Learning through Difficult Times: Evidence from Financial Analysts

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Abstract: We document that financial analysts who experienced industry shocks over their career (experienced analysts) make more accurate earnings forecasts and more informative recommendation changes. The effect is unlikely to be explained by improved access to management as we find a stronger effect of industry shock experience after Regulation Fair Disclosure. Exogenous coverage termination of experienced analysts have real impacts on affected firms' information environment. Overall, the evidence suggests that analysts can acquire industry expertise by learning through difficult times.

Key words: Industry shocks; Experience; Forecast accuracy; Analysts

1. Introduction

Sell-side financial analysts are prominent information intermediaries in capital markets. They engage in private information search, perform prospective analysis aimed at forecasting a firm's future earnings and cash flows, and conduct retrospective analysis that interprets past events. Regulators and other market participants view analysts' activities and the competition among analysts as enhancing the informational efficiency of security prices. Given the valuable service analysts provide to market participants, numerous studies have been devoted to what determines the quality of analyst research. On the one hand, academic studies show that a number of innate attributes and external factors including analysts' ability, general and firm-specific experience, incentives, task complexity, the prestige of their brokerage house, and access to firm management are related to their forecasting performance (Mikhail et al., 1997; Clement, 1999; Malloy, 2005; Cohen, Frazzini, and Malloy, 2010). On the other hand, practitioners in the survey of Institutional Investor (*II*) indicate that one of the most important attributes of a good analyst is the in-depth industry knowledge.[1] Consistent with *II*'s survey evidence, Bradley, Gokkaya, and Liu (2017) find that analysts produce better forecasts and more informative recommendations on firms related to their preanalyst work experience.

However, related industry work experience may not be the only way for an analyst to acquire industry expertise. Given the importance of industry expertise in determining their output and career outcomes, analysts should have strong incentives to gain industry knowledge through other channels. In this paper, we study whether analysts can also gain industry

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[1] Each October, *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.

experience through industry shocks and how such experience relates to their subsequent performance. Our conjecture is motivated by Arrow (1962)'s seminal work on learning by doing, who states that *learning can only take place through the attempt to solve a problem and therefore only takes place during activity*. Kempf et al. (2017) provide evidence supporting this learning by doing argument, as they find that a fund manager who has experienced industry shocks become more skilled subsequently.

To test the idea, we follow Kempf et al. (2017) and define a shock for a given industry-quarter if the value-weighted industry return is ranked in the bottom four across all 48 Fama-French industries in that quarter. We then identify experienced analysts as those who have experienced industry shocks over their career. We use large negative industry returns to define industry shocks for several reasons. First, studies find that analysts tend to exert more effort and investors pay more attention to analyst research in bad times (Loh and Stulz, 2018). This suggests that learning will be most effective in bad times when high-quality feedback is readily available. Second, a large literature in psychology documents that bad events have a greater impact on individuals than comparable good events. For example, Baumeister et al. (2001) made the following observations when arguing "Bad is stronger than good":

The greater power of bad events over good ones is found in everyday events, major life events (e.g., trauma), close relationship outcomes, social network patterns, interpersonal interactions, and learning processes. Bad emotions, bad parents, and bad feedback have more impact than good ones, and bad information is processed more thoroughly than good.

Based on this measure, we examine how analysts' performance is related to their industry shock experience. Using a comprehensive sample of 1,978,053 earnings forecasts on 6,172 firms over the period of 1983 to 2015, we find that the relative forecast error of analysts with industry shock experience is significantly lower than that of inexperienced analysts. In our empirical specification, we control for various analyst and forecast characteristics that are associated with forecast accuracy as documented by previous studies, including general and firm-specific forecasting experience, brokerage size, and the timeliness and frequency of forecasts. More importantly, we also include analyst by quarter and firm by quarter fixed effects, so our identification comes from variation across firms within the same analyst's portfolio in the same time and variation across different analysts' forecasts on the same firm in the same time. We are able to do this because (1) for an analyst covering more than one industry (70% of analysts), she may have shock experience for firms in one industry but not for firms in another industry, even when she covers both sets of firms at the same time; (2) for firms with multiple analysts following, some analysts will have industry shock experience while others do not. After controlling for the paired fixed effects and an extensive list of controls, we find forecasts issued by analysts with industry shock experience is 0.89% more accurate than those made by inexperienced analysts. The effect is economically sizeable, as analysts need about 3.7 more years of firm-specific experience to achieve the same level of improvement in forecast accuracy.

After documenting that experienced analysts improve their forecast accuracy, it is natural to ask how this improvement in performance is achieved. One potential channel could be that analysts are able to cultivate a good relationship with firm managers in a difficult industry environment, and hence enjoy better access to management subsequently.[2] If this channel

[2] Cohen et al. (2010) find that analysts gain comparative information advantages through educational ties with

dominates, the result should be much weaker after the passage of Regulation Fair Disclosure (Reg FD), which prohibits firm managers from selectively disclosing material nonpublic information to analysts. However, we find the impact of industry shock experience on forecast accuracy becomes even stronger after Reg FD, suggesting that improved access to firm management is unlikely to explain our findings. Rather, the stronger effect observed in the post-Reg FD period suggests that experienced analysts who have a better understanding and in-depth knowledge of the industry now have an even larger comparative advantage relative to inexperienced analysts who cannot get access to private information as easily as before.

Next, we investigate whether market participants can properly value analysts' industry shock experience by examining market reactions to recommendation changes issued by experienced analysts versus inexperienced analysts. The results show that experienced analysts' upward and downward recommendation changes elicit stronger market reactions than those of inexperienced analysts, *after controlling for analyst*quarter and firm*quarter fixed effects*. For instance, upward (downward) recommendation changes issued by experienced analysts are associated with 0.22% (0.41%) higher (lower) 3-day announcement returns compared to recommendations issued by inexperienced analysts. As a benchmark, the median 3-day announcement returns for upward (downward) recommendation changes is 1.60% (-1.48%). These results suggest that market indeed places more weight on experienced analyst forecasts than on inexperienced analyst forecasts.

We further examine whether experienced analysts have any real impacts on firms'

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senior officers and board members of firms that they cover, thus they outperform on stock recommendations. Green et al. (2014) state that access to management is an important source of analysts' informational advantage and generally leads to more informative analyst research.

information environment using the exogenous termination of analyst coverage due to brokerage closures. Following Kelly and Ljungqvist (2012), we identify 55 brokerage closure events during 2003 and 2012, which leads to a reduction in analyst coverage that is exogenous to the covered firms' characteristics. Consistent with Kelly and Ljungqvist (2012), we confirm that firms losing analyst coverage experience a significant increase in information asymmetry, a reduction in stock liquidity, and lower stock returns during the event window. More importantly, these effects are significantly greater for losses of experienced analysts compared to losses of inexperienced analysts. For example, the cumulative abnormal returns (CAR) over the 3-day window around exogenous termination of analyst coverage is on average 0.94% lower for the loss of experienced analysts compared to the loss of inexperienced analysts. This difference persists for the entire trading month, implying that coverage termination of experienced analyst exerts more negative impacts for affected firms' information environment than losses of inexperienced analysts.

Our final test concerns what motivates analysts to learn through industry shocks and improve performance. One possibility is that those analysts who successfully navigate through industry shocks have better future career outcomes. Consistent with this conjecture, we find analysts gaining experience during industry shocks are 46% more likely to become an *II* all-star analyst.

