Overcorrection: The Spillover Effect of Analysts' Learning after Forced CEO Departures*

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This draft: March 30, 2023

Abstract

Learning is an effective way for financial analysts to improve their performance. In this paper, we investigate analysts' learning behavior and its spillover effect following forced CEO departures (FCDs). Our study shows that analysts who correct their past optimism for FCD firms (i.e. learning) also tend to issue less optimistic earnings forecasts for the unaffected firms in their portfolios (i.e. overcorrection). Specifically, we find that the decrease in their optimism is larger for analysts who have less experience, were previously overly optimistic, cover firms with worse information environments, and have a heavy workload. Furthermore, we find these analysts' forecasts following FCDs are also more accurate and generate stronger market reactions. Overall, our findings suggest that analysts learn from FCD events by issuing less optimistic forecasts and benefit from the corresponding spillover effect for the unaffected firms.

Keywords: Financial analysts, Learning, Forecast accuracy, Managerial departure

JEL Codes: G24, G41, D83

*We thank helpful comments from Camillo RIVA, Hao MA, and all the participants of the ESSEC SRS. All errors and omissions are our own.

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1 Introduction

As financial professionals, sell-side financial analysts are expected to give accurate investment opinions to clients. However, it has been observed that analysts occasionally issue biased earnings forecasts that can be either optimistic or pessimistic (De Bondt and Thaler 1990; Lim 2001). When explaining analysts' biased forecasts, prior research attributes the forecast errors to analysts' behavioral biases (Hilary and Menzly 2006; Cen et al. 2013; Bradshaw et al. 2016; Hirshleifer et al. 2019) or their economic motives such as trading commissions, career incentives, and access to management (Cowen et al. 2006; Ke and Yu 2006;Hilary and Hsu 2013). Meanwhile, it is widely documented that sell-side analysts can enhance their performance by learning from other sources such as new technologies (Jame et al. 2022), their peers (Do and Zhang 2020; Cen et al. 2019; Kumar et al. 2022), and their experience (Mikhail et al. 1997;Clement et al. 2007). In this paper, we investigate the spillover effect of analysts' learning behavior through the lens of forced CEO departures (FCDs) [1]. By analyzing the correction of past optimism for affected FCD firms, we explore how analysts adjust their earnings forecasts for the unaffected firms in their portfolios, namely the **overcorrection**. We aim to shed light on how analysts learn from FCD events and whether they benefit from the spillover effect of their learning.

There are compelling reasons to believe that sell-side financial analysts can learn from forced CEO departure events. During normal times, there are frequent interactions between analysts and CEOs. To cater to clients, analysts approach firm executives for superior information through all channels, including firm conference calls, analyst days, and private meetings (Green et al. 2014; Soltes 2014; Kirk and Markov 2016). Meanwhile, analysts' earnings forecasts exert pressure on CEOs since they are expected to meet or beat the consensus expectations of analysts. As a consequence, analysts face a trade-off between issuing favorable forecasts and maintaining access to management (Chen and Matsumoto

[1]The terminology "forced CEO turnovers" is also used in the prior literature, we do not distinguish *forced CEO departures* from *forced CEO turnovers* in this paper.

2006; Libby et al. 2008.).

When CEOs are forced out, analysts need to quickly incorporate this new information into their forecast revisions. Generally, a timely update following the firm adverse events not only reflects analysts' reputation concerns (Meng 2015; Lee and Lo 2016), but also helps to meet investors' information needs under high uncertainty circumstances (Jennings 2019). Put together, analysts' learning behavior following FCDs is an outcome of the joint effects of the CEO-analyst's everyday interplay and the analysts' concerns related to their reputation or clients' needs during special times.

Studying analysts' learning behavior after FCDs is empirically challenging due to identification problems. First, forced CEO departures are often the result of poor job performance, making it difficult to disentangle the effects of the FCD event per se from overall unfavorable firm performance. This means that any changes in analysts' forecasts for FCD (affected) firms may reflect a combined response to both factors. Second, some research elaborates on the monitoring role that analysts play and suggests that analysts' coverage can accelerate forced CEO turnovers (Wiersema and Zhang 2011; Mergenthaler et al. 2012), as CEOs are often evaluated against earnings or revenue benchmarks including analysts' consensus forecasts (Brown and Caylor 2005). To address these challenges, we focus on the effect of FCD events on analysts' forecasts for the unaffected firms in their portfolios. For those unaffected firms, the FCD events are plausible exogenous and any changes in the analysts' forecasts are less likely to be contaminated by their own performance.

To provide a background, I first implement firm-level analyses using identified FCDs from the open data source. In Gentry et al. 2021, the authors hand-collected and then classified CEO departure events into forced and voluntary CEO departures. On the aggregate level, we find that analysts make huge upward-biased mistakes before FCDs. Compared with those of voluntary CEO departures, the consensus analysts' forecasts are on average 12% more optimistic in the four consecutive quarters before the FCDs[2]. Since forced CEO departures are not fully ex-ante predictable and analysts face substantial valuation uncertainty before the events, these mistakes are more likely to be driven by their lack of experience or judgment incapability but not economic incentives. After FCDs, analysts quickly correct their mistakes by issuing less optimistic forecasts in the following quarter. This finding suggests that analysts do learn from FCD events and reduce their optimism after FCDs [3].

In this paper, our primary goal is to study the spillover effect (overcorrection) of analysts' learning behavior. Therefore, we estimate the change in optimism in quarterly earnings forecasts for unaffected firms in analysts' portfolios. For each analyst who has ever experienced an FCD event (affected analyst), we measure their individual level optimism using methods from Cuculiza et al. 2021, by computing the stock price-scaled forecast optimism relative to the most recent consensus forecast. Our main independent variable is *Fcd*, a dummy variable that equals one for forecasts issued within the 30-day window following an FCD. Our key prediction is that the coefficient estimate on *Fcd* would be negative and statistically significant, indicating that affected analysts are more likely to issue less optimistic forecasts than their unaffected peers.

For all regression specifications at the individual level, we include a set of controls for firm and analyst characteristics as well as various fixed effects. Specifically, we add the joint analyst-firm fixed effect to the models to remove systematic bias at the analyst-firm-pair level, such as affiliation relationships. We also control for the year-quarter fixed effect to absorb time-driven changes in optimism, such as revisions related to the macroeconomic environment. In other words, we compare an analyst's relative optimism during a specific time period with her relative optimism at other times regarding the unaffected firm.

The individual-level estimation results support our prediction. The coefficients for *Fcd*

[2] In this paper, we do not aim at answering why analysts make aggregate level mistakes before FCD. A possible explanation for analysts' bias could be their herding behavior (Trueman 1994; Bernardo et al. 2000; Clement and Tse 2005) or social learning behavior (Kumar et al. 2022).

[3] The aggregate level mistakes and learning behavior is the starting point of the paper. To demonstrate that the overcorrection occurs only following FCDs, we conduct firm-level simulation tests and find that analysts are not always making huge upward mistakes. Detailed results are reported in Figure A1.

in our specifications range between -0.018 and -0.014, with t-values between 5.99 and 4.86[4], showing that analysts are issuing significantly less optimistic forecasts for unaffected firms. These results support our hypothesis that analysts learn from FCDs but also overcorrect for the unaffected firms.

Next, we conduct cross-sectional analyses to test whether the spillover effects are influenced by analyst characteristics. Specifically, we examine whether analysts with more forecasting experience and those who were less optimistic in the past are less likely to be subject to overcorrection. It is ex-ante unclear whether experience or previous optimism contributes to the spillover effect of learning. On the one hand, more experienced analysts and those who were less optimistic in the past 1) were less likely to make mistakes before the FCDs, but if they do 2) were less likely to be impacted by such irrelevant events (Mikhail et al. 2003; Do and Zhang 2020). On the other hand, analysts with sophisticated skills or those who were less optimistic in the past might be better at learning from their experiences, leading to a larger overall benefit of learning. Consistent with the former conjecture, we find that more experienced analysts and those who were previously less optimistic were less likely to overcorrect.

To investigate whether the spillover effect of learning is more pronounced for certain types of firms, we conduct cross-sectional tests on firm attributes. First, we study the extent to which the information environment affects the strength of the spillover effect. Conceptually, since better information environments facilitate their valuation, analysts covering firms with superior information environments tend to make revisions that are less affected by FCDs. In line with this prediction, we find firms' information environment, as proxied by firm size, is negatively associated with the spillover effect[5]. Second, we hypothesize that the degree of overcorrection may be larger when analysts face other constraints. Existing literature suggests that market participants perform worse under multitasking conditions

[4]T-statistics are in absolute value.

[5]Information environment increases with firm size because larger firms tend to have more analysts coverage and more forthcoming disclosure policies (Brennan and Hughes 1991; Lang and Lundholm 1996).

due to limited attention (Hirshleifer and Teoh 2003; Hirshleifer et al. 2009; Driskill et al. 2020). Accordingly, we predict that analysts are more likely to issue less optimistic forecasts on days with concurrent earnings announcements. Consistent with our hypothesis, we find that overcorrection is more pronounced for analysts with heavy workloads.

It remains uncertain whether analysts' forecasts are more or less accurate when their optimism decreases. Whether learning improves analysts' accuracy for unaffected firms depends on the magnitude of the spillover effect. For this purpose, we estimated the change in proportional mean absolute forecast errors (PMAFE) for these affected analysts following FCDs. Our results show that the forecast errors of analysts following FCDs are significantly smaller, indicating that affected analysts become relatively more accurate, and the overcorrection originating from their learning behavior helps them to debias and eventually improves their performance.

The results in the previous section suggest that analysts benefit from the spillover effect of learning from FCD by issuing more accurate forecasts. Prior research has also shown that the market rewards conservative analysts who respond more strongly to bad news (Hugon and Muslu 2010). Naturally, we are curious about whether investors react differently to less optimistic forecast revisions issued by affected analysts. To capture investors' recognition of analysts' research quality improvement, we use abnormal excess returns and control for the magnitude of analysts' revisions. We find that stock price reactions are stronger for revisions issued in the 30-day window after FCDs. This finding indicates that the market rewards affected analysts who benefit from the spillover effect of learning.

Our main results about individual-level overcorrection remain robust under a battery of cases. Specifically, we consider four different scenarios. First, we only consider forecasts for unaffected firms that are dissimilar to the affected FCD firms to ensure analysts do not learn from other channels[6]. Second, we remove the affected firms with more than two affected

[6]When computing the similarity, We consider the text-based product market industry classification. We argue that unaffected firms with the smallest similarity with the FCD firms tend to have fewer economic links thus less likely affected by that firm.

analysts to eliminate the possibility of herding. Third, we implement our estimation using an alternative CEO turnover data set to account for errors in the original data. Lastly, we use alternative definitions of both independent and dependent variables and repeat our estimations using nonlinear models. Following Bourveau and Law 2021, we also perform two simulation-based falsification tests using placebo FCD events to lend more credibility to our results. These additional robustness checks confirm that our findings are unlikely to be spurious.

We interpret the reduced optimism for unaffected firms as a byproduct of analysts' learning from FCDs. Our argument is based on two premises: First, FCD events are unpredictable; Second, reduced optimism does not capture analysts' economic incentives, such as access to new CEOs. To confirm the first premise, we test the change in affected analysts' optimism before the FCDs and find no evidence supporting the pre-existing optimism reduction. To address the second premise, we examine the change in analysts' optimism after voluntary departure events and find no evidence that analysts trade off forecast optimism for management access following voluntary CEO departures. Also, analysts are not behaving less aggressively during the conference calls after FCDs, ruling out the management access explanation.

