Noise from Other Industries: Overgeneralization and Analyst Beliefs*

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Abstract

How do analysts form earnings expectations? This paper documents that analysts' beliefs are influenced by the recent performance of other industries that they cover. I show that negative shocks to one coverage industry lead analysts to make more pessimistic earnings forecasts for firms in another industry. Those pessimistic forecasts are less accurate and lower than the actual earnings. Analysts are affected even if the focal firms have no relationship with the shocked industry. These findings are consistent with the notion that analysts heuristically overgeneralize other industries' performance and incorrectly lower their expectations based on noise rather than information. Moreover, I demonstrate that analyst overgeneralization has significant effects on financial markets: the resulting increase in analyst disagreement induces higher trading volumes and larger return volatilities, and the resulting analysts' pessimism leads to temporary underpricing.

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1 Introduction

Equity analysts are key information agents in financial markets. They process information about coverage companies and produce earnings forecasts that help investors evaluate firms' future prospects. It is therefore important to understand how analysts form beliefs about firms' earnings. In this paper, I exploit the diversity of analysts' coverage industries to study whether analysts' earnings expectations differ depending on the performance of other coverage industries. Comparing earnings forecasts made by *different* analysts for the *same* firm in the *same* quarter, I find that analysts become more pessimistic following negative shocks to the other industries that they cover. The resulting analysts' disagreement and pessimism have significant effects on the trading volumes and price movements of the focal firms.

There are two potential channels through which shocks to other coverage industries can affect analysts' expectations about the focal firms. First, these industry shocks may contain valuable information about the focal firms that is only learned by analysts covering those industries and is not accessible to the other analysts. Industry coverage facilitates information acquisition, especially soft information obtained through their social networks (Cohen, Frazzini, and Malloy, 2010). Accumulated industry expertise also allows analysts to better assess the effects of the industry shocks (Bradley, Gokkaya, and Liu, 2017). Moreover, analysts who do not cover the shocked industries may have limited attention and may therefore overlook the impact of related news events on the focal firm (e.g., Hirshleifer and Teoh, 2003; Cohen and Frazzini, 2008). Consequently, analysts covering shocked industries can obtain a comparative information advantage and incorporate superior information in their earnings forecasts.

The second channel is implied by a common behavioral phenomenon known as overgeneralization, which is the process of overly extending evidence from an unrepresentative sample to reach broad and inaccurate conclusions (e.g. Beck, 1979; Clark, Beck, and Alford, 1999; Walton, 1999). This mechanism can lead analysts to overgeneralize an industry-specific shock to form expectations about the state of the world (e.g., economic conditions and business cycles). As a result, even though the industry shocks do not encompass any useful information about the focal firms, analysts would still adjust their forecasts accordingly as if the shocks were informative. Because the affected forecasts are essentially based to noise rather than information from other industries, I refer to this channel as the noise channel. I conduct a number of tests to distinguish between the *information* channel and the *noise* channel, and the evidence supports the second mechanism.

My main findings can be illustrated with the following example. Consider two equity analysts covering a coal mining company, COAL Corp, in 2011.[1] Analyst A additionally covers two firms in the transportation industry, while analyst B covers a gold mining company. Forecasts made by both analysts are usually close to the consensus and to the actual earnings. However, when forecasting COAL's earnings for fiscal quarter 2011Q3, their opinions diverge significantly. While analyst B issues an EPS forecast of $0.32 on September 21, which is near the consensus of $0.34, analyst A holds an exceptionally negative view about COAL and issues a forecast of $-0.28 on September 22, accompanied by a one-day price drop of 3.1%. My hypothesis suggests that analyst A's distinct pessimism is due to the recent performance of the transportation industry, which fell by 19% over the period from June 22 to September 21. Because the gold mining industry has not experienced such negative shocks, analyst B's forecast does not deviate from the consensus or from his historical standards. This difference in opinions has substantial effects on the firm: between September 20 and 22, the option-implied volatility increases by 43% and the daily trading volume increases by about 150%. Analyst A's pessimistic forecast eventually turns out to be inaccurate, as COAL announces its earnings of 2011Q3 to be $0.35 per share later in October.

This example represents a systematic pattern across the universe of equity analysts in the I/B/E/S database over my sample period from 1993 to 2016. To capture analysts' belief shocks resulting from other coverage industries' performance, I define industries based on the 49 Fama-French industry classifications and use the corresponding portfolio returns to measure industry shocks. Consistent with the notion that other coverage industries' performance affects analysts' expectations, I find that analysts produce significantly more pessimistic earnings forecasts following negative shocks to the other industries they cover. Specifically, suppose a given industry experiences a cumulative return of -10% in a quarter, analysts who cover this industry will issue on average 2.6% more pessimistic earnings forecasts for the firms operating in another industry relative to their peers who cover the same firm at the same time but do not cover the shocked industry. This effect is more pronounced (up to 4.2%) when analysts are forecasting for firms with more information asymmetry.

I further investigate why industry shocks turn into belief shocks that influence analysts' expectations. Do analysts acquire more information by learning from negative shocks to the other industries and foresee companies' unfavorable earnings (*information*)? Or do they just heuristically overgeneralize other industries' performance and become overly pessimistic (*noise*)? First, I test the effect of belief shocks on analyst forecast accuracy. The information hypothesis predicts

[1] This example comes directly from my sample, but for courtesy I change the name of the company and analysts and adjust the exact calendar dates.

that analysts acquire superior information and thereby produce more accurate forecasts, whereas the noise hypothesis predicts that analysts observing more negative performance would incorrectly adjust their expectations and therefore produce less accurate forecasts. Second, I estimate the effect of belief shocks resulting from related and unrelated industries separately. Two industries are considered unrelated if they are not in the same three-digit NAICS code industry, have no industry-level or firm-level supplier-customer relationships, and do not belong to the same product market. Because shocks to unrelated industries are less likely to encompass useful information about the focal firms, the information hypothesis predicts an insignificant effect of those belief shocks, while the noise hypothesis predicts a significant effect because overgeneralization also applies to unrelated industries.

The results of these two tests provide strong evidence in support of the noise channel. Following a belief shock of -10%, the affected analysts are about 2.2% less accurate because their forecasts are much lower than the realized earnings. This effect is economically sizable, as analysts need about 7.3 years more of firm-specific experience to offset this inaccuracy. Negative shocks to *both* related and unrelated industries significantly lower analysts' expectations and mislead them to make inaccurate forecasts. These findings are difficult to reconcile with any information stories, but they conform to the idea that analysts heuristically overgeneralize other industries' performance and incorrectly lower their expectations based on noise.

To identify the effects of belief shocks, I control for stock $\times$ fiscal year-quarter fixed effects in all specifications to exploit variation *within* firm-quarters by comparing earnings forecasts made by analysts with *different* belief shocks for the *same* firm at the *same* time. These fixed effects capture firm-quarter variation resulting from factors that make a particular company's earnings easier (or harder) to predict for *all* analysts in some quarters than in others, or from events that make *all* analysts more pessimistic (or optimistic) in some quarters than in others. Examples of such factors are voluntary management disclosures, merger rumors, and worker strikes. My results remain virtually the same when I control for time-varying observable analyst characteristics such as their experience and workload. Moreover, I use calendar quarter fixed effects to control for time trends (e.g., business cycles) that affect all analysts issuing forecasts around the same time for different firms, and analyst $\times$ stock fixed effects to control for all unobserved but time-invariant analyst characteristics, such as talent, education, industry expertise, and firm-specific preferences.

Using other industries' stock market performance to identify analyst belief shocks has a number of advantages. First, industry performance is arguably exogenous to analysts' personal characteristics. Second, reverse causality is implausible because it is unlikely that any single analyst can influence the performance of an entire industry. Third, it is much more difficult to come up with any confounding factors that would drive industry performance and analysts' earnings forecasts for firms in a different industry simultaneously. In contrast, firm-level performance is more ambiguous because of the potential correlation between stocks covered by the same analyst. Studies such as Israelsen (2016) document excess comovement among stocks covered by the same analyst. Finally, industry returns capture industry-wide shocks such as (de)regulations and technology innovations, which, compared to firm-level idiosyncratic shocks, are more likely to influence analysts' expectations about the state of the world.

Throughout this paper, I take analyst coverage as given and remain agnostic about why analysts cover particular companies or industries. This implicit assumption is unlikely to contaminate my results for two reasons. First, because analysts' industry coverage remains mostly time-invariant in my sample, it has already been absorbed by the analyst × stock fixed effects. Second, analysts are more likely to initiate coverage for firms about which they have favorable expectations (e.g., McNichols and O'Brien, 1997; Tehranian et al., 2013). Therefore, analysts' endogenous coverage choices would prevent me from finding any effects of the negative belief shocks.

It is noteworthy that I do not find a similar effect from positive belief shocks. Analysts mainly respond to negative shocks. This asymmetry is likely due to the negativity bias—that is, events of a more negative nature have a greater impact on one's behavior and cognition than those with equal intensity but of a more positive nature (e.g., Baumeister et al., 2001). It is also consistent with the findings in the psychology literature that individuals tend to overgeneralize negative news much more than positive ones (e.g., Walton, 1999).

One potential concern is whether my results merely capture analyst distraction instead of changes in analyst expectations. One may argue that analysts issue relatively lower earnings forecasts for focal firms because they are distracted by other coverage industries with salient negative performance. This argument is difficult to reconcile with the large body of literature that shows that, if anything, sell-side analysts are optimistic by default. Nevertheless, I formally test this possibility by examining analyst forecast revisions. I find no evidence of distraction because analysts revise their forecasts with the same frequency when other industries perform extremely well or poorly. On the contrary, shocks to other industries lead analysts to revise forecasts in the same direction and magnitude, reinforcing the view that shocks to other industries influence analyst beliefs.

Further robustness tests show that my baseline results are persistent in different subperiods of my sample and are robust to alternative industry classifications based on the Fama-French 12-industry classification, the three-digit GICS industries, industries based on two-digit SICH codes, and the Hoberg and Phillips (2016) 10-K text-based 50-industry classification (FIC-50). My findings are not merely driven by specific crisis episodes or any particular industry (mis)classifications.

When using earnings surprises to decompose belief shocks into expected and unexpected components, I find that analysts respond to both expected and unexpected shocks. Additionally controlling for the relative performance of coverage firms reveals that a negative industry shock lowers analysts' beliefs more if their coverage firms in that industry are substantially affected by the shock. Analysts are also more likely to overgeneralize industry-wide shocks than firm-level idiosyncratic shocks. However, while more experienced analysts working for bigger brokerage houses are on average more accurate, these factors do not mitigate the impact of overgeneralization.

Having established empirical support for the effect of overgeneralization on analysts' expectations, I examine its impacts on the financial market, as many investors rely on analysts' forecasts to evaluate firms' future prospects and make trading decisions. Using a simple speculative trading model in the flavor of Kandel and Pearson (1995), I demonstrate how analyst belief shocks, which induce differences in analysts' opinions, lead to higher trading volume and larger return volatility. Moreover, the model predicts that analysts' negative belief shocks could exert downward price pressure and induce underpricing.

I then provide empirical evidence supporting the theoretical predictions. Aggregating data at the firm $\times$ fiscal year-quarter level, I find that after controlling for common trends and time-invariant firm heterogeneity, a one-standard-deviation increase in belief shock dispersion translates to 5.7%-6.4% more analyst disagreement about the coverage firms and is associated with up to 5.2% higher daily trading volume and 2.7% larger stock return volatility. Analyst overgeneralization seems to aggravate information asymmetries and increase uncertainty about firms' fundamentals.

Finally, firms with more analysts affected by negative belief shocks experience a significant decline in stock price prior to earnings announcements. This downward price pressure effect is more pronounced for firms with *ex-ante* higher information asymmetry. Consistent with the underpricing prediction that the price will move up when the true information is revealed, a one-standard-deviation more negative belief shocks is associated with a 63.6% higher positive reversal upon earnings announcements relative to the average, conditional on the direction and magnitude of earnings surprises. This effect is even larger (about 93.7%) for firms with high information asymmetry. These findings imply that analyst overgeneralization has substantial effects on financial markets.

This paper contributes to several strands of literature. First, it contributes to the large body of literature on the determinants of analysts' forecast accuracy and bias (see Kothari, So, and Verdi (2016) for a recent literature review). In particular, my findings add to the literature on how psychological biases induce analysts' forecast errors (e.g., Ramnath, Rock, and Shane, 2008). I show that overgeneralization leads analysts to incorrectly adjust expectations and to consequently make inaccurate forecasts. Unlike most prior studies, this heuristic can also explain the sign of forecast errors.

Second, my results demonstrate some important asset pricing implications of analyst overgeneralization. Models based on investors with heterogeneous beliefs can explain asset price movements and trading volumes (e.g., Miller, 1977; Harris and Raviv, 1993; Kandel and Pearson, 1995). However, it is difficult to directly measure investors' beliefs. In light of analysts' role as key information intermediaries, many empirical studies, such as Diether, Malloy, and Scherbina (2002), use the dispersion of analysts' earnings forecasts as an empirical proxy for differences in opinions among investors and study how analyst disagreement affects asset returns and trading activities. The vast literature on the market impacts of analysts has also shown convincingly that their forecasts are able to move stock prices. Understanding what causes analysts to disagree or affects their expectations is therefore important for financial regulators and market participants. By establishing the effect of overgeneralization on analysts' disagreement and pessimism, I put forward a new behavioral bias that could influence market activities and drive asset prices.

Third, I contribute to the more general literature that studies the impact of experience on decision making in financial markets (e.g., Vissing-Jorgenson, 2003; Kaustia and Knüpfer, 2008; Greenwood and Nagel, 2009)). Murfin (2012) shows that banks impose stricter loan covenants when they suffer losses on their loan portfolios. In the same spirit, Koudijs and Voth (2016) demonstrate that personal experience can affect individual risk-taking in margin lending. Gurun et al. (2015) and Giannetti and Wang (2016) document that corporate scandals and Madoff-Ponzi schemes reduce households' trust and confidence in the financial market. My paper is closely related to Malmendier and Nagel (2011, 2016), who establish that personal lifetime experiences shape individuals' expectations. My findings are similar to theirs to the extent that analysts' expectations are influenced by their "recent experience", that is, recent performance of other coverage industries. However, the implication of overgeneralization is different in the sense that it can lead a multi-tasking agent to weight information from one task too heavily when making decisions for other tasks. To the best of my knowledge, this paper is the first to link overgeneralization to the belief-forming process of financial agents. Because many financial agents multitask (e.g., portfolio managers with multiple funds), this heuristic can be useful for modeling their expectations.