Our study contributes to the literature in several ways. First, our paper identifies a novel and important source of analyst skill acquired through industry shocks. As we construct the experience measure based on industry shocks, our measure is naturally different from the general and firm-specific forecasting experience that increase linearly with time and are the focus of earlier studies (Clement, 1999; Gilson et al., 2001). In addition, we find analysts' industry shock experience is valued by market participants and can affect the information environment of covered firms. Our paper thus extends the work of Bradley, Gokkaya and, Liu (2017) by showing that industry expertise can be gained by learning through difficult times in addition to preanalyst work experience.

Second, our study contributes to the growing literature on how past experience shapes economic agents' current preference and beliefs. Malmendier and Nagel (2011) show that experiences of macroeconomic shocks have long-term effects on retail investors' risk preferences. Kempf et al. (2017) document that industry experience is a first-order driver of professional investors' skills. Our paper emphasizes the importance and relevance of experience gained from past industry shocks for sell-side analysts, another important market participant. An additional advantage of using analyst as a setting to test the effect of experience is that we can measure the quality of analysts' output using forecast accuracy, as compared to fund managers whose performance can only be inferred from noisy returns.

The rest of the paper proceeds as follows. Section 2 describes the data and provides descriptive statistics. Section 3 reports the main empirical results regarding the impact of industry experience on analyst forecast accuracy and market reactions to recommendation changes. In section 4, we examine the real economic impacts of analyst industry experience on firms' information environment. In section 5, we conduct additional analyses and robustness tests. The last section concludes.

2. Data and Summary Statistics

2.1 Data

Our sample construction begins with the Institutional Brokers' Estimate System (I/B/E/S) database, from which we obtain individual analyst's quarterly earnings forecasts and firm's actual earnings per share (EPS) from 1983 to 2015. We remove analysts coded as anonymous by I/B/E/S because it is not possible to track their forecasts. We exclude stale forecasts that are more than 120 days old due to their low information content. To avoid confounding effects from earnings announcement, we also exclude forecasts that are issued less than three days before the earnings announcement day. We keep only observations with a non-missing value of the actual EPS in order to calculate forecast error.

We then merge the analyst forecast sample with CRSP/Compustat to get stock price and accounting information of firms covered by each analyst. Each stock covered by any analysts is assigned to a corresponding Fama-French 48 industry portfolio based on the 4-digit Compustat SIC code. We use CRSP SIC codes if Compustat SIC codes are not available. To construct a quarterly measure of industry experience (SExp), we convert monthly 48 industry portfolio returns to quarterly returns.[3] We remove observations with missing variables for our baseline regression. These filtering criteria result in a sample of 14,086 analysts issuing 1,978,053 quarterly earnings forecasts.

To examine stock market reactions to analysts' recommendation changes, we obtain data of stock recommendations from I/B/E/S Recommendation History data set, which contains the recommendations of individual analysts with ratings ranging from 1 (strong buy) to 5 (strong

[3] source: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

sell). Recommendation changes are computed as the current rating minus the prior rating by the same analyst. Analysts coded as anonymous by I/B/E/S are excluded. Reiterations of earlier recommendations are dropped because of their lower information content. Following Loh and Stulz (2011), we exclude recommendations that fall in the three-day window around quarterly earnings announcement dates (obtained from Compustat). We also exclude recommendation changes in which multiple analysts issued a recommendation on the same day. The resulting sample contains 57,989 recommendation changes.

To identify exogenous coverage termination of analysts, we use 55 brokerage closure events between 2003 and 2012 that affect at least two analysts as stated in Appendix I of Cen et al. (2016). The criteria used to identify brokerage closures are as follows: (1) I/B/E/S stop file has received termination notifications of EPS forecasts sent by the brokerage firm and clustered notifications are required to ensure that all stocks under coverage by the broker are terminated at the same time; (2) the brokerage firm never issues anything in I/B/E/S Detail Files for both earnings forecasts and recommendations afterwards; and (3) the brokerage firm/research division is out of business by double checking information from Bloomberg Businessweek, Capital IQ, Factiva and FINRA broker check database.

Finally, we hand collect Institutional Investor all-star analyst lists from 1983 to 2011 in order to examine how industry experience affects analysts' career outcomes.

2.2 Variable Constructions

2.2.1 Experience Based on Industry Shocks

To construct the industry shock experience measure, we first define an industry as experiencing a shock in a quarter if the value-weighted return of the industry is ranked among the bottom four across all 48 Fama-French industry portfolios in that quarter (i.e., IS = 1). Next, we compute the experience of an analyst for an industry in a given quarter ($Exp_{a,q,i}$) by adding up the incidences of shocks the analyst has experienced in that industry since she first started covering any stocks in that industry:

$$Exp_{a,i,q} = \sum_{\tau<q} IS_{i,\tau} \ , \tag{1}$$

where a indexes analysts, q indexes quarters, and IS denotes a shock in industry i in quarter τ. Then we create a dummy variable based on whether or not an analyst has experienced any industry shocks. Specifically, the dummy variable equals one if an analyst has experienced at least one shock in industry i up to current quarter q:

$$SExp_{a,i,q} = I\left[Exp_{a,i,q} > 0\right]. \tag{2}$$

Note that the industry shock experience constructed in this way refers to experience gained in economic downturns, which is different from experience gained from pure passage of time. In other words, our experience measure is not a linear function of time. Rather, it depends on an analyst's exposure to particular shocks or business cycles of covered industries.

2.2.2 Analyst Performance Measures

We use several metrics to measure analyst performance. The first and most direct measure is the earnings forecast accuracy. The second measure is based on price reactions to analyst recommendation changes. The third category concerns the impacts of analysts on firms' information environment. We describe each of these measures in detail below.

Following the literature (Malloy 2005; Green et al. 2014: Bradley et al. 2017), we measure earnings forecast accuracy using proportional mean absolute forecast error (PMAFE) constructed by Clement (1999). Specifically, PMAFE is defined as:

$$PMAFE_{a,f,q} = (AFE_{a,f,q} - \overline{AFE_{f,q}})/\overline{AFE_{f,q}} \tag{3}$$

where $AFE_{a,f,q}$ is the absolute forecast error for analyst a's forecast of firm f in quarter q, and $\overline{AFE_{f,q}}$ is the mean absolute forecast error for firm f in quarter q. The numerator compares analyst a's absolute forecast error to the average absolute forecast error of other analysts following the same stock during the same period and the denominator aims to reduce heteroscedasticity. Thus, $PMAFE_{a,f,q}$ evaluates analyst a's forecast accuracy relative to all analysts covering firm f in quarter q and controls for heterogeneities across companies, time, and industries (Ke and Yu, 2006). The lower the value of PMAFE, the more accurate the forecast. Negative values of PMAFE represent better than average forecast performance while positive values of PMAFE represent worse than average performance.

We measure the informativeness of analyst research using the market reaction to recommendation changes in the three-day event window [0, +2], where day 0 is the announcement date of the recommendation change. We compute the n-day buy-and-hold cumulative abnormal return (CAR) following event *i* as:

$$CAR_i = \prod_{t=0}^{n}(1 + R_{it}) - \prod_{t=0}^{n}\left(1 + R_{it}^{DGTW}\right) \tag{4}$$

where R_{it} is the raw return of stock *i* on day *t*, and R_{it}^{DGTW} is the return on day *t* of a benchmark portfolio with the same size, book-to-market, and momentum characteristics as stock *i* (Daniel et al., 1997). Stocks are held in the event portfolio either until the end of holding period or until the analyst changes her recommendation, whichever comes first for all holding periods.