Although we have demonstrated that the decrease in analysts' optimism is not driven by their economic incentives, another possibility is that analysts issue less upward-biased forecasts due to their pessimistic sentiment following FCD events. Forced CEO turnovers generally consist of departures induced by CEO death, illness, unfavorable performance, and misconduct. To address our concern, we decompose FCDs into two types and find that analysts exclusively issue less optimistic forecasts following FCDs related to CEO performance [7]. This finding further rules out the possibility that less upward-biased forecasts capture affected analysts' negative sentiment.

Our study contributes to prior studies that explore optimism in analysts' forecasts. Ex-

[7]As later said, the change in optimism following CEO death or illness is more like due to pessimistic mode.

isting studies have primarily focused on individual analysts' upward-biased forecasts, overlooking the joint effects among firms with shared analysts. These studies attribute optimistic forecasts to analysts' economic incentives such as trading commissions, investment banking business, or management access (Michaely and Womack 1999; Cowen et al. 2006). Our study contributes to the literature by examining how adverse firm events affect analysts' forecast optimism. Unlike optimism based on analysts' own motives regarding a focal firm, the change in their optimism after FCD stems from the difference in their portfolio constitution and propagates across firms within their portfolio.

Second, our paper adds to the literature on financial analysts' learning behavior by providing direct evidence on how analysts benefit from overall learning outcomes following FCDs. Previous studies established the time-series relationship between analysts' improved performance and their past experience (Markov and Tamayo 2006; Clement et al. 2007). Our findings extend this learning literature by demonstrating that affected analysts receive feedback from FCD events and adjust their excessive optimism not only for the affected FCD firms but also for the unaffected firms they cover. The global benefit of learning is not limited to certain firms but can expand to their overall coverage.

Choi et al. 2014 studies the analysts' forecast in a similar context. Our study differs from Choi et al. 2014 in several ways. First, they only implement firm-level analyses for Australian firms, while we emphasize the individual-level debias using the US data. Second, they find that analysts issue more optimistic and less accurate forecasts for firms experiencing FCDs, while we obtain completely **opposite** results[8]. Third, they compare firms with FCDs to those without, neglecting the ex-ante differences between analysts covering the two groups of firms. In our study, we focus on the spillover effect from the affected firms to the unaffected firms, where the affected and unaffected firms share the same analysts, and the latter is less likely subject to endogeneity problems.

Last, our paper also contributes to the literature on CEO turnovers. While most prior

[8]see section 4.1 firm-level analyses

studies discuss CEO turnovers within the scope of corporate governance, few concentrate on its effects on firm stakeholders such as sell-side financial analysts. Brochet et al. 2014 examine the analysts' coverage initiation decisions after CEOs switch to new companies, which are typically applicable to voluntary CEO turnovers. Our findings suggest that forced CEO departures have far-reaching economic implications for the financial market.

The remainder of this paper is organized as follows. In Section 2, we provide a review of the relevant literature on financial analysts and make our predictions. In Section 3, we describe our data and research design. The empirical estimations are presented in Section 4, while Section 5 reports the results of our robustness checks. Section 6 discusses potential alternative explanations for our findings. Finally, Section 7 concludes the paper.

2 Literature Review and Predictions

2.1 Biased Analysts' Forecasts

As financial intermediaries, sell-side analysts are expected to deliver accurate quantitative opinions to their clients. However, a large body of literature suggests that analysts' earnings forecasts can be biased. Earlier research on biased forecasts models the forecast error as a function of various analyst characteristics, including the forecast horizon (Kang et al. 1994; Clement and Tse 2003), analysts' experience (Mikhail et al. 1997), and their past forecast accuracy (Hong and Kubik 2003). In general, these factors capture the time-related components that affect analysts' forecasts.

In addition to the well-documented associations between analyst attributes and forecast optimism, prior research also attempts to provide more nuanced explanations for biased forecasts. Some studies attribute this bias to economic incentives related to the analysts' working process. For example, Ke and Yu 2006 argues that analysts who issue optimistic forecasts and then give downward revisions before earnings announcements experience better career outcomes. Moreover, analysts may also provide biased forecasts deliberately to facilitate management access (Lim 2001).

In contrast to analysts' strategic considerations, some literature attribute forecast errors to behavioral bias by borrowing concepts from psychology literature. Cen et al. 2013 examines the implications of anchoring bias associated with analysts' earnings forecasts and finds that analysts make more conservative forecasts. Dong et al. 2022 suggests that analysts who are subject to overconfidence bias issue less accurate forecasts. Alternatively, other factors such as cognitive distraction (Bourveau et al. 2022), decision fatigue (Hirshleifer et al. 2019), and seasonal affective disorder (Lo and Wu 2018) have also been found to influence analysts' judgment.

To the best of our knowledge, few studies have explained the biased analyst forecasts from the perspective of CEO turnovers and discussed the broader implications of forced CEO departures for financial analysts. Actually, FCDs differ from existing factors that might affect analysts' forecasts in the sense that they are specific to each analyst at a particular time, and their effect is triggered by one firm and then transmitted to other firms in the analyst's portfolio.

2.2 Analysts' Learning Behavior

Learning is a fundamental way for market participants to resolve uncertainty. Financial analysts rely on learning to figure out the dynamics of firms' earnings processes, and learning helps them better incorporate new information into their valuations. Mikhail et al. 1997 and Mikhail et al. 2003 collectively confirm that analysts learn from their experience because individual analysts learn by doing. Markov and Tamayo 2006 suggest that analysts are rational Bayesian learners who update their beliefs ex-post. All this evidence supports the argument that learning is an essential channel for analysts to improve their performance.

Numerous studies examine how analysts learn from their past experiences over time. These experiences can be general to all firms and industries, or specific to a particular firm or task. For instance, Clement et al. 2007 find that analysts learn from past restructuring experiences and those who survive benefit most from such task-specific experience. Analysts develop expertise by repeating information processing and valuation tasks, which contributes to their ability to provide better investment advice.

Analysts can also learn from other sources such as their peers and new technologies. Kumar et al. 2022 find that analysts' social learning among peers helps them improve their performance. Do and Zhang 2020 argue that analysts benefit from the arrival of star analysts. Additionally, analysts can also learn from new technologies such as Robot analysts (Cao et al. 2021), online crowdsource forecast platforms (Jame et al. 2022)[9], and social media analysts (Drake et al. 2022). These studies suggest that analysts benefit from new sources of information and make better predictions in the presence of learning targets.

2.3 Predictions

For the **affected firms**, analysts may issue less optimistic forecasts as a way to correct their previous mistakes and repair their reputation. However, the question of whether and how FCDs change their optimism for **unaffected firms** is still under debate. As sophisticated financial intermediaries, a fully rational analyst should be immune to unrelated factors such as FCDs. In other words, they should not incorporate the FCD event of one firm into their earnings projections for another firm. However, we expect that FCDs have an economic influence on the optimism and accuracy of analysts' forecasts as a result of their learning behavior.

In addition, it is unclear whether the affected analysts become more or less optimistic toward the unaffected firms. Kadan et al. 2020 cautions researchers to pay close attention to sell-side analysts' benchmarks, as the thresholds are incomparable across different brokers. Research on the anchoring bias (Cen et al. 2013) and contrast effect (Shi and Tang 2022) also suggest that analysts may not adopt a fixed benchmark when making earnings forecasts.

[9] Jame et al. 2022 argues that professional analysts can hardly learn directly from the online forecast platform (Esimize). However, we are discussing the learning process from a broader perspective, where any changes in analysts' research outcomes and behavior patterns can be viewed as the potential consequences of the learning process.

These studies indicate that an analyst's estimates of a specific firm may depend on the industry median performance (the anchor) or the earnings of bellwether firms in their portfolio (the preceding signal). Therefore, affected analysts may make more optimistic forecasts since they mistakenly regard the unaffected firms as more promising because these firms are not experiencing forced CEO turnovers.

However, learning theory provides an entirely opposite prediction. Since firms' earnings may contain noise and analysts may have different preferences between short-term and long-term forecasts, the announcement of actual quarterly earnings in normal conditions may not be critical enough for analysts to evaluate their past performance. Nevertheless, the occurrence of FCD events represents an adverse signal that triggers analysts to rethink their previous optimism. Analysts who receive feedback may realize that they were overly optimistic toward the operating situation of affected firms and subsequently make downward revisions for all the firms they are covering. If so, we may interpret the overcorrection for unaffected firms as a spillover effect of learning.

3 Data and Research Design

3.1 Data and Sample Selection

We obtained the sample of forced CEO departure events from Gentry et al. 2021[10]. In their study, CEO departures in the S&P 1500 firms were hand-collected and classified into eight categories based on motives. For our **individual-level analyses**, we include only forced CEO departures but not voluntary ones. Our final sample consists of 727 FCD events spanning from 2000 to 2018. We excluded CEO departures that occurred before 2000 for two reasons. First, the CEO departure classification depends on the accuracy of the information in press release reports and firm disclosures, and the early-stage information may not possess the same quality as that after 2000. Second, we wanted to focus on the post Regulation FD

[10]The data are available at https://zenodo.org/record/4543893#.Y_SLw3bMLaI

period to ensure the relevance of our findings. Table A2 provides descriptive statistics on the number of FCDs each year. Although double-checked for accuracy, the FCD data in Gentry et al. 2021 are hand-collected, and the departure reasons classification is sensitive to personal judgment. To lend more credibility to our study, we further turned to Peters and Wagner 2014 as an alternative data source for our robustness tests[11].

Analysts' quarterly earnings forecasts were obtained from I/B/E/S. In the FCD context, we considered all the earnings forecasts issued by affected analysts who cover the affected firms. We defined the affected firm as those that experience FCD events and affected analysts as those who covered at least one affected firm when an FCD occurs. Next, we dropped the observations for firm-quarters covered by less than six analysts to eliminate the influence of scarce coverage on our consensus forecast measurement. Furthermore, we removed forecasts given by unidentified analysts (Merkley et al. 2020)[12], forecasts for firms with a stock price less than \$1 (Cen et al. 2013), and forecasts with an absolute forecast error great than one (Bernhardt et al. 2006).

In our study, we also use data on the conference call, firm fundamentals, and stock returns. From Seeking Alpha, we collect the textual transcripts for firm earnings calls. Quarterly data on firm assets, liabilities, sales, and revenues were obtained from Compustat. Monthly stock prices, returns, and shares outstanding were sourced from CRSP. In addition, we employed the text-based firm similarity data from Hoberg and Phillips 2016 in our cross-sectional tests. Our final sample includes 514,079 individual forecasts issued by 2,536 analysts who were affected by at least one of the 727 FCD events during the 2000-2018 period.

[11] We obtained the data from `https://www.florianpeters.org/data`. Peters and Wagner 2014 relies on an algorithm and classifies CEO turnovers into forced or voluntary categories. Please refer to Appendix A for more details.

[12] Forecasts by analysts whose identifier is zero.