In addition, my paper has a number of implications for other strands of literature. Overgeneralization leads analysts to adjust expectations based on noise that is unrelated to the focal firms' fundamental values. In other words, this heuristic essentially provides exogenous variation in analysts' disagreement and pessimism. This insight could be useful for future empirical research that study the effects of investor disagreement and temporary underpricing.

My findings are also relevant from practitioners' perspective. Due to a lack of supply of industry-experienced analysts, brokerage houses face the trade-off between the costs and benefits of allocating non-industry experts (Bradley et al., 2017). I show that all analysts covering multiple industries diminish expectations and produce less accurate forecasts once they are influenced by belief shocks, even those who cover only two industries. Overgeneralization could thus be considered a potential cost of assigning analysts more industries to cover.

The remainder of the paper is organized as follows. Section 2 discusses the data and presents descriptive statistics. Section 3 outlines the conceptual framework and discusses the empirical methodology. Section 4 presents the main findings of this paper. Section 5 explores the heterogeneity of analysts. Section 6 demonstrates the profound impacts of analyst overgeneralization on financial markets. Section 7 concludes the paper.

2 Data

I obtain individual analyst quarterly earnings forecasts and actual earnings of all U.S. firms from the I/B/E/S Unadjusted Detail database. To avoid imprecision arising from I/B/E/S's rounding of forecasts, I use the CRSP cumulative adjustment split factor to split-adjust the raw unadjusted data. Information about analyst identities and brokerage firms are drawn from the I/B/E/S Recommendations database. Because I/B/E/S recommendation data are only available from 10/29/1993, my sample period starts in 1993Q4 and ends in 2016Q1. I retain analysts that are present in both the Detail and Recommendations databases. For each analyst i making a forecast about firm j for fiscal year-quarter t, I use analyst i's latest earnings forecast issued prior to the announcement of the actual earnings but not later than 30 days after the fiscal quarter-end of t. To identify analyst coverage, I use the annual forecast data and assume that analyst i covers stock j for the whole fiscal year if analyst i issues a forecast for that given fiscal year.

Next, I match all firms to Compustat Annual using CUSIPs and fiscal year-end dates, and to CRSP daily using CUSIPs and dates. I retain all matched firms and assign each firm to one of the 49 Fama-French industries based on its historical SIC code (CRSP item HSICCD or Compustat item SICH when HSICCD is missing). Fama-French 49 industry portfolio returns are downloaded from the data library of Kenneth R. French. Figure 1 depicts the fraction of I/B/E/S analysts covering at least two Fama-French industries and the average fraction of stocks covered by at least one of those analysts over the period 1993-2016. As shown, almost 70% of I/B/E/S analysts cover two or more industries, and over 90% firms are followed by one of those analysts. For robustness checks, I also consider other industry classifications, such as the Global Industry Classification Standard (GICS) industries, the two-digit SICH code, and the Hoberg-Phillips product market classification.

[Figure 1 about here.]

Finally, I exclude firms that have no analyst covering multiple industries. The final dataset consists of 1,423,192 analyst-firm-quarter observations with 12,175 unique analysts and 9,246 unique stocks. Panel A of Table I reports the number of unique stocks, the number of unique analysts, the number of unique analyst-stock pairs, the average number of analysts covering a particular stock, and the average number of Fama-French industries and of stocks covered by analysts within each calendar year of my sample period. As shown, the average number of analysts covering a given firm increased from 4.0 in 1993 to 9.7 in 2016. Analysts' workloads have not changed a great deal, remaining around 10 firms in 3 different FF-49 industries. The diversity of coverage industries is thus a common feature throughout my sample period.

[Table 1 about here.]

Panel B of Table I reports the summary statistics of the variables used in this study. My main dependent variables of interest are earnings forecast and forecast errors. To measure how different an analyst's forecast is from the consensus among other analysts, I follow prior research and compare her forecast to the average of all analysts who issue forecasts for the same firm i and fiscal year-quarter t (Clement, 1999; Hong and Kubik, 2003; Kothari et al., 2016). This controls for any firm-quarter factors that influence all analysts' expectations. I therefore define

$$\text{Adjusted EPS Forecast}_{ijt} = \frac{\text{Raw Forecast}_{ijt} - \text{Mean Forecast}_{jt}}{\text{SD Forecast}_{jt}}, \tag{1}$$

where Raw Forecast$_{ijt}$ is the raw earnings per share forecast in dollars made by analyst i for the earnings of fiscal quarter t of stock j, which is split-adjusted using the CRSP cumulative adjustment split factor from the CRSP Daily file; Mean Forecast$_{jt}$ and SD Forecast$_{jt}$ are, respectively, the mean and standard deviation of forecasts made by all analysts for firm j and fiscal quarter t. The denominator standardizes forecasts such that they are comparable across firms. Note that after demeaning, a forecast below 0 implies that an analyst is more pessimistic relative to her peers covering the same firm at the same time.

As for forecast errors, prior research mostly uses the PMAFE (proportional mean absolute forecast error) to measure analyst inaccuracy (e.g., Clement, 1999; Malloy, 2005), which is defined as

$$\text{PMAFE}_{ijt} = \frac{\text{AFE}_{ijt} - \text{Mean AFE}_{jt}}{\text{Mean AFE}_{jt}}, \tag{2}$$

where AFE_{ijt} denotes the absolute value of the forecast error (forecast minus actual) for analyst i's forecast of firm j for fiscal quarter t, and Mean AFE_{jt} is the average AFE of all analysts covering firm j for fiscal quarter t. This variable controls for any firm-quarter factors that affect forecast accuracy. Moreover, the sign of the forecast errors is also important when comparing analysts' expectations with firms' actual earnings. Therefore, I follow the intuition behind the PMAFE measure to define

$$\text{Forecast Errors}_{ijt} = \frac{\text{FE}_{ijt} - \text{Mean FE}_{jt}}{\text{Mean AFE}_{jt}}, \tag{3}$$

where FE_{ijt} is forecast earnings minus actual earnings.

These three variables and all of the firm-quarter level continuous dependent variables are winsorized at the 1% and 99% levels. Detailed definition of the control variables are presented in Table A1. The construction of the belief shocks is explained in the next section.

3 Empirical methodology

In this section, I first use a simple conceptual framework to illustrate the role of other coverage industries' performance in shaping analysts' expectations. I then discuss the identification of belief shocks and describe the empirical strategy for estimating the effect of those shocks on analysts' earnings forecasts.

3.1 Conceptual framework

Suppose that analyst i's forecast for firm j's earnings of fiscal quarter t is given by

$$F_{ijt} = \sum_{k=1}^{M} \theta_k \cdot \Pi_{jkt} + \sum_{k=1}^{K} \delta_k \cdot P_{ijkt} + \eta_{ijt}, \tag{4}$$

where analyst i makes a forecast based on public signals $\Pi_{jt} = (\Pi_{j1t}, \ldots, \Pi_{jMt})'$ and her private information and incentives $P_{ijt} = (P_{ij1t}, \ldots, P_{ijKt})'$ about firm j. Public signals Π_{jt} could be macroeconomic factors such as interest rate hikes and tax cuts, or firm-specific events such as voluntary management disclosures and M&A deals, which are observable to all analysts covering firm

j. Private signals P_{ijt} could include private information obtained from the analyst's social network or pressure from the analyst's brokerage house to issue favorable forecasts. This representation of analyst forecasts is motivated by the large body of literature on sell-side analysts' forecasts (see Kothari et al. (2016) for a recent survey).

This paper tests the idea that analyst i derives some private signals about firm j from collecting and processing information about her other coverage industries. As in the example above, covering the poorly performing transportation industry seems to lower analyst A's earnings expectation about the focal firm COAL. More formally, suppose that analyst i covers stocks in κ other industries, I conjecture that she obtains private signals $\zeta_{ijt} = (\zeta_{ij1t}, \ldots, \zeta_{ij\kappa t})'$ from researching those industries. Conforming to the notion that those private signals could affect analyst beliefs, I refer to them as "belief shocks" in the rest of the paper. Taking these belief shocks into account, I can rewrite Equation (4) as

$$F_{ijt} = \theta' \Pi_{jt} + \beta' \zeta_{ijt} + \delta' Z_{ijt} + \eta_{ijt}, \tag{5}$$

where $Z_{ijt} = P_{ijt} \setminus \zeta_{ijt}$. That is, the subjective analyst forecast depends on publicly available information, the analyst's belief shocks from other coverage industries, and her other private information and incentives. Next, I explain the identification of belief shocks.

3.2 Identifying belief shocks

Consider an analyst i making an earnings forecast for stock j in fiscal quarter t is exposed to potential belief shocks from the other industries she covers in quarter t. I construct the belief shocks (BS) to this analyst with respect to firm j as

$$BS_{ijt} = \sum_{k \in S_{it}^{-j}} w_{ikt}^{-j} \times IndRet_{ikt}, \tag{6}$$

where S_{it}^{-j} denotes the set of stocks followed by analyst i in quarter t, *excluding* stocks in the same Fama-French 49 industry as stock j, thereby allowing only shocks from industries other than that of stock j; the weight w_{ikt}^{-j} captures how important stock k is to analyst i; and $IndRet_{ikt}$ is the cumulative return of the Fama-French industry of stock k over the quarter before analyst i issues the most recent earnings forecast for stock j in quarter t. If an analyst covers stocks in only one Fama-French industry, I set the BS variable to be zero. I now explain the construction of w_{ikt}^{-j} and $IndRet_{ikt}$ in more detail.

First, w_{ikt}^{-j} is meant to capture the weight of stock k to analyst i in quarter t. To this end, I define the weight for each stock k in S_{it}^{-j} as

$$w_{ikt}^{-j} = \frac{mve_{kt}}{\sum_{l \in S_{it}^{-j}} mve_{lt}}, \tag{7}$$

where mve_{lt} denotes the market value of equity of stock l at the fiscal year-end preceding fiscal quarter t. Alternatively, I consider equal weights in (6) to measure belief shocks and obtain similar results, as shown in Table VI.

Second, $IndRet_{ikt}$ is meant to capture the performance of the Fama-French industry of stock k over a period before analyst i issues the most recent earnings forecast for stock j in quarter t. Suppose that analyst i issues the forecast on day τ, I compute the cumulative returns of the Fama-French industry of stock k over the window $[\tau - 90, \tau]$.[2] It is noteworthy that my results are robust to different windows. I have experimented with various window spans, from 60 days to 180 days, and the results are similar to those presented here.

Constructing the belief shocks in this way has the following advantages. First, it relies on stock market performance of industries other than that of stock j, which is arguably exogenous to the characteristics of analyst i. Second, I use industry-level performance rather than firm-level performance to mitigate the potential concern of omitted-variable bias. For instance, analyst i might become more pessimistic for other reasons (other private signals) and might therefore issue more pessimistic earnings forecasts for both stock j and k. The pessimistic forecast about stock k might also put downward pressure on the price of stock k. In this case, analyst i's more pessimistic forecast about stock j is not due to the bad performance of stock k. However, a single analyst's forecast is unlikely to drive the performance of the whole industry, and thus using industry-level performance resolves this endogeneity issue. Third, industry returns capture industry-wide shocks rather than firm-level idiosyncratic shocks, which are more likely to influence analysts' expectations about the state of the world. Finally, on a cognitive level, extreme returns in an industry are more salient and more likely to affect analysts' beliefs. The BS variable captures this effect because the BS variable moves in the same direction and magnitude with the industry returns by construction.

3.3 Estimating the impact of belief shocks

I conjecture that the performance of other industries influences analysts' expectations about the focal firm and thus affects their earnings forecasts. Substituting the constructed measure of belief shocks for ζ_{ijt} in Equation (5), I can examine how analysts' forecasts respond to these belief shocks

[2] In some cases, the analyst issues the forecast a few days after the fiscal quarter-end day τ_1. For such cases, I compute $IndRet$ over the window $[\tau_1 - 90, \tau]$.

by estimating the following model:

$$y_{ijt} = \alpha_{jt} + \beta \times BS_{ijt} + \varepsilon_{ijt}, \tag{8}$$

where i indexes analysts, j indexes firms, t indexes fiscal year-quarters, and y_{ijt} is the dependent variable of interest (e.g., EPS forecast and forecast errors). The main coefficient of interest is β, which measures the effects of belief shocks, BS_{ijt}. This coefficient would be significantly positive if analysts' earnings expectations are affected by the performance of other industries they cover.

The stock $\times$ fiscal year-quarter fixed effects, α_{jt}, allow me to compare earnings forecasts made by two analysts with *different* belief shocks for the *same* firm at the *same* time. These fixed effects capture all publicly available information (i.e., Π_{jt} in Equation (5)) and therefore can control for firm-quarter variation driven by factors or events that affect the expectation of *all* analysts, making them more pessimistic (or optimistic) in some quarters than in others. Examples of such events are shareholder litigations and merger rumors. To absorb the firm-quarter fixed effects, I follow the literature (e.g., Clement (1999); Malloy (2005); Bradley et al. (2017)) to demeaning both the dependent and the independent variables within each firm-quarter group, which gives

$$\widetilde{y}_{ijt} = \beta \times \widetilde{BS}_{ijt} + \widetilde{\varepsilon}_{ijt}. \tag{9}$$

The tilde indicates demeaned variables henceforth. Note that the main dependent variables of interest, the adjusted EPS forecast and (absolute) forecast errors, are already demeaned and scaled within firm-quarters by construction.

In addition, I control for some observable analyst-specific characteristics that previous studies have found to affect analysts' forecasts: analysts' overall experience and firm-specific experience in years, the number of industries and stocks covered by analysts, and employer size (Clement, 1999; Bradley et al., 2017). These variables capture a part of analysts' private information and incentives, i.e., Z_{ijt} from Equation (5). Detailed definitions of these variables are presented in Table A1.