To quantify a firm's information environment and stock liquidity, we use bid-ask spreads, Amihud illiquidity measures (Amihud, 2002), and stale returns measure (Lesmond et al., 1999). Bid-ask spread is computed as (ask–bid)/[(ask+bid)/2] using daily closing bid and ask data from CRSP. Amihud illiquidity is calculated as the natural log of one plus the ratio of the absolute stock return to the dollar trading volume and multiple by 10^6. Stale returns measure is the percentage of trading days with zero or missing returns in CRSP.

2.2.3 Control Variables

Mikhail et al. (1997) find that analyst experience is an important determinant of forecast accuracy. We include general experience (GExp), which measures the number of years since an analyst first began to issue earnings forecast on any stock, and firm-specific experience (FExp), which measures the number of years an analyst has covered a specific firm. Clement (1999) documents that resources available to the analyst, forecast characteristics, and portfolio complexity also matter for analyst performance. Hence, we use brokerage size (BrSz), measured as the total number of analysts working at the brokerage firm of the forecasting analyst, to capture resources available to analysts. As for forecast characteristics, we control for forecast timeliness and analyst effort. Timeliness is proxied by the number of calendar days between the forecast issue date and the earnings announcement date (Age) (Clement, 1999), and analyst effort is proxied by the number of forecasts issued by an analyst for a particular firm during the year ending five days before the current forecast (Fre) (Green et al., 2014). Finally, we use the number of firms followed by an analyst in a quarter (FmFlw) to represent portfolio complexity.

2.3 Summary Statistics

Table 1 presents the summary statistics of key variables, with Panel A for dependent variables, Panel B for analyst characteristics, and Panel C for other control variables used in our analyses. Appendix 1 provides detailed definitions of all variables. Continuous variables are winsorized at the 1% and 99% percentiles to reduce the impact of outliers. Due to the differences in sample construction, size, and period, the number of observations related to each dependent variable varies. Panel C is based on the sample of recommendation changes, which consists of 57,989 firm-quarter observations from 1993 to 2013.

As reported in Panel A, the average PMAFE is -9.53% and the market reacts to recommendation upgrades (downgrades) with an average CAR [0, 2] of 2.20% (-1.99%). An analyst makes 1.70 forecasts for each firm each quarter on average. As shown in Panel B, 36% of analysts have experienced industry shocks. On average, an analyst in our sample has provided forecasts for 8.10 years and covered each firm in her/his portfolio for 9.90 quarters. An average brokerage house has 60 sell-side analysts making earnings forecasts. The average number of days between forecasts and earnings announcements is 67.48. An average analyst issues 1.36 forecasts for a particular firm during the quarter ending five days before the current forecast and covers 13 firms each quarter. All of these values are similar to existing studies (De Franco and Zhou, 2009; Bradley et al., 2017). Summary statistics of other control variables are shown in Panel C and they are largely in line with Green et al. (2014).

3. Main Results

In this section, we first examine the forecast performance of experienced analysts compared to inexperienced analysts. We then use the Regulation Fair Disclosure setting to evaluate the underlying mechanisms through which industry shock experience improves analyst performance. Lastly, we study whether investors value analysts' industry experience by examining market reactions to recommendation changes.

3.1 Industry Shock Experience and Forecast Accuracy

To test whether analysts experiencing industry shocks issue more accurate forecast, we employ the following baseline regression:

$$PMAFE_{a,f,q}^{i} = \beta_1 SExp_{a,i,q} + \beta_2 X_{a,f,q} + \lambda_{a,q} + \lambda_{f,q} + \varepsilon_{a,f,q} \tag{5}$$

where $SExp_{a,i,q}$ is an indicator equal to 1 if analyst a has ever experienced shocks in industry i by quarter q, $X_{a,f,q}$ is a vector of analyst-firm-quarter level control variables known to influence forecast accuracy. It includes general and firm-specific experience, brokerage size, age and frequency of forecast, and the number of firms followed by analyst a. $\lambda_{a,q}$ and $\lambda_{f,q}$ represent analyst×quarter fixed effects and firm×quarter fixed effects, respectively. These fixed effects ensure that we are identifying variation in forecast error across stocks covered by the same analyst at the same time and variation across different analysts' forecasts issued on the same firm at the same time. Standard errors are double-clustered at the analyst and firm level. Our main coefficient of interest is β_1, which captures the impact of industry shock experience on forecast accuracy.

Table 2 reports the regression results. Column (1) does not control for any fixed effects. SExp has a negative and statistically significant coefficient of -0.514 (t = -4.45), suggesting that experiencing industry shocks improves analyst forecast accuracy. Column (2) controls for firm×quarter fixed effects that absorb time-varying firm characteristics. The coefficient on SExp becomes -0.583 and remains highly significant (*t* = -4.32). Column (3) further includes analyst × quarter fixed effects that control for time-varying analyst characteristics. The coefficient is still significantly negative while the magnitude becomes even larger (-0.889, *t* = 4.24). Therefore, all three models indicate that earnings forecasts issued by experienced analysts are significantly more accurate than those by inexperienced analysts. These results are also economically significant. For example, in column (3), the coefficient of -0.889 implies that analysts with industry shock experience produce 0.89% more accurate earnings forecast than those issued by inexperienced analysts. As a comparison, analysts need about 3.7 years more of firm-specific experience to achieve the same level of forecast accuracy improvement.

The coefficients of control variables are in line with the prior literature (Mikhail et al., 1997; Clement, 1999; Green et al., 2014; Bradley et al., 2017). Both general experience and firm-specific experience of analysts reduce forecast errors. Analysts who work for a larger brokerage house are likely to possess more resources and result in better forecast accuracy. The older the forecast, the higher the forecast error, suggesting that stale forecasts are less informative. Forecast frequency is positively related to forecast accuracy. Lastly, analysts who have a complex portfolio (i.e., those who cover more firms) have inferior forecast performance.

Besides baseline regressions, we also examine whether industry experience gained through past shocks is more valuable during the subsequent industry shock periods. We test this conjecture by including an interaction term between industry shock experience and a dummy variable IS indicating industry shock period. Columns (4) to (6) of Table 2 present the results. All the coefficients on interaction term SExp×IS are negative and significant, suggesting that the outperformance of experienced analysts relative to inexperienced analysts is particularly pronounced in industry downturns. For example, column (6) shows that conditional on being in an industry shock period, analysts with industry shock experience issue forecasts that are on average 1.16% more accurate. Notably, all coefficients on SExp remain significantly negative, suggesting that analysts' industry shock experience improves forecast accuracy not only during bad times, but in other normal periods as well.

3.2 How Does Industry Shock Experience Translate into Better Performance?

Results from the previous section show that forecasts issued by experienced analysts are superior to those issued by inexperienced analysts. The natural question to ask is how does industry shock experience translate into better forecast performance? One plausible channel is that analysts gain more in-depth knowledge of an industry during industry downturns. Loh and Stulz (2018) document that greater uncertainty during bad times causes investors to rely more on analyst research, which should incentivize analysts to spend more effort, collect more fundamental information and seek a better understanding of the industry. As a result, these experienced analysts later on become more capable in analyzing covered firms' industry trends, competitive threats, positioning within the industry, the impact of regulatory risk, etc.