3.2 Research Design

3.2.1 Firm-level Analysis

To investigate analysts' learning behavior, we begin by employing a firm-level difference-in-difference model that allows us to detect changes in their consensus forecasts for affected firms. We use the firm-quarter panel date for a nine-quarter window centered on the quarter in which the affected firm experiences an FCD[13]. To build up a control group, we add consensus forecasts around voluntary CEO departures to our model in a similar manner[14]. As another type of CEO turnover, voluntary CEO departures differ from FCDs in that they reflect the personal choice of the incumbent[15]. Our firm-level model is as follows:

$$\mathrm{Optimism}^{\mathbf{F}}_{\mathrm{j,t}} = \alpha + \beta_1 \mathrm{Post}_{\mathrm{j,t}} + \beta_2 \mathrm{Forced}^{\mathbf{F}}_{\mathrm{j,t}} + \beta_3 \mathrm{Post}_{\mathrm{j,t}} \times \mathrm{Forced}^{\mathbf{F}}_{\mathrm{j,t}} + \gamma \mathrm{X}^{\mathbf{F}}_{\mathrm{j,t}} + \tau_{\mathrm{t}} + \delta_{\mathrm{j}} + \varepsilon_{\mathrm{j,t}}$$

where j denotes the affected FCD firm and t denotes time. We use the superscript **F** to represent the firm-level measures. $\mathrm{Optimism}^{\mathbf{F}}_{\mathrm{j,t}}$ is defined as the difference between the consensus analysts' forecasts and the firms' actual earnings, scaled using the stock price at the end of the previous fiscal quarter. The consensus forecast is the median value of the latest analyst forecasts issued before the earnings announcement date. $\mathrm{Post}_{\mathrm{j,t}}$ is an indicator variable that equals one for the four quarters following the FCDs, and $\mathrm{Forced}^{\mathbf{F}}_{\mathrm{j,t}}$ is an indicator to label the treatment group.

$\mathrm{X}^{\mathbf{F}}_{\mathrm{j,t}}$ denotes the firm-specific characteristics that may impact the analysts' aggregate projection on the firm's quarterly earnings. These variables include firm size, return on

[13] It is worth noting that the window length for the event level is not a crucial parameter, as our focus is on the individual level optimism adjustment immediately following FCD.

[14] Gentry et al. 2021 classifies CEO retirement (category number 5) and job-hopping (category number 6) as voluntary departures. We include forecasts for departures coded as CEO retirement and job-hopping in our control groups.

[15] In general, voluntary CEO departures include CEO retirement and job-hopping. If the incumbents leave for their age reason or new opportunities, the departures are less likely driven by firm performance.

assets, market-to-book ratio, quarterly stock return, and the number of analysts covering the firm. In addition to these control variables, we also incorporate firm and time fixed effects, denoted as τ_t and δ_j respectively. The firm fixed effects control for firm-specific time-invariant variables that may affect our results, while the time fixed effects account for any time trends, such as the FCD wave following industry shocks.

In Table 1, Panel A, we present descriptive statistics for the variables used in our firm-level analysis based on the sample data. The mean value of firm-level consensus optimism is 0.21, a positive value driven by the upward bias for affected firms before FCDs ("the mistakes"). The mean value of $\text{Forced}^{\mathbf{F}}_{\text{j,t}}$ is 0.25, suggesting that 25% of CEO departures are involuntary.

3.2.2 Individual-level Analysis

Most importantly, our primary target is to investigate the spillover effect after FCD events. To this end, we employ a pooled OLS model to test whether analysts who cover affected firms become less optimistic for the unaffected firms in their portfolios. Building on the approach used by Cuculiza et al. 2021, we specify our individual-level model as follows:

$$\text{Optimism}^{\mathbf{A}}_{\text{i,j,t}} = \alpha + \beta \text{Fcd}_{\text{i,t}} + \gamma \text{X}^{\mathbf{A}}_{\text{i,j,t}} + \tau_{\text{t}} + \delta_{\text{i,j}} + \varepsilon_{\text{i,j,t}}$$

where i indexes analysts, j indexes unaffected firms, and t indexes time. We use the superscript $\mathbf{A}$ to denote the individual analysts' measures. Specifically, $\text{Optimism}^{\mathbf{A}}_{\text{i,j,t}}$ represents the stock price-scaled distance between an individual analyst's forecast and the most recent consensus forecast of her unaffected peers covering the same firm j at time t . Our primary variable of interest, *Fcd*, is an indicator variable that equals one if the forecast is issued within 30 days following any FCD[16]. The coefficient β captures the change in the affected analysts' forecast optimism for the unaffected firms from before to after the FCD relative to

[16]Our choice of a 30-day window length follows Cuculiza et al. 2021. Since financial analysts are professional intermediaries, we conjecture that they are subject to overcorrection only in the short term. In section 6, We also detect a significant spillover effect after the 30-day window with an attenuated magnitude.

their unaffected peers. β takes a negative value if the affected analyst issues less optimistic forecasts than their peers covering the same firm.

$\mathrm{X}^{\mathbf{A}}_{\mathrm{i,j,t}}$ is a set of control variables accounting for time-varying firm and analyst characteristics identified in the previous research (e.g. Clement and Tse 2003; Clement et al. 2007). Our measures of firm fundamentals include firm size, return on assets, market-to-book ratio, and number of analysts following the firm. Additionally, we control for analyst attributes that may influence their forecast optimism, such as portfolio size, general experience, firm-specific experience, brokerage size, horizon, and past accuracy. We also control for the daily stock returns' comovement between the affected firm and the unaffected firm in the 90 days prior to the forecast, which captures the rational component in analysts' expectation of unaffected firms' earnings due to the ex-ante economic link between the affected and unaffected firms (Hameed et al. 2015)[17].

In addition to the control variables, we include analyst-firm and time fixed effects. Incorporating the analyst-firm fixed effect provides two benefits. First, by including this fixed effect, we can capture time-invariant analyst-firm pair effects such as underwriting affiliation relationships and other analysts' coverage incentives. Second, as our individual-level learning effect is identified within each analyst-firm pair, our results are not likely to be driven by analysts' coverage initiation or termination before or after the FCD. We also include the year-quarter fixed effect to control for unobservable time trends.

Panel A in Table 1 presents the summary statistics for individual-level forecasts. Based on the prior consensus forecast, the mean optimism of analysts is -0.043, which is similar to the optimism measure used in studies such as Kumar et al. 2022. This value supports the argument that analysts are gradually revising their forecasts to more beatable ones. Additionally, 4.6% of the affected analysts' forecasts are issued within 30 days of an FCD event.

[17]To calculated stock price comovement, We require the are at least 60 trading days for the affected-unaffected firm-pair in the three months before the forecast revision. If a forecast is following multiple FCDs, we consider the stock comovement between the unaffected firm and the affected firm that experience the FCD most recently.

4 Empirical Results

4.1 Firm Level Analyses: Learning from FCDs

We begin by demonstrating that analysts make aggregate-level errors before FCDs. In Figure 1, we present the consensus analysts' forecast relative to the actual earnings of affected firms during the nine quarters surrounding the FCDs. The solid red (blue) line displays the mean optimism for analysts covering firms with forced (voluntary) CEO departures, while the dashed lines represent the 95% confidence intervals for the mean optimism values in each quarter. We observe that analysts covering firms with voluntary CEO departures consistently issue slightly pessimistic forecasts. Conversely, their peers in the FCD group make considerable upward mistakes in the four quarters leading up to the FCDs. Despite the large dispersion, the affected analysts as a whole promptly correct their bias after FCD occurs[18]. This pattern suggests that analysts are financial professionals who learn from FCDs and incorporate new information quickly.

Table 2 presents the results of our multivariate estimates on firm-level. Prior to FCD events, analysts covering affected firms are more optimistic than those covering voluntary CEO departure firms. However, following the FCD event, the aggregate optimism of affected analysts significantly decreases. Given that the interaction term is both statistically and economically significant, we are confident to conclude that analysts learn from their past mistakes and then quickly adjust their beliefs.

[18]Figure 1 indicates that the analysts' debiasing process begins in the quarter in which FCD takes place. This is because we use all individual analysts' forecasts to construct aggregate optimism, and these individual forecasts may be issued both before and after the FCD. In the next section, we turn to OLS estimation and consider the exact dates of forecasts following FCD to tease out the overcorrection from the mixed effects embedded in the panel data.

4.2 Individual Level Analyses: The Spillover Effect

If the quick adjustment by analysts for affected firms reflects their learning process, it raises the question of whether they overcorrect for unaffected firms. Our baseline results under different specifications are presented in Table 3. In column (1) of Table 3, we report our estimates without control variables and fixed effects. Our main variable of interest, *Fcd*, is negative and statistically significant, indicating that relative to their peers, affected analysts issue less optimistic forecasts for unaffected firms in their portfolio. In column (2), we include a set of firm and analyst characteristics as control variables. Similar to the results in column (1), the coefficient of *Fcd* remains statistically significant with a comparable magnitude. In columns (3) and (4), we further include analyst-firm fixed effects and year-quarter fixed effects to control for unobservables at the quarter and analyst-firm pair level. Consistent with our hypothesis, the estimates for *Fcd* are negative and significant at the one percent level in both columns (3) and (4).

The coefficients in Table 3 are fairly large and appear to be economically meaningful. For instance, the coefficient in the model (4) suggests that moving an affected analyst's forecast from normal time to the 30-day window following FCDs is associated with a 3.4% (=0.014/0.41) decrease in relative forecast optimism relative to the standard deviation. It is worth noting that we are capturing the spillover effect of analysts' learning for the unaffected firms, it is reasonable the effect is consequently smaller than the self-motivated learning for affected firms.

4.3 Cross-sectional Analyses: Who Overcorrect?

In the previous section, we demonstrated that analysts overcorrect following FCDs since they issue less optimistic forecasts for unaffected firms. Nevertheless, it is possible that some affected analysts express a smaller degree of overcorrection than others. In this section, we conduct cross-sectional analyses to explore the heterogeneity in the affected analysts' optimism reduction.

4.3.1 Analyst Characteristics

Previous research (Mikhail et al. 1997; Bradley et al. 2017) argues that analysts' performance improves with their experience, including the analysts' general experience, firm-specific experience, and industry-related experience before becoming an analyst. This argument suggests that experience should decrease the likelihood of overcorrection. To test if more experienced analysts are less likely to overcorrect, we perform regression analysis including the interaction between *Fcd* and the analysts' overall experience. The results are reported in Panel A of Table 4. In all specifications, more experience is associated with a smaller effect of FCD. This result suggests that analysts with more experience benefit less from the spillover effect of learning, which is consistent with Do and Zhang 2020.

As mentioned in the firm-level analyses, there is a wide dispersion in analysts' expectations for the earnings of the affected firms, as indicated by the confidence interval in 1. Therefore, affected analysts are not making the same mistake to the same extent: some of them may have been more optimistic about the affected firms before FCD than others. Those who are previously over-optimistic may continue holding an optimistic attitude toward those unaffected firms after FCD. This argument is consistent with prior research that shows analysts' short-term forecasts are auto-correlated (Abarbanell and Bernard 1992; Linnainmaa et al. 2016; Veenman and Verwijmeren 2018). By contrast, analysts' mistakes before FCDs may reflect their inability to provide accurate forecasts. As a result, those who are overly optimistic about the affected firms may be subject to overcorrection to a larger extent. The inability supposition is in line with Hilary and Hsu 2013, which suggests that less skilled analysts are unable to provide consistent forecasts and may make forecasts that are either overly optimistic or overly pessimistic.