Moreover, I include the calendar year-quarter fixed effects to control for common time trends such as macroeconomic shocks or business cycles, which could influence the expectations of analysts covering different firms but making their forecasts around the same time. I also include the analyst $\times$ stock fixed effects to control for any unobserved but time-invariant factors in Z_{ijt}, such as analysts' skill, education, and industry expertise. I use analyst $\times$ stock fixed effects instead of analyst fixed effects alone to account for unobservable heterogeneity within the same analysts across the different stocks that they cover. For example, analysts might consistently spend more time and effort on a particular firm than on other firms they cover, or they may consistently be more pessimistic or accurate about a particular stock than about other stocks they follow.

Therefore, my final regression model takes the form

$$\widetilde{y}_{ijtq} = \alpha_q + \alpha_{ij} + \beta \times \widetilde{BS}_{ijt} + \gamma' \widetilde{X}_{ijt} + \widetilde{\varepsilon}_{ijtq}, \tag{10}$$

where q indexes the calendar year-quarter in which the analyst i issues the forecast, α_q denotes the corresponding year-quarter fixed effects, α_{ij} denotes the analyst $\times$ stock fixed effects, and $\widetilde{X}_{ijt}$ is a vector of control variables demeaned within firm-quarters. I two-way cluster the standard errors by calendar year-quarter and by analyst $\times$ stock to account for possible correlations within cohorts of analysts who make forecasts around the same time and for potential serial correlation within the tenure of an analyst following the same stock. This clustering yields the most conservative standard errors.

To allow for differences in analysts' responses to the sign of the belief shocks, I also estimate the effects of negative and positive shocks separately. If analysts respond to negative and positive shocks differently, not allowing for such potential asymmetry could downward bias the estimate of β in Equation 10 towards zero. The following model accounts for the potential asymmetry:

$$\widetilde{y}_{ijtq} = \alpha_q + \alpha_{ij} + \beta_1 \times \widetilde{BS}^-_{ijt} + \beta_2 \times \widetilde{BS}^+_{ijt} + \gamma' \widetilde{X}_{ijt} + \widetilde{\varepsilon}_{ijtq}, \tag{11}$$

where I denote negative and positive belief shocks by BS^-_{ijt} and BS^+_{ijt}, respectively. The negative shock $BS^-_{ijt} = \min(BS_{ijt}, 0)$, and the positive shock $BS^+_{ijt} = \max(BS_{ijt}, 0)$. To assess the effect of extreme shocks and salient performances, in some specifications I also replace BS^-_{ijt} and BS^+_{ijt} with the indicator variable of the bottom decile (D1) and top decile (D10) of the BS_{ijt} variable, respectively, where D1 and D10 capture the salient negative and positive performances, respectively. Both β_1 and β_2 would be significantly positive if analysts respond to both negative and positive belief shocks.

The main identifying assumption to obtain an unbiased estimate of β (or $\beta_{1,2}$) is $\text{cov}(BS_{ijt}, \varepsilon_{ijtq}) = 0$. Because the error term ε_{ijtq} contains analysts' *unobserved time-varying private* information and incentives that are not captured by X_{ijt} and α_{ij}, the assumption essentially means that the belief shock variable does not systematically covary with any other unobserved private signals about firm j obtained by the analyst. This assumption is justified because the belief shock variable is constructed based on the performance of other coverage industries, which is arguably exogenous to analysts' unobservable (even time-varying) personal characteristics. It is also highly unlikely that a single analyst can influence the performance of an entire industry. Moreover, any proponent of the existence of confounding factors would have to explain how they relate to the industry shocks and analysts' earnings forecasts for firms in a different industry simultaneously, and why they do not affect other analysts who cover the same firm at the same time.

Another implicit identifying assumption is that analyst coverage is exogenously given and orthogonal to analysts' earnings forecasts and coverage industries' performance. In practice, however, which firms or industries an analyst chooses to cover is certainly not random. I argue that the endogenous nature of analysts' coverage decisions is not likely to contaminate my results. Note that analysts tend to cover the same set of industries throughout their careers, because analysts have information advantages and social connections in industries in which they have experience and expertise, so it is costly for them to switch (Bradley et al., 2017). Thus, using the analyst × stock fixed effects mitigates the endogeneity concerns by controlling for this time-invariant heterogeneity. Fewer than 15% of the analysts in my sample have changed their industry coverage more than twice during the sample period, and excluding those analysts does not affect my results qualitatively. Moreover, studies on analyst coverage decisions (e.g., McNichols and O'Brien (1997) and Tehranian et al. (2013)) document that analysts are more likely to cover stocks about which they have favorable expectations. I also show in Appendix B that coverage initiation is not associated with more negative belief shocks. Therefore, analysts' endogenous coverage choices would, if anything, actually work against my findings on the effect of negative belief shocks.

4 Main results

This section presents my main empirical results. I document that analysts issue significantly more pessimistic earnings forecasts when they observe (salient) negative performance of other coverage industries. These downward-biased forecasts are less accurate and lower than the actual earnings, which suggests that analysts overgeneralize negative shocks to other industries and become overly pessimistic about the state of the world.

4.1 Earnings forecasts

While my main tests are designed to address identification issues, Figure 2 shows that the effect of belief shocks on analyst forecasts is pronounced even in the raw data. I divide the data into

10 subsamples based on the domain of belief shocks and compute the mean and the corresponding 90% confidence interval of the adjusted EPS forecasts in each subsample. Because EPS forecasts have been demeaned within each firm-quarter group, negative forecasts imply that analysts are more pessimistic relative to their peers covering the same firm at the same time. The plot displays a strong correlation between analyst forecasts and negative belief shocks. The more negative the belief shock is, the more negative the analyst forecast becomes, which implies that analysts tend to be more pessimistic relative to the consensus when other coverage industries perform worse. Interestingly, analysts seem to respond mostly to negative belief shocks. There is no clear correlation between forecasts and positive belief shocks.

[Figure 2 about here.]

To formally test the effect of belief shocks on analysts' earnings forecasts, I first estimate Equation (10) in Table II. The dependent variable is adjusted EPS forecast, which is computed as in Equation (1). All of the specifications control for the stock $\times$ fiscal year-quarter fixed effects by demeaning all variables within firm-quarters to compare forecasts issued by *different analysts making forecasts for the same firm in the same quarter*. I also control for an analyst's overall and firm-specific experience, the number of stocks and different Fama-French 49 industries covered by the analyst, the size of the analyst's brokerage house, and the calendar year-quarter fixed effects. In column (1), the coefficient on the belief shock variable is positive and statistically significant ($t = 2.996$), which implies that analysts observing more negative (positive) performance of other industries make significantly more pessimistic (optimistic) earnings forecasts. The coefficient estimate remains similar in column (2), where I additionally include the analyst $\times$ stock fixed effects to control for time-invariant but unobserved analyst characteristics such as talent, education, and industry expertise. Because the full sample contains all analysts, including those covering only one industry, one might be concerned about an unfair control group. In column (3), I resolve this issue by focusing on the subsample consisting only of analysts covering multiple industries. As is shown, the results are not sensitive to the sample selection. If anything, the coefficient on the belief shock variable even increases slightly.

[Table 2 about here.]

To test the effects of positive and negative belief shocks separately, I estimate Equation (11) in columns (4) and (5). Column (5) includes analyst $\times$ stock fixed effects. It is interesting to note that the effect of belief shocks seems to come mostly from the negative performance of the other industries. The estimated coefficient on the negative shocks is large and statistically significant ($t =$ 2.847 in column (5)), while that on the positive shocks is negligible and statistically insignificant. Because the negative shock variable only takes negative values, the positive coefficient implies that the analysts issue significantly lower forecasts in comparison to their peers when the performance of the other industries is worse (more negative returns). Going a step further, I replace the negative and positive belief shock variables, respectively, with the indicator variable of the bottom decile (D1) and the top decile (D10) of the belief shock variable in column (6). As is shown, only salient negative performance has a significant impact on analyst forecasts ($t = -3.531$).

The estimated effect of belief shocks is also economically meaningful. From column (5), for example, if analysts observe a negative performance of -10% from the other industries, their forecasts are about 2.6% standard deviations lower than the consensus, relative to other analysts whose coverage industries are not affected by such negative shocks. The estimate in column (6) suggests that upon a salient negative shock resulting in negative returns of -9% and lower (the bottom decile), affected analysts become on average about 4.4% more pessimistic about the firm's earnings relative to their peers.

Table II confirms the asymmetry shown in Figure 2 that the effect of positive belief shocks is negligible. This kind of asymmetry in the reaction to negative and positive shocks is, however, not exceptional. Studies in both economics and finance have provided abundant evidence that individuals or financial agents often react more or exclusively to negative news or shocks than to positive ones (e.g., Kahneman and Tversky, 1979; Barberis, Shleifer, and Vishny, 1998; Tetlock, 2007; Williams, 2014). Psychologists formally refer to this asymmetry as the negativity bias, and it has been investigated and verified in many different domains, especially the formation of impressions (e.g., Baumeister, Bratslavsky, Finkenauer, and de Vohs, 2001; Rozin and Royzman, 2001). Another potential explanation is that analysts tend to be overly optimistic by default (e.g., DeBondt and Thaler, 1990; Abarbanell and Bernard, 1992; Kothari et al., 2016). Because analysts are already optimistic on average, even though they might respond to positive shocks and adjust their forecasts accordingly, their final forecasts might not deviate sufficiently from other analysts' optimistic forecasts for econometricians to detect any significant difference. The results on forecast revisions provided in Section 4.2.3 lend support to this conjecture. Given the trivial effect of positive belief shocks on the final forecast (see Tables II and VI), I focus on the effect of negative belief shocks henceforth.

In sum, my estimation results show that negative shocks to other coverage industries lead analysts to make significantly more pessimistic earnings forecasts, which is consistent with my conjecture that the performance of other coverage industries plays an important role in shaping analysts' expectations about focal firms' earnings. I next investigate the underlying mechanisms through which analyst forecasts are affected by those negative belief shocks.

4.2 Information versus noise

There may be two channels through which industry shocks can influence analysts' expectations. First, shocks to other industries may encompass useful information about the focal firms, and this information is only acquired by analysts covering those industries and is not accessible by other analysts. Covering a particular industry provides analysts with better access to material information, such as through conference calls with firm officials (Cohen et al., 2010). Industry expertise also gives analysts a competitive advantage in their ability to analyze the impacts of the industry shocks (Bradley et al., 2017). Analysts who do not cover the shocked industries may have limited attention and may therefore overlook the impacts of other industries' events on the focal firm (e.g., Hirshleifer and Teoh, 2003; Cohen and Frazzini, 2008). Consequently, analysts covering shocked industries have a comparative information advantage and incorporate superior information in their earnings forecasts. I refer to this channel as the *information* channel.

In contrast, the alternative channel follows the implications of a well-known cognitive bias called overgeneralization. Overgeneralization, also known as hasty generalization, is the tendency to draw a broad conclusion about a population based on evidence from a small sample group that does not accurately represent the entire population (e.g., Walton, 1999). Multi-tasking individuals with this cognitive bias may overgeneralize the outcomes of or experience with one task when making decisions for other tasks even though the outcomes of one task are not at all informative about the other tasks. It is noteworthy that the psychology literature has also found strong evidence for the asymmetric effect of positive and negative shocks: individuals tend to overgeneralize negative events much more than positive ones (e.g., Beck, 1979; Clark et al., 1999). Under this channel, even though the negative industry shocks do not sufficiently represent the whole economy or have any useful information about the focal firms, analysts might still heuristically overgeneralize those shocks to lower their expectations about economic conditions and therefore become more pessimistic about the focal firms. Consequently, the pessimistic forecasts made by affected analysts are driven by noise rather than information. I refer to this second channel as the *noise* channel.

To investigate whether analysts learn from the other industries' performance, the *information* channel, or whether they heuristically overgeneralize shocks to other industries, the *noise* channel, I first test the effect of belief shocks on analysts' forecast accuracy. The information channel predicts that analysts acquire superior information and therefore produce more accurate forecasts, whereas the noise channel predicts that analysts observing more salient performance would incorrectly adjust their expectations and thus produce less accurate forecasts.

Second, I estimate the effect of belief shocks resulting exclusively from arguably unrelated industries, i.e., industries that are neither horizontally nor vertically linked with the focal firm's industry. The information channel predicts that the effect of belief shocks on forecasts is no longer significant because analysts are less likely to acquire useful information from unrelated industries. In contrast, the noise channel still predicts a significant effect of belief shocks on forecasts because the overgeneralization also applies to unrelated industries.

4.2.1 Forecast accuracy

In Table III, I first use signed forecast errors as the dependent variable to estimate the effect of negative belief shocks on analyst forecast accuracy. I consider signed forecast errors because it is important to detect whether forecast errors move in the same direction as the belief shocks. More specifically, does the negative performance of other industries indeed lead to less accurate forecasts that are below the actual realized earnings?

[Table 3 about here.]

Column (1) estimates Equation (10) to test the overall effect of belief shocks on signed forecast errors, while column (2) estimates Equation (11) to examine the effects of positive and negative belief shocks separately, but only the coefficients on the negative shock are reported as those on the positive shock are negligible. All specifications include the stock $\times$ fiscal quarter, calendar quarter, and analyst $\times$ stock fixed effects. As is shown in column (2), the coefficients on the negative belief shock variable are positive and statistically significant, which suggests that analysts influenced by those negative shocks make significantly more negative forecast errors than those made by their peers. Estimating the effect from salient negative shocks in column (3) leads to the same conclusion.

Relatively more negative forecast errors could mean that their forecasts are significantly lower than the actual earnings realized by the firm, but it could also mean that their forecast errors are closer to zero when their peers make larger and more positive forecast errors. Note that the former would imply that analysts affected by negative shocks issue less accurate forecasts, whereas the latter would imply that they make more accurate forecasts. To disentangle these two confounding results, I use PMAFE, i.e., the absolute forecast errors, as the dependent variable in column (4) to (6).

As shown, the coefficient on the negative belief shock variable in column (5) is negative and statistically significant, which suggests that the magnitude of the forecast errors increases significantly when the performance of the other industries are more negative. Analysts affected by negative belief shocks issue significantly less accurate earnings forecasts than their peers do. The coefficient estimate of -0.217 suggests that if other coverage industries experience a negative return of -10%, the forecast accuracy of affected analysts drops by about 2.2% relative to their counterparts, whose coverage industries do not experience such negative shocks. This effect is economically sizable, as analysts need about 7.3 years more of firm-specific experience to offset this inaccuracy.