Prior studies document that access to firm management leads to more informative research by analysts. Cohen et al. (2010) find that analysts with educational ties to senior officers of covered firms issue recommendations that are more informative. Similarly, Green et al. (2014) find that access to firm management at broker-hosted investor conference is an important source of analysts' information advantage. Thus, another possible channel is that analysts are able to cultivate a good relationship with firm managers in a difficult industry environment, perhaps due to the importance of analyst support in such periods. The good relationship between analysts and management formed in industry downturns may facilitate the flow of private information and improve forecast performance for analysts in subsequent periods.

To disentangle these two channels, we utilize the setting of Regulation Fair Disclosure (Reg FD). Reg FD, passed by the SEC on October 23, 2000, prohibits disclosures of material nonpublic information to selective parties including sell-side analysts. Prior studies show that Reg FD is effective in curbing the private information flow between managers and analysts (Cohen et al. 2010; Koch, Lefanowicz, and Robinson 2012). If the improved forecast accuracy of experienced analysts is mainly due to access to private information, we should expect the effect of industry shock experience to be much weaker or even disappear in the post-Reg FD period. However, if experienced analysts have better forecast performance because of their superior industry knowledge gained in economic downturns, the effect should persist in the post-Reg FD period. We use the following regression model to conduct the test:

$$PMAFE^{i}_{a,f,q} = \beta_1 SExp_{a,i,q} + \beta_2 \text{Reg FD} + \beta_3 SExp_{a,i,q} \times Reg\ \ FD + \beta_4 X_{a,f,q} + \lambda_{a,q} + \lambda_{f,q} + \varepsilon_{a,f,q} \tag{6}$$

Our variable of interest is the interaction between industry shock experience dummy SExp and the indicator Reg FD, which indicates the post-Reg FD periods. The channel of private information flow would predict a significantly positive β_3.

Table 3 reports the results. We find that the coefficients on SExp×Reg FD are negative and significant, regardless of which specification is used. The negative coefficient on SExp× Reg FD means the impact of industry shock experience on forecast accuracy becomes even stronger after Reg FD, suggesting that improved access to private information is unlikely to explain our findings. Rather, the result suggests that experienced analysts who have a superior understanding and in-depth knowledge of the industry now have an even larger comparative advantage relative to inexperienced analysts who cannot get access to private information as easily as before.

Our second test of the underlying mechanisms focuses on analyst effort. If experienced analysts make better forecast mainly due to their superior industry knowledge, they should be more active in revising forecasts. On the other hand, the channel of private information does not predict an increase in analyst effort. To test, we use the number of forecasts issued by an analyst to proxy for analyst effort. Formally, our model is as follows:

$$Activity^{i}_{a,f,q} = \beta_1 SExp_{a,i,q} + \beta_2 X_{a,f,q} + \lambda_{a,q} + \lambda_{f,q} + \varepsilon_{a,f,q} \qquad (7)$$

The dependent variable *Activity* is measured as log (1+ number of forecasts issued by an analyst per firm-quarter). Table 4 reports the regression results. Column (1) does not include any fixed effects, column (2) controls for firm×quarter fixed effects, and column (3) controls for analyst×quarter fixed effects and firm×quarter fixed effects. For all regression specifications, the coefficient on SExp is positive and statistically significant, suggesting that analysts with industry shock experience exert more effort to improve their forecasts, perhaps due to their better understanding of industry dynamics.

3.3 Market Reactions to Recommendation Changes

Having established that analysts with industry experience make better forecasts, we next investigate whether the market can recognize the more valuable research by experienced analysts. If investors highly value analysts' industry expertise as indicated by *II*'s survey, market reaction to recommendation changes issued by analysts with industry shock experience is likely to be more pronounced.

Similar to Green et al. (2014), we consider the direction of recommendation changes as well as their magnitudes when examining the price impact of recommendation changes. We first define a recommendation change as an upgrade (a downgrade) if the revised recommendation is more favorable (unfavorable). Then we explore the effect of industry shock experience on the informativeness of recommendations by regressing the three-day buy-and-hold cumulative abnormal return CAR[0,+2] on the industry shock experience indicator (SExp) and the absolute value of recommendation changes (RecChange).[4] The regression model also includes control variables from equation (6), analyst×quarter fixed effects, and firm×quarter fixed effects. We estimate the following panel regression:

$$CAR^{i}_{a,f,q} = \beta_1 SExp_{a,i,q} + \beta_2 RecChange_{a,f,q} + \beta_3 X_{a,f,q} + \lambda_{a,q} + \lambda_{f,q} + \varepsilon_{a,f,q} \quad (8)$$

Table 5 presents the results. Columns (1) to (3) in Panel A show the results for market reactions to recommendation upgrades. We find that market reactions to experienced analysts' upward recommendation changes are indeed more pronounced. The coefficient on SExp in column (3) implies that market reactions to recommendation upgrades issued by experienced analysts are 0.22% greater than those issued by inexperienced analysts. As expected, the coefficient on RecChange is significantly positive, suggesting that larger absolute recommendation changes lead to significantly higher market reactions. Other control variables

[4] We winsorize CAR[0,+2] at the 1st and 99th percentiles to reduce the impact of firm-specific events not captured by our filters. Our results are also robust to using non-winsorized returns.

are of signs in line with the literature (Green et al., 2014; Bradley et al., 2017).

Columns (4) to (6) in Panel A report the results for market reactions to recommendation downgrades. Similar to the findings for upgrades, market reactions to recommendation downgrades issued by experienced analysts are about 0.4% stronger than those issued by inexperienced analysts.

To ensure the robustness of our findings, we re-estimate equation (8) by pooling the sample of recommendation upgrades and downgrades together. We first multiply cumulative abnormal returns by -1 for downgrades and then include an upgrade dummy variable to account for the fact that upgrades are likely to be more informative than downgrades (Green et al., 2014). The results presented in Panel B confirm that recommendations issued by experienced analysts are more informative. Specifically, column (3) shows that the recommendations issued by analysts with industry shock experience elicit 0.32% higher announcement returns.

To sum up, the findings in Table 5 suggest that market participants place greater weight on recommendations issued by analysts with industry shock experience.

4. Analyst Industry Shock Experience and Firms' Information Environment

In this section, we examine the real impacts of experienced analysts on the financial market. Given they mainly act as an information intermediary, analysts should play a particularly important role in shaping firms' information environment. Several recent papers use analyst coverage termination resulting from brokerage mergers and closures as quasi-natural experiments and find affected firms face significantly higher information asymmetry and cost of capital after coverage termination (Kelly and Ljungqvist, 2012; Derrien and

Kecskes, 2013). Given our findings that analysts with industry shock experience produce more informative research, it is reasonable to expect that losses of experienced analysts should have a greater impact on firms' information environment than losses of inexperienced analysts.

To that end, we identify 55 brokerages that stopped releasing analyst forecasts between 2003 and 2012 using the I/B/E/S Stopped Estimation File and applying the filters in Cen et al. (2016). We focus on brokerage closures only because in our setting, the brokerage house could choose which analysts to keep in the case of brokerage mergers, so the termination decisions become endogenous. Appendix 2 presents a complete list of brokerage closure events. The 55 brokerage firms employed 628 analysts (not including junior analysts without coverage responsibilities), so an average brokerage closure involves 11 analysts, and an average analyst covers 8 stocks, consistent with findings in Kelly and Ljungqvist (2012).

Using a difference-in-differences approach (DiD) approach, we compare the change of information environment of treatment firms and that of control firms. We measure firms' information environment using bid-ask spread, Amihud illiquidity (Amihud, 2002), and stale return measure (Lesmond et al., 1999). Treatment firms are those that lose at least one analyst due to a brokerage closure. The criteria for selecting control firms follow Bradley et al. (2017). We require that candidate control firms 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 brokerage closures.