To formally test the effect of past optimism on analysts' overcorrection, we conducted regression analysis by adding the interaction term between *Fcd* and analysts' past optimism.

Past optimism for the affected analysts was calculated as the median value of analysts' optimism on the **affected firms** during the four quarters before the FCD. The estimation results are reported in Panel B of Table 4. The coefficients for the terms *Fcd* and the interaction are both negative and statistically significant, suggesting that analysts who were previously more optimistic are also more likely to overcorrect. This result supports our inability hypothesis that less skilled analysts are associated with larger overcorrection.

4.3.2 Firm Characteristics

There could also be cross-sectional variation in firm characteristics that influence the effect of spillover effect. First, we study the role of a firm's information environment. Conceptually, larger firms tend to have a better information environment in which analysts are less likely to overcorrect. However, the magnitude of the spillover effect of learning could be more significant for larger firms if affected analysts allocate more effort to those firms (Harford et al. 2019)[19].

To examine potential cross-sectional differences, we extended our individual-level regressions by adding the interaction term between *Fcd* and *Size*, where *Size* is measured as the logarithm of market capitalization. Panel A of Table 5 reports the estimation results. The interaction term is positive and statistically significant in all specifications, indicating that analysts' overcorrection following FCDs decreases with firm size. This finding is consistent with the argument that a better information environment limits the spillover effect as richer information prevents overcorrection from happening.

Our main argument is that analysts issue less optimistic forecasts for unaffected firms after FCDs, which reflects their irrational overcorrection driven by learning behavior. Therefore, we expect this bias to be larger when affected analysts are subject to additional cognitive resource constraints, such as limited attention. Driskill et al. 2020 finds that analysts' respon-

[19] Harford et al. 2019 argue that analysts tend to allocate more effort to firms that are more decisive to their careers, such as larger firms, firms with higher trading volume, and firms with a larger proportion of institutional investors.

siveness deteriorates under concurrent announcements, and those facing multiple earnings announcements strategically allocate their attention. Given that analysts are obliged to deliver timely revisions during the earnings seasons, we suggest that the analysts' overcorrection increases when they have a heavy workload.

To investigate the impact of limited attention on analysts' overcorrection, we introduce the variable *Bundled_EA* as a measure of the number of earnings announcements on the same day that analysts issue forecasts. We interact *Bundled_EA* with the *Fcd* and present the results in Panel B of table 5. Our results indicate that the interaction term is positive and significant, which suggests that the reduction in analysts' optimism is larger when they face cognitive resource constraints due to concurrent announcements. These findings remain robust to the inclusion of control variables and fixed effects, providing evidence that workload plays a role in analysts' overcorrection following FCD.

4.4 Forecasts Accuracy

However, we cannot determine whether analysts benefit from the spillover effect without knowing its effect on forecast accuracy. We can only be confident that affected analysts learn from FCDs and their overall performance improves if less optimistic forecasts for the unaffected firms are also more accurate. To examine the change in affected analysts' accuracy after FCDs, we follow Clement 1999 and construct the performance measure proportional median absolute forecast error (PMAFE).

Particularly, PMAFE is calculated as follows:

$$PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \overline{AFE}_{j,t}}{\overline{AFE}_{j,t}}$$

where $AFE_{i,j,t}$ is the absolute forecast error for analysts i's forecast of firm j for quarter t and $\overline{AFE}_{j,t}$ is the median absolute forecast error for firm j in quarter t. Note that $PMAFE$ is a measure of relative inaccuracy; therefore, a larger value of $PMAFE$ indicates that the affected analyst is less accurate than her peers covering the same firm j in quarter t.

Table 6 reports the regression results. The coefficients for *Fcd* are negative and significant, indicating that affected analysts are relatively becoming more accurate in the 30-days window after FCDs. Despite that overcorrection reflects analysts' irrational revision, our results provide evidence that irrational behavior can eventually bring benefits. Furthermore, our results suggest that forecasts with shorter horizons are more accurate, and analysts with larger portfolio sizes tend to be less accurate. These findings are consistent with those in related literature, such as Clement and Tse 2005 and Kini et al. 2009.

4.5 Market Reactions

Previous sections show that affected analysts issue less optimistic and more accurate forecasts as a result of the spillover effect of learning from FCD. In this section, we investigate whether investors unravel their improved performance and react stronger to their revisions. Veenman and Verwijmeren 2018 find that analysts' short-term predictable pessimism is not fully reflected in market prices. Given that analysts' forecast revisions are ex-ante unpredictable for the unaffected firms, it is unclear how the market will react to the forecast revisions made by affected analysts following FCDs.

To test our hypothesis, we adopt the methodology of Hirshleifer et al. 2019 and Jung et al. 2019. In our empirical model, we regress the firm's two-day cumulative abnormal return on the interaction term between the *Fcd* and the *Revision*. The two-day abnormal return is calculated as the market-adjusted excess return over the day of and the day following analyst forecast revisions. The other main dependent variable, *Revision*, is computed as the distance between the current earnings forecast and the preceding forecast of the same affected analyst, scaled by the stock price.

Table 7 presents the estimation results. In all specifications, we find the coefficients on $Fcd \times Revision$ are positive and significant. The results in the last column indicate that the market reaction to a revision following FCD is 0.1% larger than that to a revision with similar magnitude out of the FCD event periods. This evidence supports the argument that the affected analysts' forecast revisions generate a stronger market response after FCDs. These market reaction estimates complement the forecast accuracy results by showing the benefits from an alternative spillover effect of their learning behavior.

5 Robustness Tests

We conduct a battery of tests to ensure the robustness of our baseline analyses on the spillover effect of learning. Specifically, our conclusions are unchanged if we 1) exclude unaffected firms with high product similarity, 2) exclude unaffected firms with more than two affected analysts, 3) use an alternative CEO turnover data set, and 4) use different variables and econometric models.

5.1 Industry Level Shocks

Our earlier findings lend support to the spillover hypothesis, which suggests that affected analysts unintentionally lower earnings forecasts for unaffected firms following FCDs. However, an essential assumption behind this hypothesis is that FCDs are idiosyncratic to individual firms. Nevertheless, Jenter and Kanaan 2015 argue that the industry performance is a decisive driver of FCDs[20]. If affected analysts anticipate industry shocks and issue less optimistic forecasts for unaffected firms, we cannot attribute their behavior to the overcorrection.

To mitigate this concern, we conduct additional estimates where we limit our sample to unaffected firms with the least economic ties to the affected firms. For each affected analyst and each FCD event, we dynamically select the unaffected firm with the largest product similarity distance to the affected firms in the analyst's portfolio (Hoberg and Phillips 2016). Our results in panel A table 8 show that affected analysts issue less optimistic forecasts even

[20] In Jenter and Kanaan 2015, the authors suggest that the probability of CEO turnover doubles as the industry component of firm performance decreases from the 90th to the 10th percentile. They focus on both voluntary and forced CEO turnovers. However, in our context, we only focus on FCDs, which are more likely to be specific to a particular firm.

for firms with the smallest product-market similarity, and the economic significance of the spillover effect is over two times larger than that in our full sample estimates[21]. This finding suggests that we do capture the spillover effect of learning behavior and that our results are not driven by industry-level shocks affecting both affected and unaffected firms.

5.2 Herding Behavior

Previous studies document the herding behavior among analysts covering the same firm(Bernardo et al. 2000; Welch 2000). According to herding theory, the affected analysts may issue less optimistic optimism following their peers, such as all-star analysts. To address the concern that affected analysts actually mimic their peers, we conduct additional analyses on a subsample where herding is less likely to occur. Specifically, we restrict our sample of unaffected firms to those with at most two affected analysts. Given that we have already excluded firms covered by fewer than six analysts, there is at most one peer out of five analysts that a focal affected analyst can potentially herd on.

Panel B of Table 8 reports the results for the aforementioned subsample. The results suggest that analysts make less optimistic forecasts for the unaffected firms for which herding is almost impossible. Furthermore, we observe that the coefficients are larger than those in our baseline estimations. A possible explanation for the stronger effect in the fewer-affected analysts' subsample is that larger overcorrection is due to a worse information environment, which is similar to our investigation of cross-section variation in firm size in 4.3.2.

5.3 CEO Turnover Data Set from Peters and Wagner

Our study relies on the reasonable classification of CEO turnovers. Gentry et al. 2021 identifies CEO departures from news coverage and SEC filings and then codes the CEO

[21] Financial analysts rely on public information in their research. For firms with stronger economic connections, public information concerning both firms is richer. As a result, analysts are less likely to be subject to overcorrection. By contrast, for two dissimilar firms, bilateral information can be scarce except for the shared analyst coverage. As a consequence, the magnitude of the spillover effect tends to be larger.

departures into multiple motifs[22]. Even though their coding schemes and categorization are double-checked by doctoral students and researchers, the classification of whether a departure is forced or voluntary is still sensitive to human judgments. To alleviate such concern, we resort to an alternative FCD data set maintained by Peters and Wagner (Peters and Wagner 2014; Jenter and Kanaan 2015). They use refined criteria and exclusively focus on forced turnovers.

Panel C Table 8 presents the results obtained using the secondary FCD dataset under an identical empirical design as our baseline estimation. Consistent with the findings from the original dataset, our primary dependent variable, *Fcd*, is negative and statistically significant for all specifications. These results suggest that the main effect of overcorrection is robust across different classifications of CEO turnovers.

5.4 Alternative Measures and Models

The primary dependent variable in our study, $\text{Optimism}^{\mathbf{A}}_{\text{i,j,t}}$, quantifies the divergence between an analyst's earnings forecast and the closest consensus forecast. As an alternative way to measure individual optimism, we follow Bourveau and Law 2021, which considers only the last forecast for an individual analyst in each fiscal quarter and divides forecast optimism by the standard deviation of the consensus forecast. In Panel D of Table 8, the coefficient on *Fcd* in column (1) is significant and negatively correlates with optimism, suggesting that our results remain robust to the alternative measure of optimism.

Our primary explanatory variable, *Fcd*, is a dummy variable that takes the value of one for forecasts issued by affected analysts during the 30-day window following a CEO dismissal. For firms that dismiss their CEOs, it is possible that they strategically force their CEOs out before earnings seasons to reduce the following impact on earnings announcements. In such cases, we may capture the analysts' reduction in relative optimism who are systematically walking down before the earnings announcement. To address this possibility, we extend

[22]See. Gentry et al. 2021 section 3 for more details

the window length to 90 days when constructing the *Fcd* dummy. This approach allows us to detect the changes in optimism for forecasts issued both before and after the earnings season. Column (2) of Panel D in Table 8 shows that the spillover effect slightly attenuates but remains negative and statistically significant at the 1% level.

As alternative approaches, we utilize logit and probit models to achieve higher interpretability. In these nonlinear models, the outcome variable becomes an indicator variable that takes the value of one if the earnings forecast is higher than the closest consensus forecast. Columns (3) and (4) report the corresponding estimation results. Under the probit (logit) model, affected analysts are 6.4% (3.9%) more likely to issue relatively less optimistic forecasts for unaffected firms following FCDs. Relative to its standard deviation, the forecast following FCDs translates into a 15.4% (9.4% in the logit model) decrease in their optimism. This effect is economically meaningful[23].