To assess the effect of salient negative shocks, I focus on the coefficient of the bottom decile (D1) variable in column (6), which is 0.048 and statistically significant ($t = 6.076$). If analysts observe a salient negative performance from the other industries in the bottom decile (lower than -9%), their forecast accuracy is about 4.8% lower than that of their peers, which analysts need about 16 years more of firm-specific experience to offset.

Moreover, I find no evidence that those negative shocks encompass information that improve analysts' accuracy in the future, as lagged belief shocks have no significant impact on forecast errors (see Appendix C). Another potential concern is whether my findings are driven by analysts' overreaction to their past forecast errors. If analysts form diagnostic expectations (Bordalo, Gennaioli, Ma, and Shleifer, 2018a; Bordalo, Gennaioli, and Shleifer, 2018b), they might overcorrect for past forecast errors and make overpessimistic forecasts subsequently if their previous forecasts have been overoptimistic. I show in Appendix D that the effects of belief shocks are not affected by analysts' response to past forecast errors.

Overall, the results are strongly in favor of the noise hypothesis: analysts overgeneralize negative shocks in other industries and lower their expectations about firms' earnings incorrectly, resulting in inaccurately low earnings forecasts relative to the actual earnings. Inconsistent with the information hypothesis, analysts do not provide more accurate forecasts when they experience negative performance in other industries.

4.2.2 Unrelated industries

As discussed by Bradley et al. (2017), analysts with industry experience and expertise are often in limited supply. Even for brokers having analysts with related industry expertise, those analysts have only limited attention and may be too busy to cover new companies. The brokerage houses would therefore have to assign companies to analysts who are available but lack the related industry experience and knowledge. As a result, some analysts might cover firms in two or more unrelated industries.

This misallocation provides a natural setting to distinguish between the information channel and the noise channel. Namely, shocks to unrelated industries are less likely to encompass useful information about focal firms. The information hypothesis predicts that analysts would only respond to related industries' performance and not (or much less) to unrelated industries' performance. The noise hypothesis predicts that analysts would overgeneralize shocks to related and to unrelated industries and make less accurate forecasts regardless of the industry relatedness.

To identify industry relatedness, I use the three-digit NAICS codes as industry classification to compute the belief shock variable. This industry classification allows me to identify vertically linked industries, i.e., industries that have supplier or customer relationships. I detect possible economic links using the 2007 U.S. Input-Output Tables from the Bureau of Economic Analysis, which are based on the NAICS codes and which provide detailed information on the flows of the goods and services among industries[3]. I define supplier-customer industries as those industries with any flows to a given industry. In addition, I detect firm-level customer-supplier links by using the network relationships constructed by Barrot and Sauvagnat (2016). They obtain the identity of large customers of all public US firms, which, under regulation Statement of Financial Accounting Standards (SFAS) No. 131, are obliged to report the identify of any customer representing more than 10% of total reported sales. Moreover, I use the Compustat Segment files to identify business and operating segments of conglomerate companies that have a different industry classification than the company's primary sector. Finally, to detect horizontal links in product markets, I utilize the 10-K text-based network industry classification (TNIC-3) data developed by Hoberg and Phillips (2016).[4]

Specifically, suppose that an analyst covers industries I_1 and I_2, with two different three-digit NAICS codes. When computing the belief shock of this analyst with respect to stock k in industry I_1, I consider industry I_2 *unrelated* if (1) I_1 and I_2 have no flows of goods and services with each other in the Input-Output table (no industry-level supplier-customer links); (2) firm k has no large customer in industry I_2 (no firm-level supplier-customer links); (3) firm k has no subsegment operating in industry I_2; and (4) firm k has no product market rivals in I_2 (i.e., none of the firms in I_2 is associated with firm k in the TNIC-3 database). Otherwise, I_2 is classified as a related industry for firm k. Figure 1 plots the percentage of analysts in the I/B/E/S database who cover

[3]I use the 2007 table of the commodities by industry valued at purchasers' prices under Use Tables/After Redefinitions/Purchaser Value (`https://www.bea.gov/industry/io_annual.htm`).

[4]I thank the authors of Barrot and Sauvagnat (2016) and Hoberg and Phillips (2016) for making their data publicly available.

companies in such unrelated industries. As is shown, around 20% of I/B/E/S analysts cover neither horizontally nor vertically linked industries. Because I only have TNIC-3 data for the period from 1996 to 2015, the following analysis focuses on this subperiod of my sample.

In Panel A of Table IV, I restrict the sample to the firms with at least one analyst who covers an unrelated industry, and I use the specification in columns (2), (5), and (6) from Table II and columns (1) to (3) from Table III to estimate the effect of the belief shocks resulting exclusively from unrelated industries. As is shown, the results are similar to the baseline results based on all other coverage industries: the estimated coefficient on the negative belief shock variables is significantly positive, while that on the indicator variable D1 of salient negative shocks is significantly negative, implying that negative shocks to unrelated coverage industries lead analysts to make incorrectly lower earnings forecasts for the focal firms. The magnitude and t-statistics of the coefficients are smaller than those in the baseline, which is not surprising because the effects of belief shocks from related industries are omitted in this setting. Nevertheless, the results in Panel A provides evidence in support of the noise hypothesis: even though negative shocks to unrelated industries are not likely to be informative about the focal firms, they still influence analysts' expectations for the focal firms.

[Table 4 about here.]

An interesting follow-up question is how analysts respond differently to the performance of related and unrelated industries. Is it possible that the information hypothesis applies to related coverage industries while the noise hypothesis applies to unrelated ones? In Panel B of Table IV, I focus on a subsample of analysts who cover related and unrelated industries, and estimate their response to belief shocks from related and unrelated industries separately. The specifications are the same as in Panel A.

As is shown, negative shocks to both related and unrelated coverage industries lead analysts to make inaccurate pessimistic forecasts, which is difficult to reconcile with the information hypothesis. Despite the substantial reduction in the sample size, the statistical significances of negative belief shocks from unrelated industries still increases slightly relative to those in Panel A, after controlling for the effects of belief shocks from related industries. The coefficient estimates of belief shocks from related industries are larger than those from unrelated industries, which suggests that analysts' expectations are more influenced by related industries' performance. This findings is reasonable because analysts are more likely to believe that shocks from related industries are informative about the focal firms than those from unrelated industries. However, unreported tests of the equality of coefficients indicate that the difference in the two coefficients is not statistically significant in any of the specifications. The effects of belief shocks from related and unrelated industries seem to add up to the total effects from our baseline results in Tables II and III.

Taken together, the results in this section suggest that the negative performance of other coverage industries leads analysts to incorrectly lower their expectations and produce less accurate forecasts. Belief shocks from both related and unrelated industries seem to only provide noise rather than useful information about the focal firms. These findings lend support to the noise channel and soundly reject the information channel. Analysts heuristically overgeneralize negative shocks to their other coverage industries, become more pessimistic about the state of the world, and therefore issue downward-biased earnings forecasts relative to their peers who do not cover the shocked industries.

4.2.3 Forecast revisions

One potential concern is whether my results are driven by analyst distraction. Kempf et al. (2017), for example, study investor distraction by using extreme positive and negative industry returns as a proxy for attention-grabbing events. One may argue that shocks to other industries do not influence analysts' expectations, but rather distract their attention from the focal firms. As a result, distracted analysts issue relatively conservative earnings forecasts that turn out to be less accurate. This argument has difficulty explaining why analysts are not distracted by salient positive industry performance, and it is difficult to reconcile with the large body of literature showing that, if anything, sell-side analysts are optimistic by default. Nevertheless, I formally investigate the possibility of analyst distraction by examining analyst forecast revisions.

If analysts were just distracted by other coverage industries with extreme returns, they would allocate less effort to the coverage firm and revise their forecasts less frequently than usual. In Table V, I estimate Equation (11) in columns (1) and (2) with the total number of revisions as the dependent variable. The belief shock variables are computed here over the period from the earnings announcement date of fiscal quarter $t-1$ to that of fiscal quarter t. As is shown, neither negative nor positive extreme performance of other coverage industries affects analyst revisions significantly. Thus, there is no evidence that analysts spend less effort on the coverage firms or revise their forecasts less often.

[Table 5 about here.]

In addition, I use the following specification to estimate the effect of belief shocks on the magnitude of analyst j's r-th forecast revision for firm i in fiscal year-quarter t:

$$\widetilde{SUF}_{ijtr} = \alpha_{q(t)} + \alpha_{ij} + \beta_1 \times \widetilde{BS}^{-}_{ijt[r-1,r]} + \beta_2 \times \widetilde{BS}^{+}_{ijt[r-1,r]} + \gamma' \widetilde{X}_{ijt} + \widetilde{\varepsilon}_{ijtr}, \qquad (12)$$

where r indexes forecast revisions (within each analyst-firm-fiscal year-quarter pair). The dependent variable is the standardized unexpected forecast (SUF) computed as in Stickel (1992) and Malloy (2005) to measure revision magnitude. The belief shock variables are computed as described in section 3.2 but over the window between the announcement date of an analyst's most recent forecast r and the announcement date of her previous forecast $r-1$ for the same firm and fiscal quarter. All of the variables are demeaned within firm-quarters to control for the stock $\times$ fiscal year-quarter fixed effects. The sample contains 314,742 forecast revisions. The estimation results are shown in columns (3) and (4) of Table V. The direction and magnitude of analyst forecast revisions are strongly associated with the (salient) performance of other coverage industries: analysts revise their forecasts downwards (upwards) significantly more when the other industries experience sizable negative (positive) shocks. This finding contradicts the notion of analyst inattention, as distracted analysts would not incorporate other industries' shocks into their revisions.

In columns (5) and (6), I examine the stock price impact of forecast revisions associated with belief shocks by estimating Equation (12) with the three-day cumulative abnormal returns around the forecast revision announcement date as the dependent variable. This test provides additional evidence to distinguish whether belief shocks encompass information or noise. The forecast revisions made by analysts affected by belief shocks would have a greater impact on stock prices if those analysts bring valuable information to the market. As is shown, conditional on the direction and magnitude of the revisions, belief shocks do not significantly affect the market reactions, which again does not support the information channel. Moreover, the insignificant coefficients on belief shocks suggest that investors do not unravel the biases in analysts' forecasts resulting from belief shocks.

The findings in Table V also confirm the asymmetric effect of negative and positive belief shocks, although they suggest a less extreme version. In particular, analysts also revise forecasts upwards following positive belief shocks despite the significantly smaller magnitude. This finding lends support to the notion that as analysts are already optimistic on average, even though they might respond to positive shocks and revise their forecast upwards, their final forecasts might not differ sufficiently from other analysts' optimistic forecasts for econometricians to detect any significant difference. The asymmetric effect of negative and positive belief shocks is probably not due only to the negativity bias, but also to the analysts' average optimism.

4.3 Robustness

In this section, I show that my main findings are robust to alternative weighting schemes when constructing the belief shock variable, to different subperiods in my sample, and to alternative industry classifications. Table VI presents the results of the robustness tests. In Panel A, I reestimate the specification in columns (2), (5), and (6) from Table II with the adjusted EPS forecast as the dependent variable. In Panel B, I reestimate the specification in columns (1) to (3) from Table III with signed forecast errors as the dependent variable.

First, I estimate the effect of belief shocks computed by equally weighting analysts' coverage industries in Equation (6), which yields coefficient estimates of similar statistical significance and even slightly larger magnitude.

[Table 6 about here.]

Second, I divide the main sample period into four subperiods: before and after Regulation Fair Disclosure (Reg FD), the 2008 financial crisis period, and the post-crisis period. Reg FD, which was ratified by the SEC in 2000, prohibited selective information disclosure by firms to a subset of analysts and thus could affect analysts' private information, such as their personal connections to the management (e.g., Cohen et al., 2010). As is shown, the results in the pre- and post-Reg FD periods and in the post-crisis period are similar to the baseline. However, during the financial crisis, analysts seem to only respond to salient negative industry performance. One likely explanation is that analysts were already very pessimistic about the economy because of the crisis. Thus, only extremely negative signals could change their perspective, making them even more pessimistic, which is consistent with the main findings. In sum, the estimation results in the subperiods provide important evidence showing that my main findings are persistent over time and not solely driven by extreme negative events such as the financial crisis.

Furthermore, I consider five alternative industry classifications: Fama-French 12 industries, the three-digit Global Industry Classification Standard (GICS) industries, industries based on two-digit SICH codes, and the Hoberg and Phillips (2016) 10-K text-based 50 industry classification (FIC-50). I compute the belief shock variable using each of these five alternative industry definitions. As is shown in Table VI, the statistical significance and magnitude of the point estimates are qualitatively the same as those of my baseline results. Therefore, my findings are not likely to be driven by a particular industry (mis)classification or by measurement errors.

5 Additional analysis on belief shocks

The results thus far are consistent with the notion that other coverage industries' negative performance lowers analysts' expectations about the state of the world. Yet given the large heterogeneity of firms and analysts, the effect of belief shocks might vary for different types of analysts covering different firms. Moreover, because analysts probably hold diverse prior beliefs about each industry and only cover a particular set of firms within each industry, they might not respond identically to belief shocks coming from different coverage industries. In this section, I exploit the heterogeneity in firms and analysts' coverage portfolios to further assess how other industries' performance influences analysts' belief-forming process.

5.1 Coverage firms with high information asymmetry

I first try to isolate firm types for which the effect of negative belief shocks is particularly stark. Following the idea that analysts rely more on their private information when the coverage firm is opaque and difficult to analyze, I divide my original sample into firms with different levels of information asymmetry. More specifically, I break down the sample in three ways: firms in high-tech industries (code 3 in Fama-French 5 industries) versus firms in other industries, small firms (with below median market capitalization) versus big firms, and young firms (went IPO in less than 10 years) versus mature firms. Table VII reports the estimated effects for each subset.

[Table 7 about here.]

In Panel A, I reestimate the specification of column (5) from Table II for each subsample, with adjusted EPS forecasts as dependent variables. As is shown, the coefficient estimate on negative belief shocks is slightly larger for small and young firms, and it is particularly stronger for stocks in high-tech industries. A negative belief shock of -10% leads analysts covering high-tech stocks to become 4.17% more pessimistic relative to the baseline of 2.64%. A similar pattern emerges from the estimation results in Panel B, where I reestimate the specification of column (2) from Table III with forecast errors as dependent variables. These findings lend support to the notion that analysts covering opaque firms (especially high-tech firms) are more influenced by the negative performance of other coverage industries relative to other analysts.