Table 6 reports the results. For each information environment measure, we compute its change during a 3-month and a 6-month window. The column "Losing analysts" shows the mean DiD estimates for the full sample of firms that experienced the loss of analyst coverage. Consistent with the findings of Kelly and Ljungqvist (2012), analyst coverage terminations increase information asymmetry of affected firms.

In the next two columns, we separate the sample of treatment firms into two groups based on the exogenous termination of coverage by experienced analysts (Losing experienced analysts) and inexperienced analysts (Losing inexperienced analysts). For firms losing experienced analysts, all changes of information asymmetry measures are significant. The mean change of bid-ask spread, Amihud illiquidity and missing/zero return days in a 3-month window are 0.07%, 1.32%, and 0.72%, respectively. For firms losing inexperienced analysts, the magnitudes of changes are much smaller, both economically and statistically. Column "Difference" tests the difference in DiD between these two groups. The differences for all measures of information asymmetry are positive and significant, suggesting that firms losing experienced analysts due to brokerage closures suffer a higher degree of information asymmetry, compared with firms losing inexperienced analysts.

Theories of asymmetric information models predict that higher information asymmetry leads to higher expected return required by investors and negative market reactions to coverage termination announcement. Accordingly, we examine whether drops in coverage by experienced analysts evoke more negative price reaction. We use cumulative abnormal returns over various windows (CAR) to measure the price impact of coverage termination (Kelly and Ljungqvist, 2012; Bradley et al., 2017).

Table 7 presents the results. Columns "Losing Analysts" show the results for the full sample. Consistent with the literature, we find a loss of analyst coverage results in a significant decline in stock prices on average. For example, CAR[-1,+1], CAR[-1,+3], and CAR[-1,+5] around coverage termination are -0.597%, -0.708% and -1.091%. Using the market model and the Fama-French three-factor model to calculate CARs generates similar results. These returns are not transitory over the first trading month as the CAR[+5, +22] is not statistically different from zero. More importantly, when we separate the sample of treatment firms into two groups, the price decline is more pronounced for firms losing experienced analysts. For instance, average CARs over the [−1,+1] period are an economically and statistically significant −1.196% for loss of experienced analysts compared to -0.258% for loss of inexperienced analysts. The difference in mean DiD of -0.938% is highly significant as shown in the last column.

Taken together, results in this section suggest that a loss of experienced analysts have more pronounced impacts on firms' information environment and stock prices compared to a loss of inexperienced analysts.

5. Addition Tests and Robustness Checks

5.1 Analyst Industry Experience and Career Outcomes

In this section, we examine whether analysts with industry shock experience are rewarded by brighter career prospects. Answer to this question could help inform us what motivate analysts to learn through difficult times. One type of favorable career outcome that is particularly relevant to analysts is *all-star* analyst status. Each October, *Institutional Investor* publishes an annual list of the top-three analysts and runners-up by covered industry based on a survey of buy-side investors (Groysberg et al., 2011). "All-star" rankings are widely viewed as the most prestigious status for analysts and star analysts earn 61% more than other analysts (Groysberg et al., 2011). Thus, analysts should have strong incentives to be included in these rankings.

We run a logistic regression and estimate the effect of industry shock experience on the likelihood of becoming an *II* all-star analyst, conditional on all-star status in the previous year and analyst characteristics as in other models (lagged by one year). The logit model takes the following form:

$$Star_{a,f,y} = \beta_1 SExp_{a,i,y-1} + \beta_2 X_{a,f,y-1} + \beta_3 Star_{a,f,y-1} + \lambda_{f,y} + \varepsilon_{a,f,y} \qquad (9)$$

where $Star_{a,f,y}$ is a dummy variable equal to one if analyst a covering firm f is an all-star analyst in year y.

Table 8 reports the results. Column (1) does not include any fixed effects while column (2) controls for firm×year fixed effects.[5] The coefficients on SExp in both specifications are positive and significant, suggesting that analysts with industry shock experience are more likely to become all-star analysts than inexperienced analysts. Economically, column (2) shows the odds ratio is 1.46, suggesting that the odds of being an *II* all-star analyst are 46% higher for experienced analysts than for inexperienced analysts. Signs of control variables are consistent with the literature. General experience, firm-specific experience, and forecast frequency are positively associated with the probability of being an all-star analyst. Analysts employed by larger brokerage houses are more likely to become all-star analysts (Bradley et al., 2017). Being an all-star analyst in the prior year significantly increases the probability of being an all-star in

[5] We cannot control for analyst*year fixed effects as the dependent variable all-start status is defined at analyst-year level.

the current year.

5.2 Robustness Checks

While our main results use industry definitions based on Fama-French 48 industry classifications, one may be concerned about the robustness of our results using alternative industry classifications. To address this concern, we reclassify firms covered by analysts into industry group using Global Industry Classification System (GICS), recalculate our variables of interest, and re-examine our baseline results (equations (5) and (6)).

The results are reported in Table 9. Consistent with our baseline findings, all coefficients on SExp continue to be significantly negative, suggesting that the effect of industry experience is robust to alternative industry classification. In columns (4) to (6), we additionally control for the interaction between industry experience and post-Reg FD indicator (SExp×Reg FD). Again, we find that the impact of industry experience on forecast performance becomes stronger after Reg FD. We conclude that our findings are not contaminated by the potential noise in industry classification.

6. Conclusion

Learning from doing matters for sell-side analysts. Using a sample of analyst earnings forecasts from 1983 to 2015, we find that earnings forecasts issued by analysts with industry shock experience are more accurate than those issued by inexperienced analysts, after controlling for general and firm-specific forecasting experience and other factors that potentially explain the variations of forecast accuracy. This effect becomes stronger after Reg

FD, suggesting that superior industry knowledge, rather than access to private information, is the main channel underlying our findings. We also find that experienced analysts' upward and downward recommendation revisions lead to stronger market reactions than those of inexperienced analysts, consistent with these analysts' recommendations being more informative. Further findings reveal that experienced analysts have a significant impact on firms' information environment and stock prices, and they are more likely to become *Institutional Investor* all-stars. Overall, our results suggest that analysts can acquire industry expertise by learning through difficult times.

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Appendix 1 Variable Definitions