5.5 Placebo Tests

We next implement simulation-based falsification tests to demonstrate that the overcorrection is unique to FCD events. The advantage of the simulation is that it does not make distributional assumptions about the coefficient on the variable of interest. We begin by randomizing FCD dates while keeping the affected firm unchanged. For each iteration of our simulation, we randomly assign a date to a specific FCD event. We then reestimate model 4 of table 3 to recover the coefficient of our main explanatory variable, *Fcd*. The simulation procedure is repeated 1000 times and then the density of the coefficients is plotted in panel A Figure 2. The vertical line represents the actual coefficient of *Fcd* (-0.14), which is lower than 97% of the simulated coefficients.

In a similar fashion, we further randomize both the affected firms and the FCD dates. For each iteration of our simulation, we randomly assign a firm and a date from the Compustat universe to the FCD event. We then replicate model 4 of table 3 to recover the coefficient

[23] Compared with the standard deviation of the optimism dummy 0.064/0.416.

of our main explanatory variable *Fcd*. We repeat the simulation procedure 1000 times and then plot the density distribution of the recovered coefficient in panel B Figure 2. Again, the vertical line represents the value of our estimate of *Fcd* (-0.14) the baseline specification, which is lower than 95.2% of the simulated coefficients. Put together, the placebo test suggests that the overcorrection following FCDs is not driven by spurious correlation.

6 Alternative Explanations

6.1 Overcorrection or economic strategy?

There are two underlying assumptions behind our conclusion that affected analysts issue less optimistic forecasts because of the spillover effect of learning. First, analysts cannot anticipate the FCD events. Second, their less optimistic forecasts for the unaffected firms are the result of overcorrection rather than their strategy.

6.1.1 Pre-existing Difference in Optimism

A violation of the first assumption raises concerns that there may be ex-ante differences between affected analysts and their peers before the FCD events. If this is the case, our previous estimations would only capture the forecasts of analysts who are systematically more pessimistic than the remaining analysts covering the same unaffected firm. However, it is not a substantial concern for us as our main regressions already include analyst-firm fixed effects and various analyst attributes. To further investigate this possibility, we repeat our analysis by constructing the *Pre_Fcd* variable, which is an indicator that equals one for the forecasts made by affected analysts during the 30-day window before the FCDs. Table 10 reports the results of the forecasts for unaffected firms before FCDs. In all specifications except for the first one, the estimates of pre-FCD are statistically insignificant. The results suggest that affected analysts cannot predict FCDs and therefore do not proactively behave less optimistically before FCD.

Figure 3 further provides graphical evidence that analysts are unable to predict FCD events and their overcorrection exclusively occurs in the short window after the FCD. The graph shows that in the 90-day window prior to the FCD, affected analysts do not reduce their forecast optimism. After FCDs, the relative optimism for affected analysts significantly decreases. After the 30-day window, the reduction of optimism continues for another month and finally disappears in the third month following FCDs. Taken together, the evidence indicates that affected analysts' optimism is exclusively lower after the FCD. There are no preexisting differences between the affected analysts and their peers, and our findings do not support this alternative explanation.

6.2 Management Access Incentives

Regarding the second assumption, readers may argue that affected analysts trade off optimism to better management access. Specifically, there are two possibilities that analysts are doing so due to rational economic incentives. First, analysts issue less optimistic forecasts to please the successor, regardless of the reason for the predecessor's departure. Second, analysts strategically issue less optimistic forecasts exclusively after forced departures (not voluntary departures) as a response to their past aggressiveness.

To address the first possibility, we replicate our baseline examination to test for spillover effects following CEO voluntary departures. Estimation results in Table 9 show that the coefficients for *Fcd* are insignificant, indicating that analysts are not significantly less optimistic after CEO voluntary departures. This result rules out the possibility that analysts issue less optimistic forecasts to please the new CEOs[24].

The other remaining possibility is grounded in previous research indicating that analysts' unfavorable questions impede their access to private information channels to management (Mayew et al. 2013; Cen et al. 2021). We use the change in the verbal aggressiveness of their questions during conference calls to measure analysts' incentives for management

[24]Since making mistakes is a prerequisite of overcorrection, it is not surprising that we do not detect the spillover effect.

access. Following Comprix et al. 2022, we use *directness*, *preface*, *negative questioning*, and *follow-up questions* to proxy for aggressiveness. In addition, we also measure aggressiveness by counting the quantitative content in analysts' questions[25]. If affected analysts consider themselves as being overly aggressive before the FCDs, we expect their verbal aggressiveness to be lower after the FCDs.

Table 11 reports the results of our estimation of analysts' verbal aggressiveness during conference calls. All the coefficients for *Fcd* are insignificant in the models with different aggressive measures. These results suggest that affected analysts are not performing less aggressively towards new CEOs during their conference call participation.

Overall, our findings suggest that the affected analysts can neither predict the FCD events nor behave less aggressively to gain better access to new CEOs. Instead, the decrease in optimism reflects the spillover effect of analysts' learning from FCDs.

6.3 Overcorrection or Emotional Pessimism

The previous section shows that the reduction in optimism is not driven by economic motives but is a by-product of learning behavior. Furthermore, we can refine analysts' learning behavior and distinguish between overcorrection and emotional pessimism. Dehaan et al. 2017 find that analysts give more pessimistic earnings revisions and target price revisions in the presence of unpleasant weather. Cuculiza et al. 2021 attribute the decrease in analysts' forecast optimism after terrorist attacks to pessimistic sentiment. In the context of FCDs, we argue that the decrease in optimism is different from the pessimistic sentiment previously documented.

Table 12 reports our results for the refined FCD motives. *FCD Type I* and *FCD Type II* are two dummy variables that indicate the FCD types. *FCD type I* includes FCDs due to CEO death or illness, while *FCD type II* consists of the remaining FCDs due to job performance or misconduct. We argue that any change in analysts' optimism following the

[25] We also follow Huang et al. 2018 et al. and count the question sentences that contain "dollar" or "percent" and obtain similar results.

former type is more likely to be driven by their pessimistic sentiment. The coefficients for *FCD Type I* are statistically insignificant in the models with fixed effects, while those for *FCD Type II* are consistently negative and statistically significant. This evidence suggests that analysts' optimism is lower particularly after FCD due to job performance or misconduct. It is in line with our projection that the less optimistic forecasts are byproducts of their learning rather than the outcome of a depressed mood.

7 Conclusion

The discussion of analysts' expertise and performance has continued for decades. In an ideal world without friction, the earnings forecasts by sophisticated analysts should not depend on whether they personally cover a particular firm. The projections for one firm should only be affected by corporate adverse events, such as FCDs, in the way that the two firms are economically connected. However, we argue and demonstrate that analysts' beliefs can be largely determined by the composition of their portfolios.

In this paper, we discuss the analysts' learning behavior following FCD events. We find that analysts make significant upward-biased mistakes for the affected firms and then correct their mistakes by issuing less optimistic forecasts for both affected firms (learning) and unaffected firms (overcorrection). Surprisingly, affected analysts can benefit from the spillover effect of learning as they make more accurate and informative forecasts for unaffected firms. Our study sheds new light on the far-reaching implications of the learning behavior of market participants.

There are many venues for future research. First, it would be interesting to investigate the long-term effect of the FCDs on financial analysts. For example, how does adverse events during analysts' career (such as FCDs) shape their risk appetite? Will affected analysts become more prudent when they initiate coverage later in their careers? Second, the interaction between analysts and firm executives in the context of FCDs also lacks more insights. For instance, how do the FCDs change the social network consisting of both firm executives and analysts? Answers to these questions will not only advance our understanding of analysts' decision-making processes but also provide more insights into the objectivity and risk preference of financial intermediaries.

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Tables

Table 1: Summary Statistics

The table includes summary statistics of the main dependent and independent variables we use in this paper. Table A1 provides the definitions of the variables. The sample period is from 2000 to 2018. To be included in the sample, we require that the data for constructing all the variables used for observation are available. Panel A report the statistics for the variables used in the firm-level analyses; Panel B report variables used at the individual level.

Panel A: Variables on Firm Level						
	Observations	Mean	SD	10th	Median	90th
$Optimism^F$	14427	-0.002	1.083	-0.464	-0.037	0.313
$Post$	14427	0.431	0.495	0	0	1
$Forced^F$	14427	0.281	0.449	0	0	1
$Size^F$	14427	8.384	1.503	6.492	8.262	10.413
ROA^F	14427	0.010	0.028	-0.009	0.011	0.037
BM^F	14427	0.649	0.272	0.286	0.642	1.004
$Return^F$	14427	0.016	0.198	-0.220	0.019	0.242
$Following^F$	14427	12.527	5.802	6	11	21

Panel B: Variables on Individual Level						
	Observations	Mean	SD	10th	Median	90th
$Optimism^A$	514079	-0.043	0.410	-0.254	0	0.167
Fcd	514079	0.046	0.209	0	0	0
PMAFE	514079	-0.016	0.624	-0.822	-0.041	0.767
CAR[0,1]	514079	-0.001	0.060	-0.057	0	0.056
Revision	514079	-0.016	0.996	-0.607	0.007	0.564
Size	514079	8.897	1.553	6.862	8.916	10.947
MB	514079	0.632	0.280	0.268	0.611	1.004
ROA	514079	0.014	0.025	-0.006	0.013	0.041
Following	514079	16.634	7.130	8	16	27
Portfolio Size	514079	16.24	6.140	9	16	24
Gen_Exp	514079	9.273	4.859	3.250	8.750	16.250
Firm_Exp	514079	5.497	4.125	1	4.500	11.500
Horizon	514079	3.908	0.894	2.565	4.394	4.575
Brokerage Size	514079	2.977	0.923	1.609	3.296	3.807
Past Accuracy	514079	0.56	0.324	0.097	0.571	1
Comovement	514079	0.375	0.297	0	0.376	0.773

Table 2: Firm Level Analyses

This table displays the results of the aggregate optimism change for FCDs firms relative to voluntary CEO departures firms, in the nine quarters surrounding the departures. *Fcd* is an indicator variable that equals one if the forecast of analyst i for firm j is issued in the 30-days window following forced CEO departures, zero otherwise. All other variables are defined in Table A1. Standard errors are clustered by firm. Estimated coefficients and the t-statistics (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)
		$Optimism^F$	
Post	0.000	0.000	0.001
	(0.00)	(0.03)	(0.02)
Forced	0.190***	0.119***	0.119**
	(3.94)	(2.58)	(2.57)
Post × Forced	-0.178***	-0.114**	-0.107**
	(2.98)	(2.11)	(2.00)
Size	0.002	-0.057	-0.051
	(0.16)	(1.42)	(1.05)
ROA	-4.805***	-6.892***	-6.912***
	(5.27)	(7.29)	(7.41)
BM	0.028	-0.281**	-0.336**
	(0.39)	(2.15)	(2.37)
Return	-0.518***	-0.387***	-0.380***
	(6.33)	(4.94)	(4.86)
Following	-0.005*	0.003	0.006
	(1.73)	(0.77)	(1.56)
Firm FE	No	Yes	Yes
Year-Quarter FE	No	No	Yes
Observations	14427	14427	14427
R-squared	0.036	0.286	0.294