5.2 Analysts with different numbers of coverage industries

My baseline results suggest that analysts covering two or more industries tend to overgeneralize the negative performance of the other industries. To examine whether this varies with analysts' portfolio complexity, I split the sample based on the number of industries an analyst covers and reestimate the specification in column (5) of Table II for each subsample.

In Panel A of Table VIII, the dependent variable is the adjusted EPS forecast, computed as in Equation (1). I first use the full sample to demean all of the independent variables within each firm-quarter, to control for stock $\times$ fiscal year-quarter fixed effects, and then estimate the regression models with those demeaned variables, calendar year-quarter, and analyst $\times$ stock fixed effects for each subsample. As is shown, all of the point estimates on the negative belief shocks are positive and statistically significant, which suggests that all analysts with multiple coverage industries lower their expectations because of belief shocks, even those covering only two industries.

[Table 8 about here.]

Similar to Panel A, I divide the sample and reestimate the same specification in column (5) from Table III with forecast errors as the dependent variable in Panel B. The estimation results in Panel B confirm the baseline findings. Analysts affected by more negative belief shocks produce more negative forecast errors. The effect size is similar to the baseline results and is statistically significant regardless of the number of industries that an analyst covers. There is no clear pattern of effect size increasing over all coverage industries.

To summarize, I have shown that analysts covering multiple industries overgeneralize and consequently make less accurate earnings forecasts, including those covering only two industries. This finding is also interesting from practitioners' perspective. Due to a lack of supply of industry-experienced analysts, brokerage houses face the trade-off between the costs and benefits of assigning non-industry experts (Bradley et al., 2017). One could consider overgeneralization as a potential cost of delegating analysts more industries to cover even though they might be more talented than others.

5.3 "Expected" versus "unexpected" belief shocks

As noted above, analysts might have different interpretations of the signals coming from different coverage industries because of their heterogeneous prior beliefs about each industry. Analysts might be more likely to change their beliefs when the shocks are unexpected and different from their priors. Recall the example from the introduction: analyst A might have reacted less to the negative shock in the transportation industry if he had already foreseen this shock. However, it is empirically difficult to observe analysts' prior beliefs about these industry shocks.

[Table 9 about here.]

In Panel A of Table IX, I use analysts' earnings surprises as a weak proxy for their prior beliefs and decompose belief shocks into expected and unexpected components. Earnings surprises indicate that it is plausible that the industry shock is not anticipated by the analyst. As earnings surprises are only at the firm level and are probably correlated with unobserved analysts' private signals and therefore might contaminate the coefficient estimates, the results based on this proxy should be interpreted with this caveat in mind. I compute the average earnings surprises across firms in a given industry and identify industries with surprises if the shock and the average earnings surprise have the same sign. Likewise, industries without surprises are those in which the average earnings surprise has a different sign than that of the industry shock.

Using decomposed belief shocks and repeating the analysis from Tables II and III, I find that both expected and unexpected shocks significantly influence analyst beliefs, with similar magnitudes. Combining the effects of anticipated and unanticipated belief shocks seems to recover the coefficient estimates in the corresponding columns from Tables II and III. The finding that expected belief shocks also affect analyst forecasts is interesting and suggests that analysts seem to overgeneralize industry-wide shocks rather than firm-level idiosyncratic shocks. Thus, this result supports my approach of using industry-level performance rather than firm-level performance to construct belief shocks.

5.4 Industry shocks versus idiosyncratic shocks

As explained before, I use industry-level performance to construct the baseline belief shock variable for identification purposes. In practice, however, analysts cover a particular set of firms within each industry, rather than the entire industry. Because an industry shock affects some firms more than others, analysts covering different firms within the same industry might have diverse perceptions of the shock. Specifically, does a negative industry shock still make analysts more pessimistic when their coverage firms within that industry are actually performing well?

To address this question, I additionally construct a belief shock variable as in Equation (6) by value-weighting the stock market performance of analysts' individual coverage firms. In Panel B of Table IX, I include stock-level belief shock variables as additional control variables to my baseline specifications with the industry-level belief shocks from Tables II and III. Controlling for stock-level belief shock variables allows me to examine how analysts respond to the same industry shocks differently regarding the performance of their coverage firms. If analysts only pay attention to industry shocks that substantially affect their coverage firms, the coefficients on industry-level belief shocks would no longer be significant.

Compared to the estimates in Tables II and III, the coefficients on the baseline industry-level belief shocks are smaller in magnitude, but most remain statistically significant. The coefficients on stock-level belief shocks are in the same direction as those on industry-level variables, with higher statistical significance but smaller magnitudes, which suggests that a negative industry shock lowers an analyst's belief more if her coverage firms in that industry are materially affected by the shock and perform poorly. The effect of industry shocks is still present but diminishes if the coverage firms are not or are less affected. The larger magnitude of industry-level belief shocks relative to stock-level shocks lends further support to the notion that analysts are more likely to overgeneralize industry-wide shocks rather than firm-level idiosyncratic shocks when forming expectations about firms in other industries. Note that combining the effects of industry- and stock-level belief shocks seems to recover the baseline estimates in the corresponding columns from Tables II and III.

The higher statistical significance of stock-level belief shocks also indicates that analysts' expectations covary more closely with the performance of coverage firms. In an unreported test in which I replace industry-level belief shocks with stock-level belief shocks, the estimated effects of firm-level performance on analysts' beliefs are larger in both statistical significance and economic magnitude. Nevertheless, as discussed before, the effect of firm-level performance cannot be cleanly identified, as it is difficult to rule out reverse causality and other potential confounding factors that drive firm performance and analyst expectation simultaneously.

5.5 Does experience or the brokerage house mitigate overgeneralization?

Another interesting question is what factors mitigate the impact of overgeneralization, which results in analyst inaccuracy. I test two candidates: experience and brokerage experience. As analysts gain experience, they could become better at analyzing firms' financial reports, identifying business cycles, and teasing out noise from information. Clement (1999) and others have provided empirical evidence showing that forecast accuracy increases with experience. Furthermore, analysts employed by bigger (often more prestigious) brokerage firms are provided with more resources, such as more research assistance from junior analysts and access to soft information through privileged house calls with management, that enable the analysts to filter out more noise from other industries. Table X shows the results of my test of whether analysts' experience or employer reduces the impact of overgeneralization. I reestimate the specifications of column (5) from Table II and columns (2) and (5) from Table III, and I interact the negative belief shock variable with analysts' overall experience, firm-specific experience, and the size of the brokerage firm.

[Table 10 about here.]

If analysts with more experience or those who work for a bigger broker house are less likely to overgeneralize negative performance of the other industries, the coefficient on the interaction terms would be statistically significant and have an opposite sign than that of the negative belief shock variable. As is shown in Table X, however, the estimated coefficient on all of the interaction terms turns out to be negligible. While more experienced analysts employed by larger brokerage houses are on average more accurate, these characteristics do not prevent them from overgeneralizing negative shocks to other coverage industries.

6 Impact on financial markets

Because most investors rely heavily on analysts' forecasts to evaluate firms' future prospects and make trading decisions, differences in analysts' opinions could induce heterogeneous beliefs among investors and thereby generate more trading and price changes. Given my main findings that analysts overgeneralize shocks from other coverage industries and consequently make different forecasts, I hypothesize that those belief shocks potentially have more profound impacts on financial markets. In this section, I first develop a simple model in the flavor of Kandel and Pearson (1995) to demonstrate how analyst belief shocks could induce trading volume and return volatility, and I then provide empirical evidence conforming to the theoretical predictions.

6.1 Model

6.1.1 Setup

This simple model follows the setups in Harris and Raviv (1993) and Kandel and Pearson (1995): (1) There is a risk-free asset with a zero rate of return and a risky security with an uncertain payoff R. (2) There are three time periods: at time 1, investors form prior beliefs about the value of the asset; at time 2, they update their beliefs according to analyst forecasts; at time 3, the value of the risky asset is realized and investors consume their wealth. (3) There is a continuum of investors with total mass equal to 1 who maximize mean-variance utility $\mathbb{E}_{i,t}[W_i] - \frac{\lambda}{2}\text{Var}_{i,t}[W_i]$, where λ is the coefficient of absolute risk aversion. (4) There are two types of investors indexed by $i = 1, 2$. They hold prior beliefs that the return R is normally distributed with mean R_i and precision $h_0 = \sigma_0^{-2}$. A proportion α of traders are of type 1; without loss of generality, they are assumed to initially be more optimistic, $R_1 > R_2$. (5) There are two analysts indexed by $i = 1, 2$ who make forecasts for the risky asset R. Their forecasts are given by $F_i = R + \varepsilon_i$, where $\varepsilon_i \sim \mathcal{N}(s_i, h_\varepsilon = \sigma_\varepsilon^{-2})$. The distribution of the noise term ε_i models that analyst i overgeneralizes signal s_i from other coverage industries and makes a biased forecast for R. (6) At time 2, type i investors update their beliefs using analyst i's forecast F_i. However, they trust that analysts make an unbiased forecast for R. That is, they believe that $\varepsilon_i \sim \mathcal{N}(0, h_\varepsilon = \sigma_\varepsilon^{-2})$.

There are two key frictions in this model. The first is that type i investors update their beliefs in a naive Bayesian manner and only update beliefs with respect to analyst i's forecast, without taking into account the information sets and actions of others. In particular, at time 1, they do not take into account that at time 2, prices will be "incorrect" because the other agents are updating their beliefs and trading using different information based on the other analyst's forecast. This assumption is standard in the literature of speculative trading and information diffusion (see Kandel and Pearson (1995), Hong and Stein (1999), and Hirshleifer and Teoh (2003)). The second friction is that investors are unable to debias analyst research and are therefore misled by biased forecasts, which is supported by my results on the market reaction to analysts' revisions. Studies such as Jackson (2005) also provide empirical evidence supporting this assumption.

6.1.2 Equilibrium prices and investor holdings

At time 1, each type i investor optimizes her mean-variance preference

$$\max_{q_{i,1}} \mathbb{E}_{i,1}\left[q_{i,1}(R - P_1)\right] - \frac{\lambda}{2}\mathrm{Var}_{i,t}\left[q_{i,1}(R - P_1)\right].$$

So each type i investor demands

$$q_{i,1}(P_1) = \frac{h_0}{\lambda}(R_i - P_1)$$

of the risky asset. The aggregate demands are $Q_{1,1}(P_1) = \alpha q_{1,1}(P_1)$ and $Q_{2,1}(P_1) = (1-\alpha)q_{2,1}(P_1)$. The market-clearing condition implies that the total demand from all investors must equal the zero net supply. Hence, the market-clearing equilibrium price is

$$P_1^* = \alpha R_1 + (1-\alpha)R_2 = \overline{R}, \tag{13}$$

and the equilibrium holdings are

$$q_{1,1}^* = \frac{h_0}{\lambda}(1-\alpha)\Delta R \quad \text{and} \quad q_{2,1}^* = -\frac{h_0}{\lambda}\alpha\Delta R, \tag{14}$$

where $\Delta R = R_1 - R_2$. By assumption, $\Delta R > 0$, and the aggregate supply of securities is zero. The second type holds a short position, $q_{2,1}^* < 0$.

After analysts 1 and 2 have issued forecasts F_1 and F_2 at time 2, investors update their beliefs and resume trading. The posterior beliefs of type i investors are given by a normal distribution with mean

$$\mathbb{E}_{i,2}[R|F_i] = \frac{h_0}{h_0 + h_\varepsilon}R_i + \frac{h_\varepsilon}{h_0 + h_\varepsilon}F_i.$$

Similar to period 1, optimizing investors' mean-variance preferences and using the market-clearing condition gives the equilibrium price at time 2:

$$P_2^* = \frac{h_0\overline{R} + h_\varepsilon\overline{F}}{h_0 + h_\varepsilon}, \tag{15}$$

where $\overline{F} = \alpha F_1 + (1-\alpha)F_2$. Likewise, equilibrium holdings at time 2 are given by

$$q_{1,2}^* = \frac{(1-\alpha)}{\lambda}(h_0\Delta R + h_\varepsilon\Delta F) \quad \text{and} \quad q_{2,2}^* = -\frac{\alpha}{\lambda}(h_0\Delta R + h_\varepsilon\Delta F), \tag{16}$$

where $\Delta F = F_1 - F_2 = \varepsilon_1 - \varepsilon_2 = \Delta\varepsilon$ indicates the difference in analysts' opinions.

6.1.3 Prediction regarding asset volatility and trading volume

When I compare the prices in (13) and (15), it is clear that the absolute price change between the two periods depends linearly on the new information of analyst forecasts and on the difference in analysts' opinions,

$$|\Delta P^*| = |P_2^* - P_1^*| = \frac{h_\varepsilon}{h_0 + h_\varepsilon}|F_2 - P_1^*| + \frac{\alpha h_\varepsilon}{h_0 + h_\varepsilon}|\Delta\varepsilon|. \tag{17}$$

Because a larger fluctuation of the security price is equivalent to higher return volatility, a greater dispersion in analyst opinions could increase the return volatility of the underlying risky asset.

Furthermore, calculating the change in the equilibrium holdings in (14) and (16), I can show that it is also linearly related to the difference in analyst forecasts. Because the net supply of the risky security is assumed to be zero, the absolute value of the change in the aggregate holdings by type i investors represents the trading volume in period 2. Taking the absolute difference between

(14) and (16) yields the trading volume

$$TV = |Q^*_{1,1} - Q^*_{1,2}| = \frac{\alpha(1-\alpha)h_\varepsilon}{\lambda}|\Delta\varepsilon|. \tag{18}$$

The trading volume is therefore also proportional to the difference in analysts' opinions.

Recall that analyst i's bias ε_i is assumed to depend on her belief shock s_i from the other coverage industries, namely, $\mathbb{E}[\varepsilon_i] = s_i$, which implies that $\mathbb{E}[|\Delta\varepsilon|] = |s_1 - s_2| = |\Delta s|$. This leads to an important empirical prediction regarding the impact of analysts' belief shocks on financial markets.