Variable	Definition
Panel A: Dependent Variables	
PMAFE	The proportional mean absolute forecast error calculated as the difference between the absolute forecast error (AFE) (in $) for an analyst on a firm and the mean absolute forecast error (MAFE) for the firm scaled by the mean absolute forecast error for the firm.
CAR (%)	DGTW value-weighted market-adjusted cumulative abnormal return.
Market CAR (%)	Cumulative abnormal returns based on the market model. The market model factor loadings are estimated over a one-year preevent window ending 11 days before the termination of analyst coverage.
FF (1993) CAR (%)	Cumulative abnormal returns based on the Fama-French three-factor model. The Fama-French three-factor model factor loadings are estimated over a one-year preevent window ending 11 days before the termination of analyst coverage.
Activity	log (1+an analyst's number of forecasts per firm-quarter)
Bid-ask spread (%)	100 * (ask–bid)/[(ask+bid)/2] using daily closing bid and ask data
Amihud illiquidity (%)	log(1+ absolute stock return/(dollar trading volume/10^6))
Missing/zero ret days (%)	The percentage of trading days with zero or missing returns in the corresponding time window.
Panel B: Analyst Characteristics	
Shock experience (SExp)	Dummy variable equal to 1 if the forecast is issued by an analyst with shock-related forecast experience, and 0 otherwise.
Genral experience (GExp)	Number of years since an analyst first issued an earnings forecast (for any firm)
Firm-specific experience (FExp)	Number of quarters since an analyst first provided earnings forecast for a firm.
Brokerage size (BrSz)	Total number of analysts working at the brokerage firm of the forecasting analyst.
Forecast age (Age)	Number of calendar days between the forecast issue date and the earnings announcement date.
Forecast frequency (Fre)	Number of forecasts issued by an analyst for a particular firm during the quarter ending five days before the current forecast.
Firms followed (FmFlw)	Number of firms followed by an analyst in a quarter.
Panel C: Other Control Variables	
IS	Dummy variable equal to 1 if the value-weighted industry return is ranked among the bottom 4 across all 48 Fama-French industries in a quarter and 0 otherwise.
Reg FD	Dummy variable equal to 1 after the passage of Reg FD and 0 otherwise
Upgrade	Dummy variable equal to 1 if the research is favorable (e.g., a recommendation change from hold to buy or an upward revised earnings forecast) 0 otherwise.
Downgrade	Dummy variable equal to 1 if the research is unfavorable and 0 otherwise.
Abs(Rec change) (RecChange)	Absolute value of the recommendation change. For example, going from a hold (=3) to a strong buy (=1) would have a value of two.

Appendix 2 Lists of Brokerage Closures

Our sample includes all brokerage closure events between 2003 and 2012. We use the following three screening criteria to identify broker closure events (Cen et al., 2016): (1) The brokerage sends end EPS estimate notifications to I/B/E/S stop file. Brokerage firms terminate coverage of certain stocks now and then, we only include those stop notifications sent by the brokerage when the rest stocks under coverage were terminated at one time in order to avoid possible misspecification; (2) The brokerage firm never issues earnings forecasts or recommendations in I/B/E/S Detail EPS File and Recommendation File afterwards; (3) Information from Bloomberg Businessweek, Capital IQ, Factiva and FINRA broker check database confirms that the brokerage firm is out of business.

ID	Date	Brokerage Name	ID	Date	Brokerage Name
1	Apr-03	Commerce Capital Markets	29	Jun-07	Prudential Equity Group
2	Jul-03	The Chapman Company	30	Jul-07	First Dallas Securities
3	Sep-03	Bluefire Research	31	Oct-07	Cathay Financial
4	Jan-04	Cantillon Co.	32	Dec-07	Aperion Group
5	Jan-04	Semi-Equity Partners	33	Apr-08	Henley Company
6	Jan-04	Hudson River Analytics	34	Oct-08	Coker & Palmer Inc.
7	Feb-04	Montauk Capital Markets	35	Nov-08	JSA Research
8	Mar-04	Royalist Research	36	Feb-09	Stanford Group Company
9	Oct-04	Schwab Soundview Capital markets	37	Apr-09	Dutton Associates
10	Nov-04	Whitaker Securities	38	Nov-07	Nollenberger Capital
11	Mar-05	JB Hanauer Co.	39	Jun-09	Wasserman Associates
12	Mar-05	HD Brous Co.	40	Oct-09	Utendahl Capital Partners
13	May-05	Tradition Asiel Securities	41	Dec-09	The Robins Group
14	Jun-05	Terra Nova Institutional	42	Dec-09	Ragen Mackenzie
15	Jun-05	IRG Research	43	Feb-10	FTN Equity Capital Markets
16	Aug-05	Wells Fargo Securities	44	Feb-10	Pali Research
17	Sep-05	Granite Financial Group	45	Jun-10	Jesup & Lamont Securities
18	Jan-06	Southwest Securities	46	Aug-11	Signal Hill Group
19	Mar-06	Halpern Capital	47	Aug-11	Broadpoint Capital
20	Mar-06	Arabella Securities	48	Jan-12	Wealth Monitors
21	May-06	Variant Research Corp	49	Feb-12	Kaufman Bros
22	Aug-06	Foresight Research Solution	50	Mar-12	Collins Stewart
23	Sep-06	New York Global Securities	51	Apr-12	Morgan Joseph Co.
24	Sep-06	Moors & Cabot Capital	52	Jun-12	Auriga USA
25	Oct-06	Infinium Securities	53	Jul-12	Pritchard Capital Partners
26	Dec-06	Miller Johnson Steichen Kinnard	54	Oct-12	Thinkequity
27	Mar-07	DE Investment Research	55	Dec-12	Avian Securities
28	Apr-07	Cohen Company			

Table 1 Summary Statistics

This table reports summary statistics, with Panel A for the dependent variables, Panel B for analyst characteristics, and Panel C for other control variables used in our analyses. Analyst data are from I/B/E/S from 1983 to 2015, firm characteristics are from Compustat, and stock price data are from CRSP. The number of observations used in different analyses varies. Panel C is based on the sample for recommendation changes, which consists of 57,989 firm-quarter observations from 1993 to 2013. See Appendix 1 for a detailed description of these variables.

Variables	N	Mean	p25	Median	p75	Std. Dev.
Panel A: Dependent Variables						
PMAFE (%)	1,978,053	-9.53	-51.24	-10.78	20	61.59
CAR[0,+2] Upgrade (%)	27,771	2.20	-0.64	1.60	4.41	5.05
CAR[0,+2] Downgrade (%)	30,218	-1.99	-4.27	-1.48	0.77	5.56
Activity	1,576,392	0.95	0.69	0.69	1.10	0.29
Panel B: Analyst Characteristics						
SExp	1,978,053	0.36	0	0	1	0.49
GExp	1,978,053	8.10	3	7	12	6.14
FExp	1,978,053	9.90	3	7	14	9.50
BrSz	1,978,053	59.84	24	51	91	42.24
Age	1,978,053	67.48	50	71	90	25.90
Fre	1,978,053	1.36	1	1	2	0.64
FmFlw	1,978,053	13.34	9	12	17	7.19
Panel C: Other Control Variables						
IS	1,978,053	0.07	0	0	0	0.25
RegFD	1,978,053	0.68	0	1	1	0.47
Upgrade	57,989	0.48	0	0	1	0.50
RecChange	57,989	0.06	-1	1	1	1.46

Table 2 Industry Shock Experience and Forecast Accuracy

This table reports regression results for analyst earnings forecast error. The dependent variable is the proportional mean absolute forecast error (PMAFE). Standard errors are double-clustered at the analyst and firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
SExp	-0.514***	-0.583***	-0.889***	-0.431***	-0.461***	-0.754***
	(-4.45)	(-4.32)	(-4.24)	(-3.60)	(-2.68)	(-4.03)
SExp×IS				-0.729**	-0.364**	-0.403**
				(-2.05)	(-1.99)	(-2.56)
GExp	-0.042***	-0.039***	-0.877*	-0.044***	-0.050**	-1.009
	(-3.83)	(-3.30)	(-1.90)	(-3.94)	(-2.35)	(-1.03)
FExp	-0.061***	-0.049***	-0.060***	-0.062***	-0.105***	-0.068***
	(-8.82)	(-6.69)	(-6.85)	(-8.93)	(-12.76)	(-7.11)
BrSz	-0.018***	-0.020***	-0.026*	-0.017***	-0.011***	-0.037**
	(-13.08)	(-14.01)	(-1.68)	(-12.93)	(-7.06)	(-2.16)
Age	0.176***	0.195***	0.203***	0.176***	0.178***	0.180***
	(92.05)	(91.12)	(81.20)	(91.83)	(72.29)	(62.42)
Fre	-11.409***	-10.490***	-9.673***	-11.408***	-7.447***	-5.977***
	(-140.50)	(-126.69)	(-104.89)	(-139.68)	(-80.91)	(-57.64)
FmFlw	0.202***	0.131***	0.263	0.201***	0.076***	0.048
	(24.59)	(13.68)	(0.04)	(24.37)	(7.15)	(0.00)
IS				0.351	0.258	0.565
				(1.17)	(0.40)	(0.73)
Intercept	-6.279***			-6.238***		
	(-28.42)			(-28.05)		
Fixed effects	None	Firm×quarter	Analyst×quarter Firm×quarter	None	Firm×quarter	Analyst×quarter Firm×quarter
N	1,978,053	1,978,053	1,978,053	1,978,053	1,978,053	1,978,053
R^2	0.034	0.165	0.179	0.034	0.166	0.179
Adj. R^2		0.118	0.132		0.118	0.131