Table 3: Individual Level Analyses

This table displays the results of the individual analysts' optimism change in their earnings forecasts following FCDs. $Optimism^A$ is the quarterly earnings forecast of analyst i for firm j minus the closest consensus forecast for firm j before the forecast, divided by the stock price of firm j at the end of the previous quarter. The final values are multiplied by 100 for better presentation. *Fcd* is an indicator variable that equals one if the forecast of analyst i for firm j is issued in the 30-days window following forced CEO departures, zero otherwise. All other variables are defined in Table A1. Standard errors are clustered by firm-analyst pair level. Estimated coefficients and the t-statistics (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)
	$optimism^A$			
Fcd	-0.017***	-0.018***	-0.016***	-0.014***
	(5.68)	(5.99)	(5.57)	(4.86)
Size		0.011***	-0.001	0.003
		(11.85)	(0.17)	(0.78)
BM		-0.059***	-0.053***	-0.032***
		(12.08)	(5.05)	(3.05)
ROA		1.560***	1.854***	1.711***
		(26.63)	(26.24)	(23.97)
Following		-0.001***	-0.003***	-0.004***
		(5.26)	(11.81)	(14.46)
Portfolio Size		0.001***	0.000	0.000
		(3.80)	(1.33)	(0.81)
Gen_Exp		0.001***	-0.007	-0.015
		(2.69)	(1.51)	(1.17)
Firm_Exp		0.000	0.010**	0.010**
		(0.49)	(2.06)	(2.15)
Horizon		0.028***	0.028***	0.028***
		(31.86)	(33.29)	(33.17)
Broker Size		-0.004***	-0.006***	-0.005***
		(3.69)	(3.17)	(2.75)
Past Accuracy		-0.011***	0.002	0.000
		(4.36)	(0.71)	(0.13)
Comovement		-0.015***	-0.017***	0.005
		(4.30)	(4.59)	(1.27)
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	514079	514079	514079	514079
R-squared	0.000	0.021	0.146	0.152

Table 4: Cross-sectional Analyses: Analyst Characteristics

This table displays the results of the cross-sectional analyses on the effect of FCDs on analysts' optimism in their earnings forecasts conditional on analyst characteristics. $Optimism^A$ is the quarterly earnings forecast of analyst i for firm j minus the closest consensus forecast for firm j before the forecast, divided by the stock price of firm j at the end of the previous quarter. The final values are multiplied by 100 for better presentation. *Fcd* is an indicator variable that equals one if the forecast of analyst i for firm j is issued in the 30-days window following forced CEO departures, zero otherwise. For brevity, the results of other control variables are not reported. Standard errors are clustered by firm-analyst pair level. Estimated coefficients and the t-statistics (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Panel A: Analysts' Experience

	(1)	(2)	(3)	(4)
	$Optimism^A$			
Fcd	-0.035***	-0.031***	-0.029***	-0.026***
	(5.37)	(4.95)	(4.80)	(4.33)
Fcd × Gen_Exp	0.002***	0.002***	0.001***	0.001**
	(3.52)	(2.75)	(2.72)	(2.55)
Controls	No	Yes	Yes	Yes
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	514079	514079	514079	514079
R-squared	0.000	0.021	0.146	0.152

Panel B: Previous Optimism

	(1)	(2)	(3)	(4)
	$Optimism^A$			
Fcd	-0.014***	-0.015***	-0.014***	-0.012***
	(4.70)	(5.19)	(4.87)	(4.33)
Fcd × Past_Optimism	-0.010***	-0.008***	-0.007***	-0.006**
	(4.03)	(3.36)	(2.60)	(2.04)
Controls	No	Yes	Yes	Yes
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	514079	514079	514079	514079
R-squared	0.000	0.022	0.146	0.152

Table 5: Cross-sectional Analyses: Firm Characteristics

This table displays the results of the cross-sectional analyses on the effect of FCDs on analysts' optimism in their earnings forecasts conditional on firm characteristics. $Optimism^A$ is the quarterly earnings forecast of analyst i for firm j minus the closest consensus forecast for firm j before the forecast, divided by the stock price of firm j at the end of the previous quarter. The final values are multiplied by 100 for better presentation. *Fcd* is an indicator variable that equals one if the forecast of analyst i for firm j is issued in the 30-days window following forced CEO departures, zero otherwise. For brevity, the results of other control variables are not reported. Standard errors are clustered by firm-analyst pair level. Estimated coefficients and the t-statistics (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Panel A: Information Environment

	(1)	(2)	(3)	(4)
	$Optimism^A$			
Fcd	-0.112***	-0.097***	-0.107***	-0.103***
	(4.84)	(4.22)	(4.79)	(4.62)
Fcd × Firm_Size	0.011***	0.009***	0.010***	0.010***
	(4.64)	(3.79)	(4.46)	(4.36)
Controls	No	Yes	Yes	Yes
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	514079	514079	514079	514079
R-squared	0.003	0.021	0.146	0.152

Panel B: Bundled Earnings Announcements

	(1)	(2)	(3)	(4)
	$Optimism^A$			
Fcd	-0.007*	-0.008**	-0.010***	-0.008**
	(1.85)	(2.04)	(2.87)	(2.12)
Fcd × Bundled_EA	-0.003***	-0.003***	-0.002**	-0.002**
	(3.66)	(3.47)	(2.13)	(2.41)
Controls	No	Yes	Yes	Yes
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	514079	514079	514079	514079
R-squared	0.000	0.022	0.147	0.152

Table 6: Forecast Accuracy

This table displays the results of the change in forecast accuracy following FCDs. PMAFE is the proportional mean absolute forecast error, which is defined as the difference between the absolute forecast error (AFE) for analyst i on firm j and the mean absolute forecast error (MAFE) for firm j at time t scaled by the mean absolute forecast error for firm j at time t. *Fcd* is an indicator variable that equals one if the forecast of analyst i for firm j is issued in the 30-days window following forced CEO departures, zero otherwise. All other variables are defined in Table A1. Standard errors are clustered by firm-analyst pair level. Estimated coefficients and the t-statistics (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)
	PMAFE			
Fcd	-0.013***	-0.012***	-0.016***	-0.015***
	(3.22)	(2.94)	(3.76)	(3.64)
Size	0.008***	0.009***	0.002	0.002
	(8.68)	(9.83)	(0.55)	(0.71)
MB	0.043***	0.043***	-0.002	-0.003
	(9.44)	(9.76)	(0.20)	(0.26)
ROA	0.137***	0.152***	0.021	0.012
	(3.22)	(3.64)	(0.43)	(0.23)
Following	0.000	0.000	0.000	0.000
	(1.09)	(0.49)	(1.45)	(1.23)
Portfolio Size	0.002***	0.002***	0.001***	0.001***
	(9.08)	(8.27)	(4.23)	(4.24)
Gen_Exp	0.00	0.00	-0.004	0.017
	(1.25)	(1.36)	(0.53)	(1.10)
Firm_Exp	-0.001***	-0.002***	0.003	0.006
	(3.41)	(5.42)	(0.50)	(0.81)
Broker Size	0.001	0.000	-0.003	-0.003
	(0.40)	(0.16)	(1.25)	(1.13)
Comovement	0.018***	0.019***	0.017***	0.019***
	(4.67)	(5.00)	(3.49)	(3.57)
Horizon	0.121***	0.120***	0.132***	0.133***
	(78.60)	(78.19)	(78.25)	(78.35)
Past Accuracy		0.073***	-0.032***	-0.033***
		(21.07)	(9.84)	(10.04)
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	514079	514079	514079	514079
R-squared	0.029	0.031	0.092	0.092

Table 7: Market Reactions

This table displays the results of the market reactions to the forecasts issued for unaffected firms following FCDs. CAR[0,1] is the two-day market-adjusted excess return for firm j, where analyst i issues an earnings forecast on day 0. *Fcd* is an indicator variable that equals one if the forecast of analyst i for firm j is issued in the 30-days window following forced CEO departures, zero otherwise. All other variables are defined in Table A1. Standard errors are clustered by firm-analyst pair level. Estimated coefficients and the t-statistics (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)
	CAR[0,1]			
Fcd	-0.001***	-0.001***	0.000	0.000
	(2.99)	(2.67)	(0.99)	(0.76)
Revision	0.005***	0.005***	0.004***	0.004***
	(32.70)	(30.01)	(27.74)	(27.83)
Fcd × Revision	0.001*	0.001*	0.001*	0.001*
	(1.86)	(1.68)	(1.86)	(1.79)
Size		0.001***	-0.007***	-0.007***
		(10.39)	(20.57)	(19.16)
MB		0.004***	-0.002*	-0.002*
		(9.82)	(1.81)	(1.80)
ROA		0.159***	0.169***	0.176***
		(27.08)	(23.66)	(24.34)
Following		-0.000***	-0.001***	-0.001***
		(8.22)	(24.63)	(25.48)
Portfolio Size		0.000**	0.000	0.000
		(2.10)	(0.96)	(1.44)
Gen_Exp		0.000	0.000	-0.002
		(0.44)	(0.70)	(1.24)
Firm_Exp		-0.000***	0.001	0.000
		(2.60)	(1.47)	(0.65)
Horizon		0.001***	0.001***	0.001***
		(10.86)	(10.64)	(10.44)
Broker Size		0.000	0.000	0.000
		(1.04)	(0.77)	(1.34)
Past Accuracy		0.000	0.000	0.000
		(0.46)	(0.86)	(0.73)
Comovement		0.00	-0.003***	-0.002***
		(1.10)	(6.40)	(5.25)
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	514079	514079	514079	514079
R-squared	0.008	0.013	0.077	0.079

Table 8: Robustness Tests

This table displays the results of the robustness tests for a variety of sample specifications. Panel A tests whether the overcorrection occurs for the unaffected firms that are dissimilar to the affected firms. Panel B tests if analysts reduce their optimism for the unaffected firms when herding is almost impossible. Panel C reposts the results when we use an alternative FCD data set. Panel D reports the results under different variable definitions and model specifications. $Optimism^A$ is the quarterly earnings forecast of analyst i for firm j minus the closest consensus forecast for firm j before the forecast, divided by the stock price of firm j at the end of the previous quarter. The final values are multiplied by 100 for better presentation. *Fcd* is an indicator variable that equals one if the forecast of analyst i for firm j is issued in the 30-days window following forced CEO departures, zero otherwise. For brevity, the results of other control variables are not reported. Standard errors are clustered by firm-analyst pair level. Estimated coefficients and the t-statistics (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Panel A: Removing Similar Firms

	(1)	(2)	(3)	(4)
	$Optimism^A$			
Fcd	-0.048***	-0.049***	-0.040**	-0.044**
	(2.63)	(2.80)	(2.23)	(2.42)
Controls	No	Yes	Yes	Yes
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	18038	18038	18038	18038
R-squared	0.001	0.025	0.137	0.150

Panel B: Removing More Than Two Affected Analysts

	(1)	(2)	(3)	(4)
	$Optimism^A$			
Fcd	-0.018**	-0.017**	-0.024***	-0.021***
	(2.42)	(2.31)	(3.07)	(2.72)
Controls	No	Yes	Yes	Yes
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	72607	72607	72607	72607
R-squared	0.000	0.027	0.280	0.284

Panel C: Alternative FCD Data Set

	(1)	(2)	(3)	(4)
		$Optimism^A$		
Fcd	-0.010***	-0.010***	-0.008***	-0.007***
	(4.29)	(4.45)	(3.78)	(3.32)
Controls	No	Yes	Yes	Yes
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	716211	716211	716211	716211
R-squared	0.000	0.020	0.141	0.146