Prediction. *If a larger dispersion in analysts' belief shocks amplifies the difference in analysts' forecasts, it would increase the return volatility and trading volume of the risky security.*

6.1.4 Prediction regarding asset returns

In this simple model, the expected price change depends on the new information in analysts' forecasts $F_{1,2}$, which are essentially determined by the signals (or belief shocks) $s_{1,2}$:

$$\mathbb{E}[P^*_2 - P^*_1] = \frac{h_\varepsilon}{h_0 + h_\varepsilon}\mathbb{E}[\overline{F} - \overline{R}] = \frac{h_\varepsilon}{h_0 + h_\varepsilon}\overline{s}, \tag{19}$$

where $\overline{s} = \alpha s_1 + (1-\alpha)s_2$. If an analyst overgeneralizes negative shocks to her other coverage industries and becomes pessimistic about this risky asset such that $\overline{s} < 0$, the expected return on this asset would be negative.

Moreover, the expected difference between P^*_2 and the asset's fundamental value R is given by

$$\mathbb{E}[P^*_2 - R] = \frac{h_0}{h_0 + h_\varepsilon}(\overline{R} - \mathbb{E}[R]) + \frac{h_\varepsilon}{h_0 + h_\varepsilon}\overline{s}. \tag{20}$$

This expression implies that analysts' belief shocks would lead the price to shift away from the asset's fundamental value. Connecting to my key empirical findings above, because analysts lower their expectations based on noise from other coverage industries, their incorrect pessimism would induce underpricing of the security. This underpricing would be more pronounced if more analysts are affected by larger negative belief shocks. Of course, when the true information is revealed to the market (realization of R in the model or firms' announcement of actual earnings in practice), the price will reverse to the fundamental value.

Prediction. *Negative belief shocks exert downward price pressure and induce underpricing.*

6.2 Empirical evidence on disagreement, trading volumes, and return volatilities

Empirically, I aggregate the data at the firm $\times$ fiscal year-quarter level, resulting in 191,724 observations, and estimate the following specification to test the prediction for the impacts of analysts' belief shocks on financial markets:

$$y_{jt} = \alpha_j + \alpha_{q(t)} + \beta \times |\Delta s|_{jt} + \gamma' X_{jt} + \eta_{jt}, \tag{21}$$

where j indexes the firm, t indexes the fiscal quarter, $q(t)$ indexes the calendar quarter in which the firm announces its realized earnings of fiscal quarter t, and y_{jt} is the dependent variable of interest (forecast dispersion, trading volume, and return volatility). For each pair of firm j and fiscal quarter t, I compute the standard deviation of the belief shocks from all analysts covering the firm as a proxy for $|\Delta s|$. Summary statistics for the firm-quarter variables are shown in Panel B of Table I. All of the specifications include firm fixed effects to capture unobserved but time-invariant heterogeneity across firms and calendar quarter fixed effects to account for common trends. The standard errors are two-way clustered by firm and calendar quarter to account for autocorrelations within the firm and correlations within the quarter.

Table XI shows the results of my test of whether analysts' opinions diverge more when dispersion in belief shocks increases. Following Diether et al. (2002), analyst forecast dispersion is computed as the standard deviation of EPS forecasts scaled by the absolute value of the mean EPS forecast. As shown in column (1), the coefficient on the belief shock dispersion is 0.332, which is statistically significant ($t = 5.089$), and the point estimate increases to 0.376 and becomes more significant when I also include time-varying firm-characteristics as control variables in column (2). In economic terms, a one-standard-deviation increase in belief shock dispersion (0.042) is associated with a 5.7% ($= 0.332 \times 0.042/0.246$) to 6.4% ($= 0.376 \times 0.042/0.246$) increase in analyst disagreement about the stock.

[Table 11 about here.]

In columns (3) and (4), the dependent variable is the trading volume, which is computed as the logarithm of the average daily stock trading volume in the period between the announcement date of the first analyst forecast and the announcement date of the actual earnings for each firm j and fiscal year-quarter t. The point estimates on belief shock dispersion are statistically highly significant regardless of the model specification. Lending support to the empirical prediction derived above, a one-standard-deviation increase in belief shock dispersion is associated with a 3.0% ($= 0.725 \times 0.042$)

to 5.2% (= 1.233 × 0.042) increase in trading volume.

I further test the empirical prediction by identifying the effect of analyst belief shocks on firms' return volatility. I measure volatility in two ways: (1) realized equity volatility as the standard deviation of daily stock returns in the period between the announcement date of the first analyst forecast and the announcement date of the actual earnings for each firm j and fiscal year-quarter t, and then annualized; and (2) option-implied volatility from OptionMetrics averaged over the same period. Both measures are widely used in the literature.

As shown in columns (5) and (6) of Table XI, firms' volatility significantly increases with the dispersion in analyst belief shocks. In addition to firm characteristics, I control for market volatility to capture the macroeconomic uncertainty around the same period. The coefficient estimate of belief shock dispersion hardly changes with the inclusion of the control variables. Economically, a one-standard-deviation increase in belief shock dispersion is associated with a 2.5% (= 0.269 × 0.042/0.445) to 2.7% (= 0.291 × 0.042/0.445) increase in stock volatility. The results are almost identical for option-implied volatility, as shown in columns (7) and (8).

6.3 Empirical evidence on underpricing

To empirically test the prediction regarding stock returns, I first identify and aggregate analysts' belief shocks that could potentially exert downward price pressure. For each firm-quarter observation, I construct a variable called *all negative shocks*, which is computed as the sum of the absolute value of negative belief shocks (i.e., $|BS^-_{ijt}|$) of all of the analysts covering firm j in fiscal year-quarter t and then scaled by the total number of analysts. This measure is an empirical proxy for $\overline{s}$ in Equations (19) and (20).

Figure 3 illustrates the impact of negative belief shocks on stock prices. Panel A uses the full sample, while Panel B focuses on the subsample of high-tech firms. I split the sample into two groups: one group of firm-quarters with some analysts affected by negative belief shocks (i.e., all negative shocks > 0), and the other group with no analysts affected by negative belief shocks (i.e., all negative shocks $= 0$). Defining firms' quarterly earnings announcement date as day 0, I trace out the market-adjusted cumulative abnormal returns from 30 days before to 30 days after earnings announcements. I choose 30 days before to start because most analysts have already issued their forecasts by then. A firm-quarter observation will only be included in the sample for a given day if there is no other forecast prior to the announcement.

[Figure 3 about here.]

As shown in Panel A of Figure 3, there is a significant decline in stock price until five days before the earnings announcement for firms affected by negative analysts' belief shocks. This downward price pressure induces an average price decline of 36 basis points. There is no such pattern for the other group of firms. The price pressure effect is more stark in Panel B. High-tech firms affected by negative analysts' belief shocks decline by as much as 95 basis points, likely due to the severe information asymmetry in those industries. Investors rely more on analysts' opinions to trade those firms. I also find a stronger reversal around the earnings announcement for affected firms, which is consistent with the underpricing prediction.

In Table XII, I formally test the underpricing prediction by reestimating Equation (21) with the three-day (-1, +1) market-adjusted cumulative abnormal return around the focal firm's earnings announcement date as the dependent variable. If more analysts are affected by negative belief shocks and consequently make incorrect pessimistic forecasts that exert downward price pressure, the announcement return would be more positive because the true information (actual earnings) is revealed. To identify the impact of analysts' negative belief shocks on stock returns, I use industry $\times$ calendar year-quarter fixed effects to control for any common trend within the same industries, such as the spillover effects from other industries. Moreover, I explicitly control for the direct market impact of earnings surprises to distinguish reversals because of better than expected earnings performance, from reversals that correct underpricing driven by analysts' unmerited pessimism.

[Table 12 about here.]

Conforming to the underpricing prediction, more analysts' negative belief shocks lead to larger price reversals around earnings announcements, as the coefficient on the all negative shock variable is positive and statistically significant in column (1). In the three days around the announcement, firms gain an additional 14 basis points (=0.023×0.06) when the analysts experience a one-standard-deviation increase in the negative belief shocks, which is an economically large effect of 63.6% relative to the average announcement return of 22 basis points. After controlling for the industry $\times$ quarter and firm fixed effects, the coefficient of interest decreases only slightly and remains significant, which corresponds to a gain of 11 basis points (=0.019×0.06) and therefore a 50% decrease. To test whether this pricing pressure effect is more pronounced for firms with a higher level of information asymmetry, I focus on the following three subsamples: high-tech industries in column (3), small firms (with below-median market capitalization) in column (4), and young firms (with IPO in less than 10 years) in column (5). Relative to the average earnings announcement returns in those subsamples, the estimated coefficient of interest suggests that a one-standard-deviation increase in analysts' negative belief shocks corresponds to a larger reversal of 92.7% (=0.034×0.06/0.0022) for high-tech firms, 72.6% (=0.023×0.06/0.0019) for small firms, and 86.7% (=0.026×0.06/0.0018) for young firms. These findings confirm my conjecture that the underpricing effect is more pronounced for firms with high information asymmetry.

Taken together, the findings in this section demonstrate that analyst overgeneralization has more profound impacts on the financial market. When there is a greater dispersion in the shocks that analysts overgeneralize, their opinions about the firm's future prospects will differ more, inducing significantly higher trading volumes and larger return volatilities. Analyst overgeneralization seems to aggravate information asymmetries and increase uncertainty about firms' fundamentals. Furthermore, when more analysts are affected by negative belief shocks, their resulting pessimism will exert significant downward price pressure and lead to temporary underpricing. This price pressure effect is more pronounced for firms with higher information asymmetry.

7 Conclusion

This paper exploits the diversity of industries that analysts cover, which is common to sell-side equity analysts. I test the hypothesis that the performances of other coverage industries play an important role in shaping analysts' expectations about the state of the world and thereby influence their earnings forecasts for their focal firms.

My main finding is that negative shocks to other coverage industries make analysts more pessimistic about the focal firms. When investigating whether these industry shocks provide analysts with additional valuable information or merely noise, I find strong evidence for the latter. Analysts' pessimistic forecasts turn out to be less accurate and much lower than the realized earnings, which suggests that analysts overgeneralize negative shocks from other coverage industries and unnecessarily lower their expectations about the focal firms. Moreover, I demonstrate that analyst overgeneralization has profound impacts on financial markets. Overgeneralization leads to larger differences in analysts' opinions about firms' future prospects and significantly increases stocks' trading volume and return volatility, aggravating information asymmetries and uncertainties about the underlying assets. Analysts' pessimism resulting from overgeneralization exerts downward price pressure and induces temporary underpricing.

The results in this paper not only introduce a new determinant of heterogeneous beliefs among financial analysts but also provide a broader implication for studying the decision-making process of multi-tasking agents, who might overgeneralize their experience with or outcome of one task when making decisions for other tasks. Moreover, because overgeneralization leads analysts to lower expectations because of other industries' performance, which is arguably unrelated to the fundamentals of focal firms, this heuristic essentially provides exogenous variation in analysts' disagreement and pessimism. This insight can be used to empirically study the effects of analyst (investor) disagreement or temporary underpricing in other settings.

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Figure 1: Analysts covering multiple industries

This figure contains two graphs: (1) the fraction of stocks out of the universe of the I/B/E/S database that are followed by at least one analyst who covers more than one Fama-Frnech 49 industry in each calendar year of my sample; (2) the fraction of analysts out of the universe of the I/B/E/S database who cover more than one Fama-French industry in each calendar year of my sample; (3) the fraction of analysts out of the universe of the I/B/E/S database who cover unrelated industries in each calendar year from 1996 to 2015. As explained in section 4.2.2, I consider two industries unrelated if they are not in the same three-digit NAICS code industry, have no supplier-customer relationships with each other, and do not belong to the same product market.

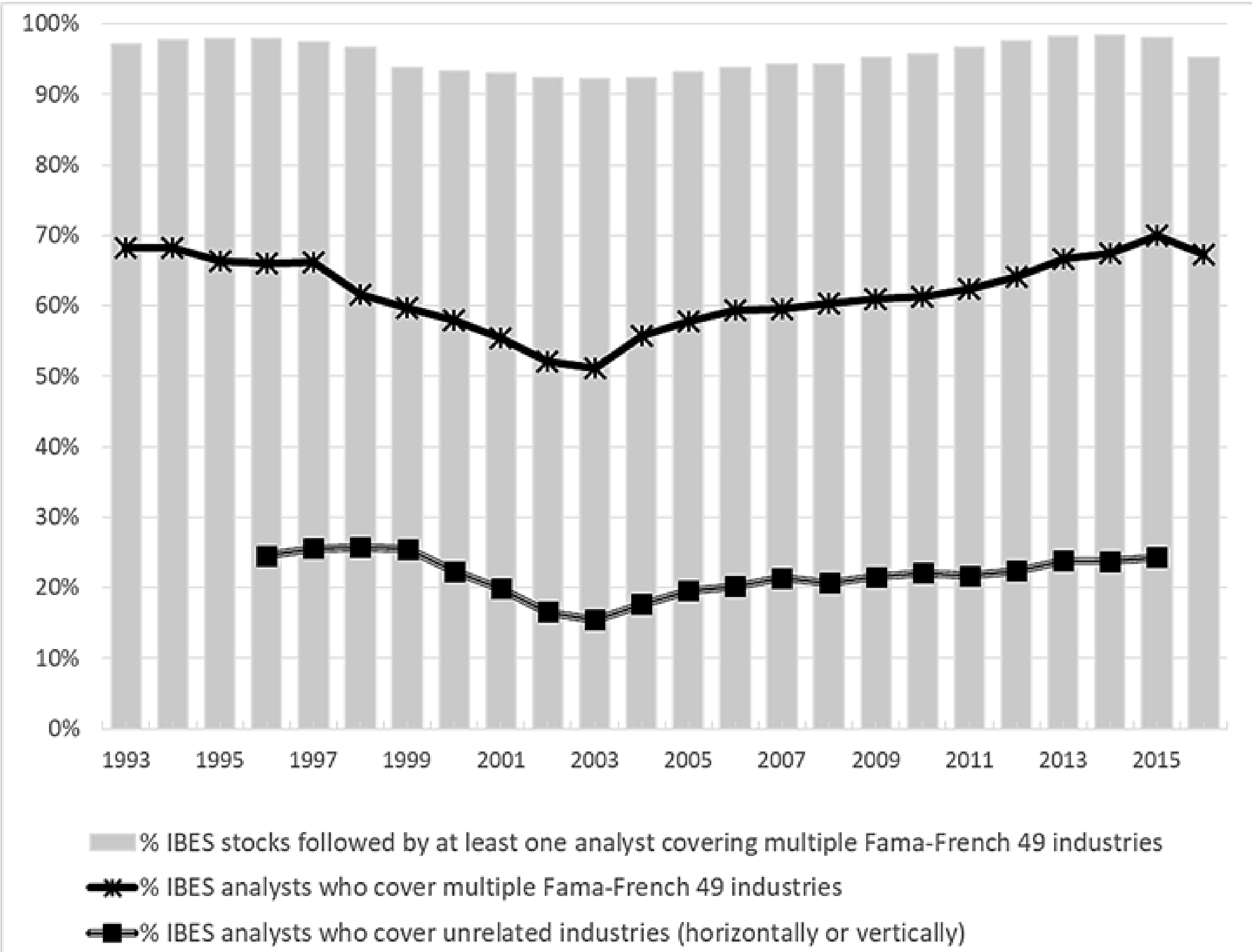


Figure 2: Analyst forecasts and belief shocks

This graph shows how analysts' adjusted EPS forecasts (y-axis), computed as in Equation (1), vary with the value of belief shocks (x-axis). I divide my sample into 10 subsamples based on the domain of the belief shocks. Belief shocks in the first subsample take values smaller than 0.20, belief shocks in the second subsample take on values in $[-0.20, -0.15)$, those in the third one take values in $[-0.15, -0.10)$, and so forth up to the tenth and final subsample taking values larger than 0.20. I plot how the average value of analyst forecasts varies across those subsamples. Error bars indicate 90% confidence intervals. Note that because analyst forecasts have been demeaned within each firm × fiscal year-quarter group, a forecast below 0 implies that an analyst is more pessimistic relative to her peers covering the same firm at the same time.