Table 3 Regulation FD and the Impact of Industry Shock Experience

This table reports the results from regressions of analyst earnings forecast error on the interaction between industry experience and a dummy indicating the post-Regulation FD period. The dependent variable is the proportional mean absolute forecast error (PMAFE). Reg FD indicates periods after the passage of Regulation Fair Disclosure. Standard errors are double-clustered at the analyst and firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
SExp	-1.751***	-1.420***	-0.684**
	(-9.53)	(-4.47)	(-2.08)
Reg FD	0.573*	-	-
	(1.67)		
SExp×Reg FD	-0.645***	-0.052***	-0.049**
	(-7.30)	(-4.17)	(-2.09)
GExp	-0.069***	-0.057*	-0.325*
	(-6.09)	(-1.69)	(-1.88)
FExp	-0.061***	-0.106***	-0.069***
	(-8.84)	(-12.45)	(-6.95)
BrSz	-0.018***	-0.012***	-0.040**
	(-13.56)	(-7.60)	(-2.23)
Age	0.171***	0.177***	0.177***
	(88.30)	(68.09)	(57.92)
Fre	-11.518***	-6.574***	-4.962***
	(-142.02)	(-69.34)	(-46.41)
FmFlw	0.205***	0.072***	0.853
	(25.02)	(6.57)	(0.05)
Intercept	-5.994***		
	(-26.32)		
Fixed effects	None	Firm×quarter	Analyst×quarter Firm×quarter
N	1,978,053	1,978,053	1,978,053
R^2	0.034	0.165	0.180
Adj. R^2		0.118	0.132

Table 4 Industry Shock Experience and Analyst Effort

This table reports regression results for analyst effort. The dependent variable is analyst effort, defined as log (1+number of forecasts issued by an analyst per firm-quarter). Standard errors are double-clustered at the analyst and firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
SExp	0.007***	0.006***	0.006***
	(5.91)	(5.17)	(4.11)
GExp	-0.001***	-0.001***	-0.001
	(-8.74)	(-16.11)	(-0.04)
FExp	0.002***	0.001***	0.001***
	(5.00)	(19.65)	(15.91)
BrSz	0.015***	0.017***	0.013***
	(3.24)	(3.57)	(2.90)
Age	-0.005***	-0.138***	-0.129***
	(-12.47)	(-16.18)	(-23.53)
Fre	0.019***	0.092***	0.102***
	(32.87)	(14.78)	(15.56)
FmFlw	-0.070***	-0.099***	-0.120***
	(-8.95)	(-5.41)	(-5.12)
Intercept	0.734***		
	(3.24)		
Fixed effects	None	Firm×quarter	Analyst×quarter Firm×quarter
N	1,115,475	1,115,475	1,115,475
R^2	0.075	0.386	0.576
Adj. R^2		0.282	0.408

Table 5 Industry Shock Experience and Market Reactions to Recommendation Changes

This table reports regression results of market reactions to analysts' recommendation changes. The dependent variable is the cumulative DGTW-adjusted abnormal return during the [0, 2] window around the announcement of a recommendation change by an analyst for a firm in a quarter. RecChange is the absolute value of the difference between an analyst's revised recommendation in a quarter and the recommendation in the previous quarter. Panel A splits the sample into two subsamples where analysts issue upgrade recommendation and downgrade recommendation. Panel B uses the pooled sample in which the cumulative abnormal returns of downgrades are multiplied by -1. Standard errors are double-clustered at the analyst and firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A	Upgrade			Downgrade		
	(1)	(2)	(3)	(4)	(5)	(6)
SExp	0.206***	0.198***	0.217***	-0.403***	-0.399***	-0.405***
	(3.06)	(2.67)	(3.41)	(-5.69)	(-3.11)	(-5.30)
RecChange	0.442***	0.353***	0.698***	-0.531***	-0.684***	-0.512***
	(7.36)	(6.83)	(3.70)	(-8.19)	(-7.34)	(-4.52)
GExp	0.003	0.005	0.003	-0.009	-0.027	-0.010
	(0.47)	(0.19)	(0.43)	(-1.35)	(-0.47)	(-1.48)
FExp	0.015***	0.013***	0.014***	-0.022***	-0.023***	-0.043***
	(4.18)	(3.27)	(3.85)	(-6.08)	(8.25)	(-6.16)
BrSz	0.008***	0.005***	0.012***	-0.007***	-0.010**	-0.018***
	(11.14)	(9.36)	(10.03)	(-9.38)	(-6.37)	(-10.72)
Age	0.012***	0.015***	0.011***	-0.006***	-0.005***	-0.006***
	(8.82)	(3.29)	(2.79)	(-4.30)	(-4.42)	(-4.60)
Fre	0.012	0.037	0.054	-0.284***	-0.205***	-0.249**
	(0.27)	(1.12)	(1.05)	(-6.11)	(-6.53)	(-2.52)
FmFlw	-0.011**	-0.001**	-0.012**	0.010*	0.013**	0.021**
	(-2.17)	(-2.02)	(-2.31)	(1.92)	(2.01)	(2.26)
Intercept	0.053***			-0.088		
	(3.30)			(-0.50)		
Fixed effects	None	Firm×quarter	Analyst×quarter Firm×quarter	None	Firm×quarter	Analyst×quarter Firm×quarter
N	27,771	27,771	27,771	30,218	30,218	30,218
R^2	0.110	0.681	0.790	0.109	0.647	0.759
Adj. R^2		0.380	0.585		0.318	0.518

Panel B	Pooled		
	(1)	(2)	(3)
SExp	0.308***	0.296***	0.317***
	(6.19)	(5.42)	(5.33)
Upgrade	0.219***	0.205***	0.179***
	(4.96)	(3.01)	(2.84)
RecChange	0.490***	0.431***	0.466***
	(10.82)	(9.51)	(10.13)
GExp	0.003	0.009	0.110
	(0.70)	(0.27)	(0.83)
FExp	0.018***	0.007***	0.055***
	(7.06)	(6.28)	(4.23)
BrSz	0.008***	0.011***	0.009***
	(14.07)	(13.49)	(14.35)
Age	0.009***	0.007***	0.005***
	(8.91)	(6.15)	(8.32)
Fre	0.152***	0.231**	0.204**
	(4.75)	(2.22)	(1.97)
FmFlw	-0.011***	-0.006***	-0.035***
	(-2.83)	(-3.19)	(-3.00)
Intercept	0.024*		
	(1.70)		
Fixed effects	None	Firm×quarter	Analyst×quarter Firm×quarter
N	57,989	57,989	57,989
R^2	0.114	0.665	0.812
Adj. R^2		0.382	0.541

