain all analysts' annual EPS forecasts over the 1983 to 2011 period from *I/B/E/S*.	2,966,210	19,424	19,237

Merge with CRSP/COMPUSTAT to obtain stock price data and firm characteristics.	2,036,023	10,563	15,531
Keep the last annual earnings forecast with a horizon between one and 12 months.	470,137	6,828	14,458
Merge sample with *I/B/E/S* recommendation file to get analysts' last name, first initial, and brokerage firm ID (estimid), which is used to identify brokerage firm names. Remove analysts without first initial, last name, or brokerage estimid, or entries for which analyst teams are given (analyst name is recorded as "research department" or contains two analyst last names). We refer to this as 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
Obtain analysts' employment history on *LinkedIn.com*.	112,973	5,581	2,505

Appendix C: Variable Definitions

All variable definitions beginning with a "*D*" are adjusted by firm-year mean values. The unadjusted variable definitions are in parentheses.

Variable	Definition
PMAFE	The proportional mean absolute forecast error calculated as the difference between the absolute forecast error (*AFE*) (in \$) 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.
Ln (Related exp length)	The length of analyst related-industry experience, measured as the natural logarithm of one plus the number of years of related industry experience.
Abs (FR)	Analyst forecast revision following Ivkovic and Jegadeesh (2004). Abs (FR) is defined as the absolute value of 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 lower. Values are multiplied by 100 and are truncated between -50% and 50%.
DGExp	The total number of years that analyst *i* appeared in *I/B/E/S* (*GExp*) minus the average tenure of 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.
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*.
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 two digit SICs followed by analyst *i* at time *t (SIC2*) minus the average number of two-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 decile brokerage house indicators for analysts following firm *j* at time *t*.
All-star	Indicator variable is one if the analyst is named to *Institutional Investor's* all-star team in current year, and zero otherwise.

Size	The natural log of market capitalization (*ME*) of the covered firm (in $ millions) by the end of the month prior to the earnings forecast.
ME	The market capitalization of the covered firm (in $millions) at 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 value-weighted index-adjusted buy-and hold abnormal return (BHARs) over the six months prior to the announcement date of the earnings forecast.
No of analysts	Number of unique analysts issuing earnings forecasts for firm *j* at time *t*.
No of other related experienced analysts	Number of other analysts excluding analyst *i* with related pre-analyst industry expertise within broker *j* at time *t*-1.
Average other related experienced analyst portsize	Average number of firms followed by other analysts excluding analyst *i* with related pre-analyst industry expertise within broker *j* at time *t*-1.
Average PMAFE	The average *PMAFE* of all the firms covered by analyst *i* at time *t*-1.
Average firm size	The average size of the all the firms covered by analyst *i* at time *t*-1.
Sales growth	Average annual growth of firm *j*'s sales over the previous three years.
Issuance	Indicator variable is one if the firm has an IPO, SEO or debt offering in the prior, current, or subsequent year, and zero otherwise.
Affiliated	Indicator variable is one if the analyst's brokerage house was the underwriter/ advisor of the covered firm's IPO/SEO/MA deal during the past three years, and zero otherwise.
% Bid-ask spread	Computed as 100 * (ask–bid) / [(ask+bid) / 2] using daily closing bid and ask data from CRSP.
% Amihud illiquidity	The natural log of one plus the ratio of the absolute stock return to the dollar trading volume and scaled by 10^6 (see Amihud (2002, p. 43)).
% Missing/zero ret days	The percentage of trading days with zero or missing returns in CRSP.
% Volatility (Earnings Announcement)	Annualized daily return volatility over the three-day window around earnings announcements for all earnings announcements that occur in the [-1,+1]-year window before or after an exogenous loss of analyst coverage.
% Abs(Earnings Surprise)	The mean absolute value of quarterly earnings surprises in a one-year

window before or after exogenous loss of analyst coverage.

CAR	CRSP value-weighted market-adjusted cumulative abnormal return.
Market Model CAR	The market model factor loadings are estimated over a one-year pre-event window ending 11 days before the termination of analyst coverage.
FF (1993) CAR	The Fama-French three-factor model factor loadings are estimated over a one-year pre-event window ending eleven days before the termination of analyst coverage.
LinkedIn dummy	Indicator variable is one if the analyst is in the *LinkedIn* sample, and zero otherwise.
Within 1 year gap	Indicator variable equal to one if the employment/graduation gap is one year or less, and zero otherwise.
Related experience-public (private) firm	Indicator variable is one if the industry of the forecasted firm is related to the analyst's prior industry work experience industry and analyst's pre-analyst employment firm is public (private), and zero otherwise.
Related experience-high (low) synchronicity	Indicator variable is one if the industry of the forecasted firm is related to the analyst's prior industry work experience industry and the forecasted firm's industry revenue synchronicity is above (below) median, and zero otherwise. Revenue synchronicity is measured as the R^2 from the firm-level estimation of the following model over the prior 12 quarters: $REV_{i,t} = a_0 + a_1\, INDREV_{i,t} + \varepsilon_{i,t}$, where *REV* is defined as revenue (saleq) divided by lagged four-quarter revenue for firm *i* and *INDREV* is the sum of revenue (saleq) for all firms in the industry (excluding firm *i*) divided by lagged four-quarter revenue for all firms (excluding firm) in the industry.
Related experience-CS (No CS) industry	Indicator variable is one if the industry of the forecasted firm is related to the analyst's prior industry work experience and the analyst has (does not have) pre-analyst related employment experience in the followed firm's customer's industry, and zero otherwise.
First mover indicator	Indicator variable is one if the analyst is the first to issue a forecast on the firm's current fiscal year earnings, and zero otherwise.
Portfolio turnover	Number of firms dropped by analyst *i* over *t*-1 and *t*.
Analysts dropping coverage	Indicator variable is one if the analyst stops covering the firm in the following year, and zero otherwise.

Number of firms followed	Number of firms followed by analyst *i* in year *t*.
Percentage related firms	Percentage of analysts covering firms that are related to the analyst's prior industry work experience.