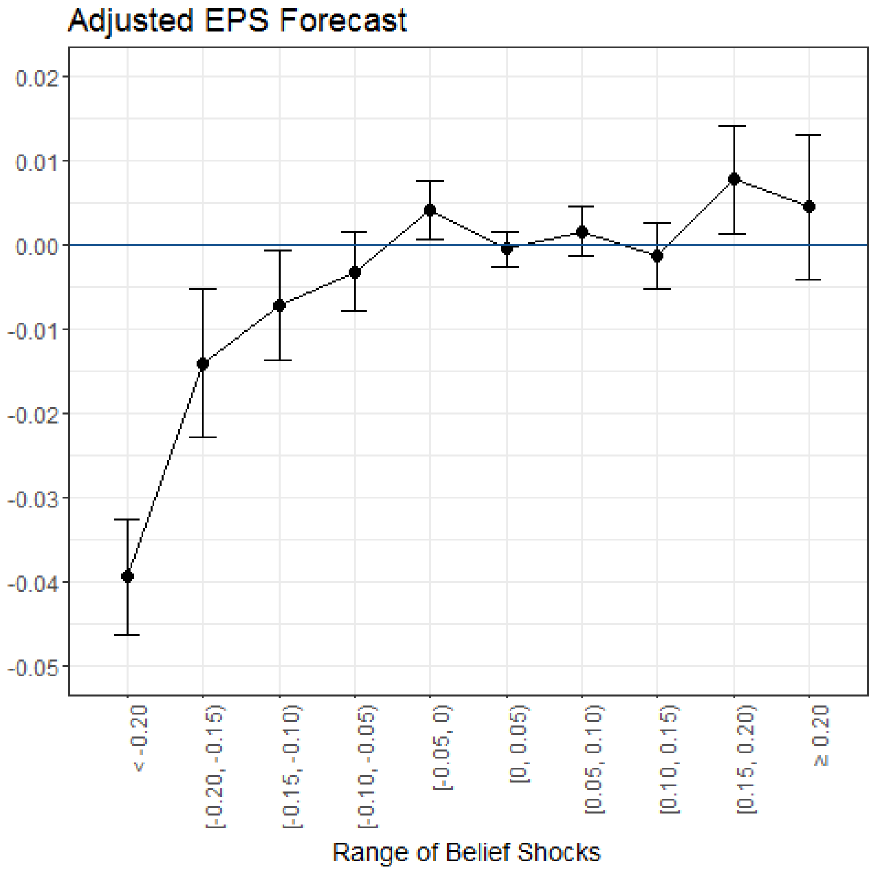
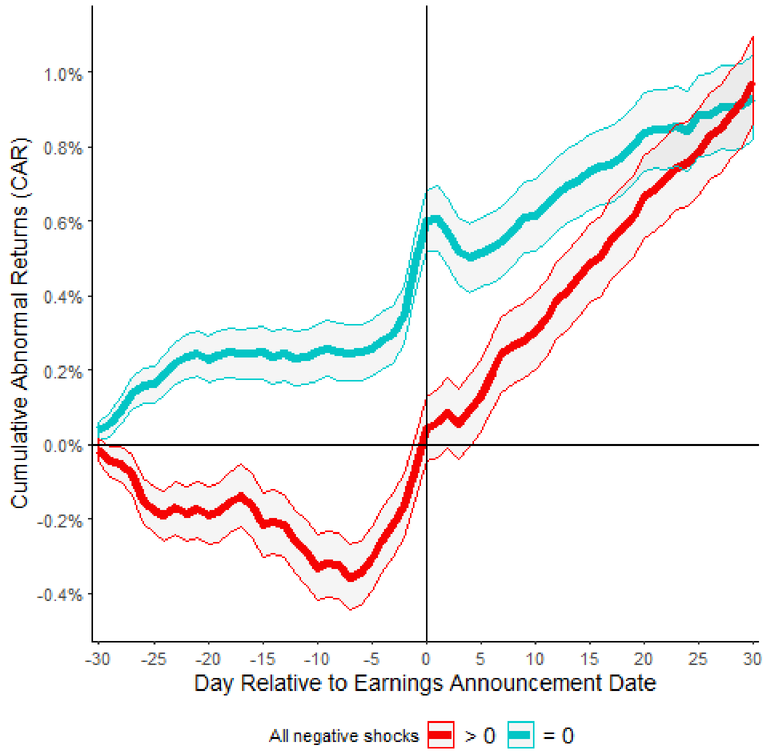


Figure 3: Impact of negative belief shocks on stock returns

This graph plots the average daily market-adjusted cumulative abnormal returns of stocks over the window (-30, +30) around the quarterly earnings announcement dates for two groups of firms. One group of firms has some analysts affected by negative belief shocks (i.e., all negative shocks > 0), and the other group of firms has no analyst affected by negative belief shocks (i.e., all negative shocks = 0). Panel A is based on the full sample, while Panel B focuses on the subsample of high-tech firms (code 3 in Fama-French 5 industries). Shading areas indicate the corresponding 90 percent confidence intervals.

Panel A: Full sample



Panel B: High Tech

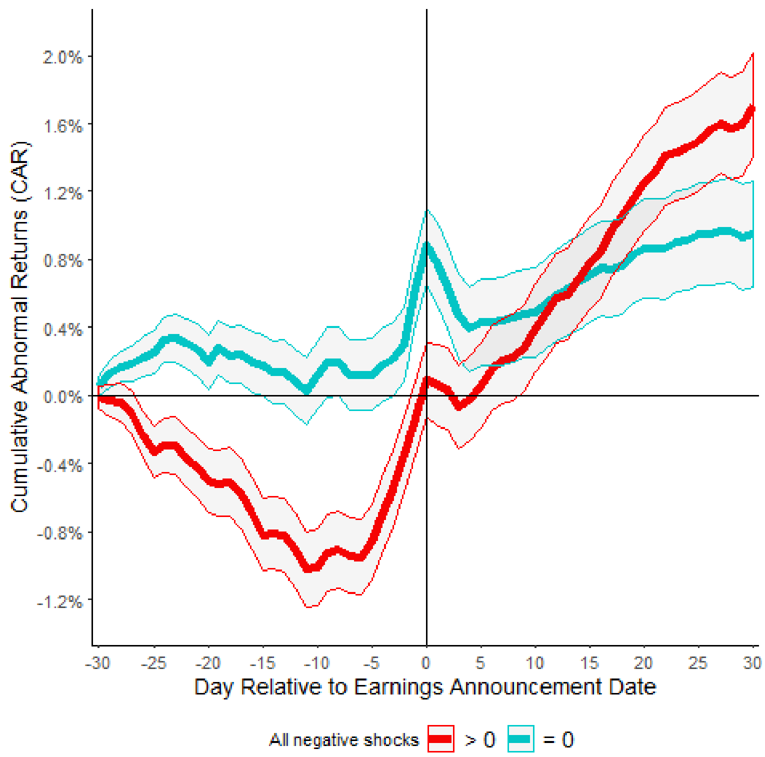


Table I: Data sample and summary statistics

This table describes the sample and reports the summary statistics of the main variables. Panel A tabulates, for each calendar year in my sample from 1993 to 2016, the number of unique stocks, the number of unique analysts, the number of unique analyst-stock pairs, the average number of analysts covering a particular stock, and the average number of Fama-French 49 industries and of stocks covered by analysts. Panel B reports the summary statistics for the main sample of analyst-stock-quarter observations for the period 1993-2016. The adjusted EPS forecast is computed as in Equation (1); forecast error is computed as in Equation (3); PMAFE is computed as in Equation (2); experience and firm experience are analysts' overall and firm-specific experience, respectively, computed as the number of years between an analyst's current earnings forecast and his/her first ever announced forecast and his/her first forecast for a particular firm; number of stocks is the number of stocks covered by an analyst; number of industries is the number of industries covered by an analyst; and broker size is the number of analysts employed by a broker in a calendar year. Adjusted EPS forecast, forecast errors, PMAFE, and all of the firm-quarter level continuous dependent variables are winsorized at the 1% and 99% levels. Detailed definitions of all the variables are presented in Table A1.

Panel A: Sample

Year	Number of Stocks	Number of analysts	Number of analyst-stock pairs	Avg. analyst coverage	By analyst: Avg. number of industries covered	By analyst: Avg. number of stocks covered
1993	1,749	1,147	9,230	4.0	3.6	10.2
1994	2,074	1,622	12,620	4.8	3.4	9.2
1995	2,190	1,773	13,609	4.9	3.3	9.1
1996	2,479	1,967	15,085	4.7	3.3	9.2
1997	2,691	2,312	16,659	4.7	3.1	8.5
1998	2,772	2,720	18,969	5.3	2.9	7.9
1999	2,694	2,896	19,843	5.7	2.7	7.7
2000	2,499	2,819	18,937	5.7	2.6	7.5
2001	2,375	2,874	19,420	6.4	2.5	7.3
2002	2,340	2,945	21,201	6.7	2.5	7.6
2003	2,326	2,773	20,925	6.8	2.5	8.0
2004	2,587	2,962	23,613	7.1	2.5	8.4
2005	2,763	3,004	24,997	7.2	2.6	8.6
2006	2,807	3,048	25,877	7.2	2.7	8.9
2007	2,941	3,046	26,894	7.2	2.8	9.1
2008	2,886	2,913	26,127	7.3	2.8	9.2
2009	2,772	2,752	26,096	7.8	2.9	9.7
2010	2,839	2,872	28,273	8.4	3.0	10.1
2011	2,872	3,022	30,364	8.6	3.1	10.3
2012	2,900	2,910	31,147	8.8	3.2	11.1
2013	3,058	2,824	32,731	8.9	3.4	11.8
2014	3,279	2,840	33,854	8.5	3.6	12.3
2015	3,432	2,748	34,470	8.5	3.7	12.8
2016	2,078	2,053	12,981	9.7	2.9	9.0

Panel B: Summary Statistics

	N	Mean	St. Dev.	Percentile				
				10th	25th	50th	75th	90th
Dependent variables								
Adjusted EPS forecast	1,423,192	0.00	0.89	-1.14	-0.62	0.00	0.62	1.15
Forecast errors	1,423,192	0.00	0.80	-1.00	-0.38	0.00	0.37	1.00
PMAFE	1,423,192	-0.02	0.67	-1.00	-0.42	-0.05	0.26	0.76
Number of revisions	1,423,192	0.37	0.67	0	0	0	1	1
Forecast revisions (SUF)	314,742	-0.18	0.99	-1.55	-0.89	-0.27	0.60	1.20
CAR(0, 1) (in %)	314,742	-0.13	4.96	-4.26	-1.83	-0.10	1.61	4.04
Main explanatory variable								
Belief Shock	1,423,192	0.02	0.10	-0.09	-0.01	0.01	0.07	0.12
Explanatory variables for robustness								
Belief Shock (EW)	1,423,192	0.02	0.10	-0.08	-0.01	0.01	0.07	0.12
Belief Shock (Related)	1,031,484	0.03	0.10	-0.07	0.00	0.02	0.08	0.14
Belief Shock (Unrelated)	1,031,484	0.01	0.08	-0.01	0.00	0.00	0.02	0.09
Belief Shock (FF12)	1,423,192	0.01	0.08	-0.06	0.00	0.00	0.06	0.10
Belief Shock (GICS)	1,411,961	0.03	0.10	-0.06	0.00	0.00	0.08	0.14
Belief Shock (Sic2)	1,423,192	0.03	0.10	-0.06	0.00	0.03	0.09	0.14
Belief Shock (HP50)	1,271,360	0.03	0.09	-0.04	0.00	0.00	0.07	0.13
Control variables								
Overall experience	1,423,192	6.47	5.03	0.88	2.39	5.34	9.52	13.81
Firm experience	1,423,192	2.85	3.24	0	0.52	1.73	4.02	7.27
Number of stocks	1,423,192	14.01	7.37	6	9	13	18	23
Broker size	1,423,192	62.85	54.82	11	22	48	89	125
Number of industries	1,423,192	3.61	2.37	1	2	3	5	7
Number of industries (FF12)	1,423,192	2.47	1.42	1	1	2	3	4
Number of industries (GICS)	1,423,192	3.00	2.07	1	2	2	4	6
Number of industries (Sic2)	1,423,192	3.78	2.40	1	2	3	5	7
Number of industries (HP50)	1,423,192	3.35	2.31	1	2	3	4	7
Number of industries (Naics)	1,423,192	3.63	2.52	1	2	3	5	7
Firm-quarter level variables								
Belief shock dispersion	191,726	0.05	0.04	0.01	0.02	0.04	0.07	0.10
All negative shocks	191,726	0.03	0.06	0.00	0.00	0.00	0.03	0.08
Forecast dispersion	191,726	0.25	0.62	0.01	0.03	0.07	0.19	0.50
Trading volume	191,726	12.62	1.64	10.51	11.53	12.61	13.69	14.74
Realized volatility	191,726	0.45	0.26	0.20	0.26	0.38	0.55	0.79
Implied volatility	134,541	0.48	0.23	0.25	0.32	0.42	0.58	0.78
EA CAR(-1, 1) (in %)	191,014	0.22	7.92	-8.71	-3.54	0.18	4.11	9.32
Earnings surprise	191,726	-0.05	1.10	-0.45	-0.08	0.03	0.14	0.43
MVE (in $mln)	191,726	4,196	9,309	141	328	937	3,031	10,362
Book-to-market	191,313	0.65	0.29	0.26	0.42	0.65	0.88	1.00
ROA	176,015	0.03	0.05	0.00	0.01	0.03	0.05	0.07
Number of analysts	191,726	11.72	8.55	4	5	9	16	24
% Multi-industry	191,726	0.55	0.25	0.21	0.37	0.55	0.71	0.86
Market volatility	191,726	20.05	7.57	12.61	14.40	18.44	23.71	28.68