Panel D: Alternative Measures

	(1)	(2)	(3)	(4)
	$Optimism^A$ in Bourveau 2021	90-Day Window	Probit	Logit
Fcd	-0.020***	-0.010***	-0.039***	-0.064***
	(2.64)	(3.79)	(4.65)	(4.64)
Controls	Yes	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	No	No
Year-Quarter FE	Yes	Yes	No	No
Observations	508193	514079	514079	514079
(Pseudo) R-squared	0.121	0.152	0.004	0.004

Table 9: Optimism Change Following Voluntary CEO Departures

This table displays the results of the change in analysts' optimism following voluntary CEO departures. $Optimism^A$ is the quarterly earnings forecast of analyst i for firm j minus the closest consensus forecast for firm j before the forecast, divided by the stock price of firm j at the end of the previous quarter. The final values are multiplied by 100 for better presentation. *Fcd* is an indicator variable that equals one if the forecast of analyst i for firm j is issued in the 30-days window following forced CEO departures, zero otherwise. All other variables are defined in Table A1. Standard errors are clustered by firm-analyst pair level. Estimated coefficients and the t-statistics (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

		(1)	(2)	(3)
		$Optimism^A$		
Voluntary Departure	-0.002	0.000	0.000	0.001
	(1.18)	(0.28)	(0.02)	(0.76)
Size		0.012***	0.003	0.007**
		(18.66)	(1.16)	(2.52)
BM		-0.061***	-0.055***	-0.034***
		(17.93)	(6.94)	(4.17)
ROA		1.521***	1.756***	1.629***
		(36.02)	(33.98)	(31.43)
Following		-0.001***	-0.004***	-0.004***
		(6.41)	(17.85)	(20.92)
Portfolio Size		0.001***	-0.000**	-0.000*
		(5.90)	(2.37)	(1.80)
Gen_Exp		0.000	-0.005*	-0.013
		(0.41)	(1.75)	(1.56)
Firm_Exp		0.000	0.007**	0.008***
		(0.22)	(2.38)	(2.75)
Broker_Size		-0.006***	-0.004***	-0.004**
		(6.74)	(2.74)	(2.50)
Comovement		-0.017***	-0.018***	0.004
		(6.90)	(6.26)	(1.20)
Horizon		0.001***	0.001***	0.001***
		(56.75)	(59.31)	(60.09)
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	1073994	1073994	1073994	1073994
R-squared	0.000	0.022	0.149	0.153

Table 10: Preexisting Optimism Tests

This table displays the results of the change in analysts' forecasts prior to the FCDs. $Optimism^A$ is the quarterly earnings forecast of analyst i for firm j minus the closest consensus forecast for firm j before the forecast, divided by the stock price of firm j at the end of the previous quarter. The final values are multiplied by 100 for better presentation. *Fcd* is an indicator variable that equals one if the forecast of analyst i for firm j is issued in the 30-days window following forced CEO departures, zero otherwise. All other variables are defined in Table A1. Standard errors are clustered by firm-analyst pair level. Estimated coefficients and the t-statistics (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)
	$Optimism^A$			
Pre_Fcd	-0.035*	-0.009	-0.009	-0.011
	(1.75)	(0.45)	(0.55)	(0.65)
Size		0.011***	-0.001	0.003
		(11.88)	(0.15)	(0.79)
BM		-0.059***	-0.053***	-0.032***
		(12.04)	(5.06)	(3.05)
ROA		1.561***	1.854***	1.711***
		(26.66)	(26.25)	(23.97)
Following		-0.001***	-0.003***	-0.004***
		(5.25)	(11.81)	(14.46)
Portfolio Size		0.001***	0.000	0.000
		(3.70)	(1.46)	(0.93)
Gen_Exp		0.001***	-0.007	-0.014
		(2.64)	(1.50)	(1.14)
Firm_Exp		0.000	0.010**	0.010**
		(0.62)	(2.05)	(2.14)
Horizon		0.027***	0.028***	0.028***
		(31.80)	(33.26)	(33.15)
Broker Size		-0.004***	-0.006***	-0.005***
		(3.67)	(3.17)	(2.74)
Past Accuracy		-0.011***	0.002	0.000
		(4.32)	(0.72)	(0.12)
Comovement		-0.014***	-0.017***	0.005
		(4.23)	(4.56)	(1.31)
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	514079	514079	514079	514079
R-squared	0.000	0.021	0.146	0.151

Table 11: Management Access Incentives: Verbal Aggressiveness

This table displays the results of the change in analysts' verbal aggressiveness during the conference calls following FCDs. *Fcd* is an indicator variable that equals one if the forecast of analyst i for firm j is issued in the 30-days window following forced CEO departures, zero otherwise. All variables are defined in Table A1. Standard errors are clustered by firm-analyst pair level. Estimated coefficients and the t-statistics (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)	(5)
	Direct	Quant	Follow-Up	Preface	Neg_Q
Fcd	-0.001	0.01	-0.008	0.005	0.005
	(0.23)	(1.61)	(1.17)	(0.81)	(0.73)
ROA	0.015	-0.027	0.333***	0.125**	0.157***
	(0.38)	(0.52)	(4.19)	(2.55)	(3.03)
Size	-0.005***	-0.008***	-0.052***	-0.009***	0.007***
	(4.15)	(5.09)	(14.93)	(5.90)	(3.78)
MB	0.008	0.036***	0.018	0.032***	0.034***
	(1.29)	(4.47)	(1.28)	(4.33)	(4.02)
Gen_Exp	-0.000***	-0.001***	-0.001***	-0.001***	0
	(2.65)	(8.38)	(6.01)	(12.66)	(0.69)
Firm_Exp	0.000***	0.001***	0.001***	0.001***	0.001***
	(2.83)	(10.64)	(8.32)	(8.52)	(12.83)
Num_Participant	-0.038***	-0.023***	-0.066***	-0.030***	0.019***
	(10.49)	(4.79)	(8.50)	(6.77)	(3.67)
Num_Call	0.007***	0.021***	0.047***	0.031***	0.024***
	(2.64)	(7.94)	(13.68)	(11.38)	(9.79)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	255055	255055	255055	255055	255055
R-squared	0.025	0.101	0.135	0.138	0.075

Table 12: Overcorrection vs. Negative Sentiment

This table displays the results of the change in analysts' optimism following different types of FCDs. $Optimism^A$ is the quarterly earnings forecast of analyst i for firm j minus the closest consensus forecast for firm j before the forecast, divided by the stock price of firm j at the end of the previous quarter. The final values are multiplied by 100 for better presentation. *Fcd_Type_I* is an indicator variable that equals one if the *Fcd* is due to illness or death, zero otherwise. *Fcd_Type_II* is an indicator variable that equals one if the *Fcd* is due to job performance or misconduct, zero otherwise. All other variables are defined in Table A1. Standard errors are clustered by firm-analyst pair level. Estimated coefficients and the t-statistics (in parentheses) are reported. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)
	$Optimism^A$			
Fcd_Type_1	0.054***	0.034**	0.015	0.016
	(3.58)	(2.17)	(0.95)	(0.99)
Fcd_Type_2	-0.018***	-0.018***	-0.016***	-0.014***
	(5.84)	(6.09)	(5.62)	(4.91)
Size		0.011***	-0.001	0.003
		(11.85)	(0.17)	(0.78)
BM		-0.059***	-0.053***	-0.032***
		(12.08)	(5.05)	(3.05)
ROA		1.560***	1.854***	1.711***
		(26.63)	(26.24)	(23.97)
Following		-0.001***	-0.003***	-0.004***
		(5.27)	(11.81)	(14.46)
Portfolio Size		0.001***	0.000	0.000
		(3.81)	(1.32)	(0.81)
Gen_Exp		0.001***	-0.007	-0.015
		(2.67)	(1.51)	(1.17)
Firm_Exp		0.000	0.010**	0.010**
		(0.50)	(2.06)	(2.15)
Horizon		0.028***	0.028***	0.028***
		(31.85)	(33.28)	(33.17)
Broker Size		-0.004***	-0.006***	-0.005***
		(3.69)	(3.17)	(2.75)
Past Accuracy		-0.011***	0.002	0
		(4.36)	(0.71)	(0.13)
Comovement		-0.015***	-0.017***	0.005
		(4.30)	(4.58)	(1.27)
Analyst-Firm FE	No	No	Yes	Yes
Year-Quarter FE	No	No	No	Yes
Observations	514079	514079	514079	514079
R-squared	0.000	0.021	0.146	0.152

Figures

Figure 1: Aggregate Upward Mistakes and Correction

This graph illustrates the aggregate level optimism for the FCD group and voluntary CEO departure group in the nine quarters surrounding the departure events. The red line represents the FCD group, while the blue line represents the voluntary departure group. The dashed lines report the corresponding 95% confidence interval for each mean value.

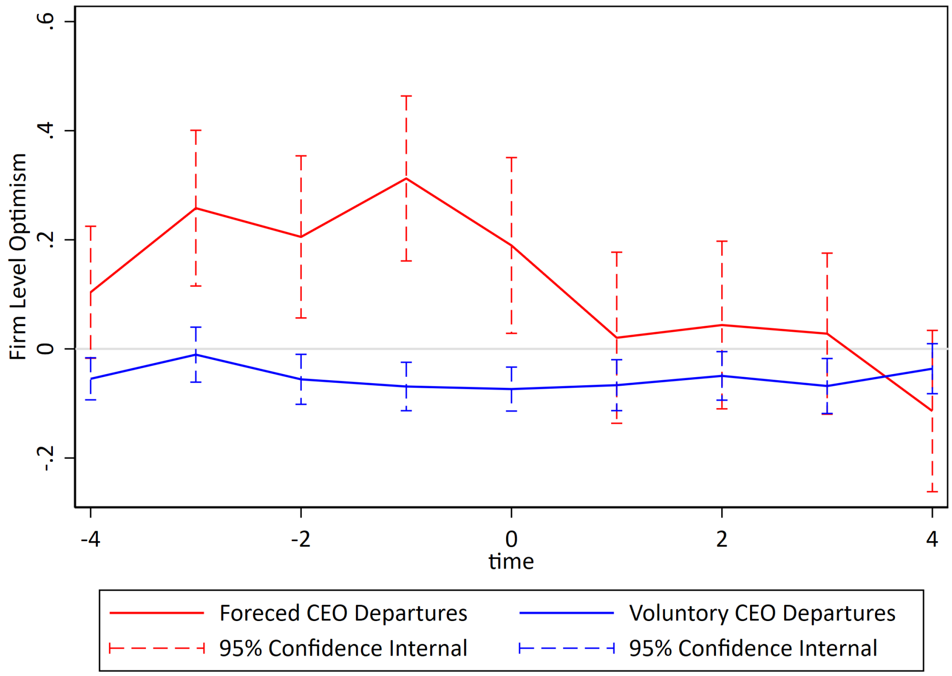


Figure 2: Falsification Tests

This graph demonstrates the results of simulation-based falsification tests. Each panel represents the density of the estimated mean value of the coefficient of *Fcd* of the model (4) in table 3 from one thousand simulations. In Panel A, we randomly assign FCD dates to the FCD events; in panel B, we randomly assign both FCD dates and FCD firms to FCD events. The red lines denote the actual coefficient on *Fcd* obtained from our individual-level baseline estimation.