Table 6 Brokerage Closures, Loss of Experienced Analysts, and Information Environment

This table reports results on the effect of exogenous brokerage closure on changes in firms' information asymmetry. Information asymmetry is measured by three- and six-month bid-ask spread, Amihud illiquidity, and percentage of days with missing or zero returns. The first column, "Losing analysts", shows the cross-sectional means of difference-in-differences (DiD) for the full sample of treatment firms losing analysts due to brokerage closures. Column (2) ((3)), "Losing experienced analysts" ("Losing inexperienced analysts"), reports results for a sample of firms losing experienced analysts (inexperienced analysts) due to brokerage closures. Column (4) reports the differences between the 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). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Difference-in-Differences						
	Losing Analysts		Losing Experienced Analysts		Losing Inexperienced Analysts		Difference
Variable (%)	N	Mean	N	Mean	N	Mean	Mean
Bid-ask spread (three-month window)	4,993	0.032**	1,877	0.065***	3,116	0.020*	0.044**
Bid-ask spread (six-month window)	4,993	0.041***	1,877	0.092***	3,116	0.025*	0.068***
Amihud illiquidity (three-month window)	4,993	0.487*	1,877	1.315***	3,116	0.026	1.289***
Amihud illiquidity (six-month window)	4,993	0.506	1,877	1.384***	3,116	0.031*	1.352**
Missing/zero ret days (three-month window)	4,993	0.264	1,877	0.719***	3,116	0.006	0.713**
Missing/zero ret days (six-month window)	4,993	0.193	1,877	0.578**	3,116	0.004	0.574*

Table 7 Brokerage Closures, Loss of Experienced Analysts, and Stock Returns

This table reports the mean difference-in-differences market reaction to a loss of analyst coverage arising from exogenous brokerage closure. Abnormal returns are calculated based on market return adjustment, market model, and Fama-French 3-factor model, respectively. The first column, "Losing analysts", reports the means of DiD for the full sample of treatment firms losing analysts due to brokerage closures. Column (2) ((3)), "Losing experienced analysts" ("Losing inexperienced analysts"), reports results for a sample of firms losing experienced analysts (inexperienced analysts) due to brokerage closures. Column (4) 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). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Difference-in-Differences						
	Losing Analysts		Losing Experienced Analysts		Losing Inexperienced Analysts		Difference
Variable (%)	N	Mean	N	Mean	N	Mean	Mean
CAR[-1, +1]	4,993	-0.597**	1,877	-1.196***	3,116	-0.258*	-0.938***
CAR[-1, +3]	4,993	-0.708***	1,877	-1.457***	3,116	-0.261*	-1.196***
CAR[-1, +5]	4,993	-1.091***	1,877	-2.274***	3,116	-0.350*	-1.925**
CAR[+5, +22]	4,993	0.046	1,877	-0.532	3,116	0.392	-0.924
Market CAR[-1, +1]	4,993	-0.623***	1,877	-1.219***	3,116	-0.276	-0.943***
Market CAR[-1, +3]	4,993	-0.812***	1,877	-1.644***	3,116	-0.298*	-1.345***
Market CAR[-1, +5]	4,993	-1.003***	1,877	-2.249***	3,116	-0.306	-1.943***
Market CAR[+5, +22]	4,993	0.015	1,877	-0.437	3,116	0.286	-0.723
FF CAR[-1, +1]	4,993	-0.618***	1,877	-1.205***	3,116	-0.260*	-0.944***
FF CAR[-1, +3]	4,993	-0.775**	1,877	-1.638***	3,116	-0.291*	-1.347***
FF CAR[-1, +5]	4,993	-0.964**	1,877	-2.188***	3,116	-0.293	-1.895***
FF CAR[+5, +22]	4,993	-0.002	1,877	-0.379	3,116	0.225	-0.604

Table 8 Industry Shock Experience and All-star Analyst Status

This table presents logistic regression results for the effect of industry experience on the probability of being an all-star analyst. The dependent variable is a binary variable equal to one if the analyst is listed as an all-star analyst in the current year's October issue of *Institutional Investor* magazine and zero otherwise. All control variables are lagged by one year. The sample is from 1983 to 2011. Standard errors are double-clustered at the analyst and firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
SExp	0.181***	0.389***
	(6.64)	(23.97)
GExp	0.061***	0.075***
	(30.06)	(30.08)
FExp	0.036***	0.033***
	(27.37)	(21.43)
BrSz	1.811***	2.260***
	(80.42)	(82.48)
Fre	0.100***	0.142***
	(6.74)	(3.40)
FmFlw	-0.131***	-0.086***
	(-5.93)	(-2.98)
Lag (Star)	0.111***	0.143***
	(11.29)	(4.95)
Intercept	-10.788***	
	(-92.99)	
Fixed effects	None	Firm×year
N	376,809	376,809
Pseudo R^2	0.258	0.281

Table 9 Robustness using GICS Industry Classification

This table presents regression results for analyst earnings forecast errors on industry shock experience. Industry classifications are based on the Global Industry Classification System (GICS). The dependent variable is the proportional mean absolute forecast error (PMAFE). Reg FD indicates periods after the passage of Regulation Fair Disclosure. Standard errors are double-clustered at the analyst and firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
SExp	-0.584***	-0.516***	-0.808***	-2.241***	-1.883***	-1.150***
	(-3.39)	(-2.77)	(-2.65)	(-7.43)	(-4.14)	(-3.39)
Reg FD				0.899***	-	-
				(3.74)		
SExp×Reg FD				-0.907***	-0.176***	-0.338***
				(-5.90)	(-3.68)	(-3.36)
GExp	-0.045***	-0.058***	-0.292**	-0.077***	-0.045***	-0.097***
	(-2.88)	(-3.65)	(-2.00)	(-4.77)	(-2.59)	(-2.86)
FExp	-0.044***	-0.028***	-0.054***	-0.043***	-0.072***	-0.047***
	(-4.74)	(-3.02)	(-4.68)	(-4.68)	(-7.24)	(-3.61)
BrSz	-0.019***	-0.022***	-0.025	-0.020***	-0.012***	-0.044**
	(-9.84)	(-10.97)	(-0.96)	(-10.24)	(-5.66)	(-2.51)
Age	0.182***	0.197***	0.198***	0.176***	0.181***	0.171***
	(63.77)	(64.34)	(51.45)	(61.07)	(51.06)	(38.45)
Fre	-10.493***	-9.768***	-8.857***	-10.643***	-6.954***	-5.211***
	(-91.01)	(-84.86)	(-64.17)	(-92.39)	(-54.60)	(-33.65)
FmFlw	0.205***	0.142***	0.494*	0.206***	0.074***	0.948*
	(15.90)	(10.16)	(1.82)	(16.02)	(4.66)	(1.93)
Intercept	-7.736***			-7.505***		
	(-23.40)			(-21.63)		
Fixed effects	None	Firm×quarter	Analyst×quarter	None	Firm×quarter	Analyst×quarter
			Firm×quarter			Firm×quarter
N	1,685,332	1,685,332	1,685,332	1,685,332	1,685,332	1,685,332
R^2	0.027	0.156	0.251	0.027	0.159	0.264
Adj. R^2		0.127	0.165		0.127	0.168