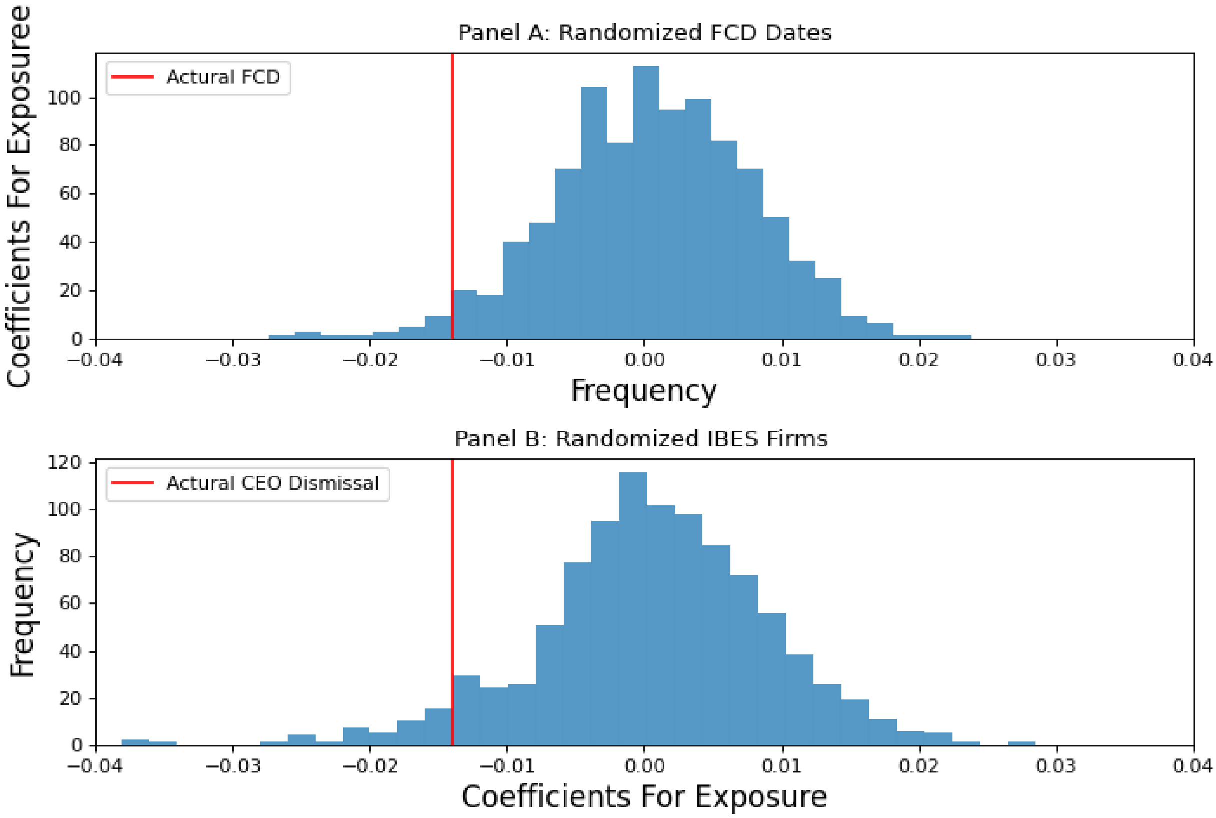
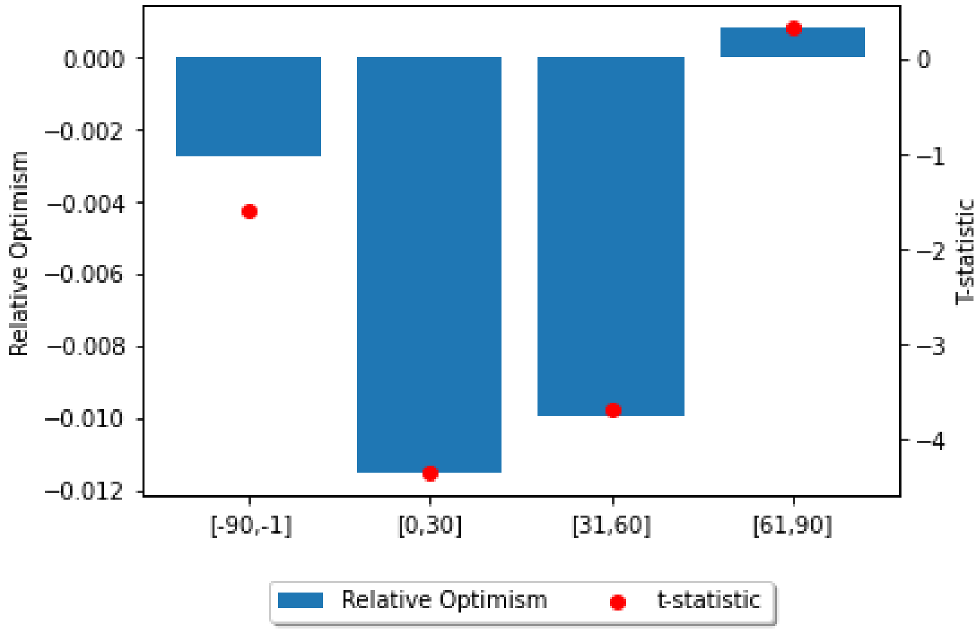


Figure 3: Time-Series Trend in Affected Analysts' Optimism

This figure plots the change in affected analysts' optimism from the 90 days before FCDs to the 90 days after the FCDs. The bars represent the coefficients for *Fcd*, and the red dots indicate the corresponding t-statistics.



Appendix

Table A1: Variable Definitions

Independent Variables	
$Optimism^F$	The difference between the last consensus quarterly earnings forecast and the actual earnings for firm j, divided by the stock price at the end of the previous quarter. The final values are multiplied by 100 for better presentation.
$Optimism^A$	The quarterly earnings forecast of analyst i for firm j minus the closest consensus forecast for firm j before the forecast, divided by the stock price of firm j at the end of the previous quarter. The final values are multiplied by 100 for better presentation.
PMAFE	The proportional mean absolute forecast error. The difference between the absolute forecast error (AFE) for analyst i on firm j and the mean absolute forecast error (MAFE) for firm j at time t scaled by the mean absolute forecast error for firm j at time t.
CAR[0,1]	The two-day market-adjusted excess return for firm j, where analyst i issues an earnings forecast on day 0.
Direct[26]	An indicator variable that equals one if the question of analyst i lacks a personal reference (self-and other-referencing indicates a lack of verbal aggressiveness) and zero if he/she includes a self-or other-reference in his/her question.
Quant	An indicator variable that equals one if analyst i asks a question containing numerical content, and zero otherwise.
Follow_Up	An indicator variable that equals one if analyst i asks a question directly after an executive replies to an earlier question, and zero otherwise.
Preface	An indicator variable that equals one if any of the questions asked by the analyst i includes a negative question, and zero otherwise.
Neg_Q	An indicator variable that equals one if any of the questions asked by the analyst i includes a negative question, and zero otherwise.
Independent Variables: Firm Characteristics	
Size	Natural logarithm of the market value of the equity at the end of the previous fiscal quarter.
BM	The ratio of the book value of assets to the market value of assets at the end of the previous fiscal quarter.
ROA	The ratio of the quarterly income before extraordinary items to the book value of assets at the end of the previous fiscal quarter.
Following	Number of analysts following firm j in the quarter t.
Comovement	Pearson's correlation of the daily stock returns between the affected FCD firm and the unaffected firm j during the three months before the forecast revision.
Num_Participant	Number of unique analysts raise questions during the conference calls.

Independent Variables: Analyst Characteristics	
Fcd	An indicator variable that equals one if analysts i issues the forecast for firm j in the 30-days window following forced CEO departures, zero otherwise.
Fcd_Type_I	An indicator variable that equals one if the *Fcd* is due to illness or death, zero otherwise.
Fcd_Type_II	An indicator variable that equals one if the *Fcd* is due to job performance or misconduct, zero otherwise.
Gen_Exp	Number of years since analyst i give the first forecast for an IBES firm and the current forecasts.
Firm_Exp	Number of years since analyst i give the first forecast for firm j and the current forecasts.
Horizon	The natural logarithm of the number of days between a forecast and fiscal quarter-end.
Portfolio Size	Number of companies covered by analyst i in a given year.
Broker Size	Number of analysts a broker employed in a given quarter.
Past Accuracy	The decile rank of analyst i on average absolute forecast error for all analysts covering firm j in the previous year.
Past Optimism	The median optimism of analyst i in the four quarters before the FCD.
Bundled EA	Number of earnings announcements in analyst i's portfolio on the day he/she issues a forecast.
Revision	The difference between the current earnings forecast and the preceding forecast by analyst i, scaled by the stock price of firm j at the end of the previous quarter. The final values are multiplied by 100 for better presentation.
Num_Call	Number of the conference call participants in the quarter t for analyst i.

Table A2: Forced CEO Departures Events by Year

This table presents the summary statistics for the forced CEO departures in the US public firms from Gentry et al. 2021 (left panel) and Peters and Wagner 2014 (right panel) (Note: Gentry et al. 2021 focus on S&P1500 firms.). The sample is from 2000 to 2018. *FCD Events* is the number of FCDs each year. *Affected Analysts* is the number of analysts covering at least one of the FCD firms. *Total Forecasts* is the total number of quarterly earnings forecasts issued by the affected analysts each year. *Affected Forecasts* is the number of forecasts issued within the 30-days window following an FCD.

	Gentry et al. 2020				Peters and Wagner 2014			
Year	FCD Events	Affected Analysts	Total Forecasts	Affected Forecasts	FCD Events	Affected Analysts	Total Forecasts	Affected Forecasts
2000	25	116	2274	97	39	159	2063	143
2001	21	101	1974	233	37	220	3071	740
2002	27	139	4542	428	29	195	5606	820
2003	44	253	11852	1019	47	328	11362	1384
2004	31	186	6902	840	42	312	8570	1585
2005	31	235	10118	968	47	393	13470	2014
2006	34	231	10787	933	51	334	12839	1456
2007	37	290	17568	1235	39	264	12323	1399
2008	48	308	18633	1493	57	392	22239	2473
2009	40	243	19048	1502	48	278	12654	1857
2010	35	237	15904	1091	39	275	16472	1637
2011	41	286	33474	1378	48	440	29731	2685
2012	44	373	58022	2032	54	489	50563	3142
2013	43	328	32982	1644	36	286	17383	1392
2014	42	393	60906	2105	51	409	45471	2417
2015	43	330	63516	1847	57	487	88208	3897
2016	46	341	41900	1731	59	492	82167	3562
2017	39	279	28707	1682	58	457	113693	3247
2018	56	322	74970	1253	62	416	168326	2973
Mean	43.5	316.8	45181.8	1487.3	55.2	425.6	88345.4	2528.5

Figure A1: Simulation Test: How Often Do Analysts Make Mistakes?

This figure displays the simulation results for the aggregate optimism in randomly selected nine quarters, where the factious FCDs happen in quarter 0. The blue lines present the time series of the aggregate optimism for the simulated 100 FCDs, while the red line depicts the real learning process for the actual FCD events.