Table II: Impact of belief shocks on analysts' EPS forecasts

This table reports the estimated effect of belief shocks on analysts' EPS forecasts. The dependent variable is adjusted EPS forecast, which is computed as in Equation (1). All of the specifications include the stock × fiscal year-quarter fixed effects by demeaning all of the variables within firm-quarters. I also include calendar year-quarter fixed effects and some analyst-specific characteristics as control variables. Detailed definitions of the control variables are presented in Table A1. In column (2), I additionally include the analyst × stock fixed effects. Column (3) shows the results of the subsample consisting of only analysts following multiple industries. In columns (4) and (5), I estimate Equation (11) to examine the effects of positive and negative belief shocks separately. In column (6), the negative and positive belief shock variables are replaced with, respectively, the indicator variable of the bottom decile (D1) and top decile (D10) of the belief shock variable. Standard errors are two-way clustered at the calendar year-quarter level and analyst × stock level, and the corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Adjusted EPS Forecast					
	(1)	(2)	(3)	(4)	(5)	(6)
Belief Shock	0.152***	0.150***	0.176***			
	(2.996)	(3.401)	(3.242)			
Negative Shock				0.219**	0.264***	
				(2.456)	(2.847)	
Positive Shock				0.076	−0.015	
				(1.467)	(−0.302)	
D1						−0.044***
						(−3.531)
D10						0.002
						(0.371)
Overall experience	−0.000	−0.702***	−0.005***	−0.000	−0.004***	−0.004***
	(−0.061)	(−8.006)	(−3.359)	(−0.077)	(−3.501)	(−3.502)
Firm experience	−0.013**	0.003	0.001	−0.009	0.008	0.005
	(−2.432)	(0.388)	(0.130)	(−1.642)	(1.125)	(0.767)
Number of industries	−0.009*	−0.020***	−0.012*	−0.009*	−0.011*	−0.010*
	(−1.875)	(−2.833)	(−1.849)	(−1.888)	(−1.846)	(−1.826)
Number of stocks	−0.021***	−0.014***	−0.011***	−0.021***	−0.015***	−0.015***
	(−10.417)	(−3.567)	(−3.552)	(−10.429)	(−5.158)	(−5.189)
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	No	Yes	Yes	No	Yes	Yes
Sample	Full	Full	Mult. ind.	Full	Full	Full
Observations	1,423,192	1,423,192	1,178,422	1,423,192	1,423,192	1,423,192
R^2	0.001	0.224	0.201	0.001	0.194	0.194

Table III: Impact of belief shocks on forecast accuracy

This table reports the effect of negative belief shocks on analysts' forecast accuracy. The dependent variable in columns (1) to (3) is the (signed) forecast error, which is computed as in Equation (3). The dependent variable in columns (4) to (6) is the PMAFE, which is computed as in Equation (2). All of the specifications control for the stock × fiscal year-quarter fixed effects by demeaning all of the variables within firm-quarters. I also control for calendar year-quarter and analyst × stock fixed effects. In columns (1) and (4), I estimate Equation (10). In the other columns, I estimate Equation (11) to examine the effects of positive and negative belief shocks separately, but only report the coefficients on the negative shock, as those on the positive shock are negligible. In columns (3) and (6), the negative and positive belief shock variables are replaced by the indicator variable of the bottom decile (D1) and top decile (D10), respectively. Standard errors are two-way clustered at the calendar year-quarter and analyst × stock level, and the corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Forecast Errors			PMAFE		
	(1)	(2)	(3)	(4)	(5)	(6)
Belief Shock	0.147***			−0.228***		
	(3.203)			(−6.819)		
Negative Shock		0.270***			−0.217***	
		(2.960)			(−5.774)	
D1			−0.049***			0.048***
			(−3.859)			(6.076)
Overall experience	−0.002**	−0.002**	−0.002**	−0.001	−0.001	−0.001
	(−2.177)	(−2.190)	(−2.179)	(−0.765)	(−0.766)	(−0.768)
Firm experience	−0.003**	−0.003**	−0.003**	−0.003***	−0.003***	−0.003***
	(−2.092)	(−2.105)	(−2.102)	(−2.767)	(−2.769)	(−2.747)
Number of industries	−0.002	0.006	0.003	0.010**	0.010**	0.006
	(−0.320)	(0.797)	(0.514)	(2.067)	(2.045)	(1.206)
Number of stocks	−0.010*	−0.010**	−0.010**	−0.011**	−0.011**	−0.011**
	(−1.905)	(−1.982)	(−1.972)	(−2.403)	(−2.404)	(−2.329)
Brokerage size	−0.014***	−0.014***	−0.014***	−0.005*	−0.005*	−0.005**
	(−5.671)	(−5.653)	(−5.681)	(−1.944)	(−1.941)	(−1.964)
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,423,192	1,423,192	1,423,192	1,423,192	1,423,192	1,423,192
R^2	0.187	0.187	0.187	0.170	0.170	0.170

Table IV: Impact of shocks to unrelated industries

This table shows how industry relatedness affects my results for the period from 1996 to 2015. Two industries are considered unrelated if they have different three-digit NAICS code industries, have no supplier-customer links, and do not compete in the same product market. In both panels, the dependent variables are the adjusted EPS forecast in columns (1) to (3) and forecast errors in columns (4) to (6). The specifications correspond to those in columns (2), (5), and (6) from Table II and those in columns (1) to (3) from III. Panel A estimates the effect of belief shocks resulting exclusively from unrelated industries for firms with at least one analyst who covers an unrelated industry, while Panel B estimates the effects of shocks to related and unrelated industries simultaneously for analysts who cover both related and unrelated industries. All of the specifications include the stock × fiscal year-quarter (by demeaning all of the variables within firm-quarters), calendar year-quarter, and analyst × stock fixed effects. Standard errors are two-way clustered at the calendar year-quarter and analyst × stock level, and the corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Subsample of firms with at least one analyst who covers an unrelated industry.

	Adjusted EPS Forecast			Forecast Errors		
	(1)	(2)	(3)	(4)	(5)	(6)
Belief Shock (Unrelated)	0.024			0.030		
	(0.900)			(1.230)		
Negative Shock (Unrelated)		0.123^{*}			0.130^{**}	
		(1.671)			(2.017)	
D1 (Unrelated)			-0.026^{**}			-0.027^{***}
			(-2.477)			(-2.593)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,031,484	1,031,484	1,031,484	1,031,484	1,031,484	1,031,484
R^2	0.196	0.196	0.196	0.190	0.190	0.190

Panel B: Subsample of analysts who cover both related and unrelated industries.

	Adjusted EPS Forecast			Forecast Errors		
	(1)	(2)	(3)	(4)	(5)	(6)
Belief Shock (Related)	0.090^{*}			0.095^{**}		
	(1.904)			(2.310)		
Belief Shock (Unrelated)	0.019			0.021		
	(0.756)			(1.009)		
Negative Shock (Related)		0.206^{**}			0.218^{**}	
		(2.134)			(2.512)	
Negative Shock (Unrelated)		0.104^{*}			0.099^{**}	
		(1.851)			(1.983)	
D1 (Related)			-0.041^{***}			-0.037^{***}
			(-2.985)			(-2.902)
D1 (Unrelated)			-0.024^{**}			-0.024^{***}
			(-2.570)			(-2.695)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	474,943	474,943	474,943	474,943	474,943	474,943
R^2	0.160	0.160	0.160	0.151	0.151	0.151

Table V: Impact of belief shocks on forecast revisions

This table reports the effect of belief shocks on analysts' forecast revisions. In columns (1) and (2), the dependent variable is the number of forecast revisions issued by analyst i for firm j regarding fiscal year-quarter t. The negative and positive belief shock variables are computed over the period from the earnings announcement date of fiscal year-quarter $t-1$ to that of fiscal year-quarter t. In columns (3) and (4), the dependent variable is the magnitude of forecast revision, which is measured as the standardized unexpected forecast (SUF) computed as in Stickel (1992). The belief shock variables in column (3) are computed over the period between the announcement date of analyst i's most recent forecast for firm j in quarter t and the announcement date of her previous forecast for the same firm and fiscal quarter. The dummy variables D1 and D10 in column (4) indicate the bottom and top deciles, respectively, of the belief shock variable computed in column (3). In columns (5) and (6), the dependent variable is the cumulative abnormal returns around the announcement of analyst i's forecast revision. All of the specifications include stock × fiscal year-quarter (by demeaning all variables within firm-quarters), calendar year-quarter, and analyst × stock fixed effects, and all of the control variables from Table II. Standard errors are two-way clustered at the calendar year-quarter and analyst × stock level, and the corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Number of Revisions		Forecast Revision		CAR(0,1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Negative Shock	0.004		0.464***		−0.003	
	(0.227)		(5.040)		(−0.650)	
Positive Shock	0.006		0.298***		0.002	
	(0.249)		(3.998)		(0.527)	
D1		−0.005		−0.063***		0.001
		(−1.105)		(−7.141)		(1.415)
D10		−0.000		0.027***		0.000
		(−0.093)		(2.795)		(0.559)
Forecast revision					0.002***	0.002***
					(11.683)	(11.649)
Overall experience	−0.002**	−0.002**	0.002	0.002	0.000	0.000
	(−2.083)	(−2.085)	(1.273)	(1.271)	(0.600)	(0.599)
Firm experience	0.015***	0.015***	−0.003	−0.003	−0.000	−0.000
	(12.198)	(12.200)	(−1.278)	(−1.260)	(−0.808)	(−0.806)
Number of industries	−0.016***	−0.016***	−0.003	−0.001	−0.000	0.000
	(−3.651)	(−3.624)	(−0.241)	(−0.106)	(−0.023)	(0.015)
Number of stocks	0.044***	0.044***	−0.010	−0.010	−0.000	−0.000
	(9.114)	(9.121)	(−0.970)	(−0.978)	(−0.062)	(−0.074)
Brokerage size	0.035***	0.035***	0.009*	0.009*	0.000	0.000
	(12.567)	(12.568)	(1.718)	(1.723)	(0.382)	(0.376)
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,423,192	1,423,192	314,693	314,742	314,693	314,742
R^2	0.225	0.225	0.251	0.250	0.314	0.314

Table VI: Robustness tests

This table shows the robustness of my baseline results to an alternative weighting scheme when constructing the belief shock variable, to different subperiods in my sample, and to alternative industry classifications. For brevity, I only present coefficients of interest, and I suppress the control variables. In Panel A, the baseline estimates in the first row refer to columns (2), (5), and (6) from Table II, and I reestimate the corresponding specifications in those columns with the adjusted EPS forecast as the dependent variable. In Panel B, the baseline estimates refer to columns (1) to (3) from Table III, and I reestimate the corresponding specifications in those columns with signed forecast errors as the dependent variable. I first present the results of belief shocks computed by using equal weighting for the industries in Equation (6). I then show the coefficient estimates when restricting the sample to four different subperiods. Furthermore, I consider five alternative industry classifications: Fama-French 12 industries, GICS industries (three-digit), industries based on two-digit SICH codes, and the Hoberg and Phillips (2016) 10-K text-based 50 industry classification (FIC-50). I compute the belief shock variable using those five alternative industry definitions. Standard errors are two-way clustered at the calendar year-quarter and analyst × stock level, and the corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Adjusted EPS forecast as the dependent variable

	Table II: (2)	Table II: (5)		Table II: (6)		
	Belief Shock	Negative Shock	Positive Shock	D1	D10	Obs.
Baseline (FF49)	0.138**	0.274***	-0.019	-0.046***	-0.001	1,423,192
	(2.548)	(2.723)	(-0.355)	(-3.201)	(-0.189)	
Alternative weight:						
Equal weighting (FF49)	0.138**	0.274***	-0.018	-0.046***	-0.001	1,423,192
	(2.568)	(2.724)	(-0.329)	(-3.209)	(-0.149)	
Subperiods:						
Pre-Reg FD: 1993-2000	0.111*	0.234**	0.026	-0.034*	0.009	281,574
	(1.711)	(2.117)	(0.289)	(-1.832)	(0.727)	
Post-Reg FD: 2001-2006	0.116	0.368***	-0.177	-0.052**	-0.003	344,654
	(1.563)	(2.681)	(-1.641)	(-2.430)	(-0.250)	
Financial crisis: 2007-2009	0.130	0.213	-0.063	-0.050*	-0.009	223,218
	(1.414)	(1.591)	(-0.690)	(-1.941)	(-0.643)	
Post-crisis: 2010-2016	0.168***	0.290**	0.078	-0.037***	0.006	573,746
	(2.709)	(2.473)	(1.145)	(-2.630)	(0.804)	
Alternative industry classifications:						
Fama-French 12	0.118**	0.220*	0.007	-0.023**	0.007	1,423,192
	(2.080)	(1.912)	(0.103)	(-2.007)	(0.911)	
GICS industry	0.087**	0.220***	-0.006	-0.034***	0.001	1,411,961
	(2.434)	(2.602)	(-0.205)	(-3.183)	(0.154)	
Two-digit SIC	0.129***	0.279**	0.026	-0.046***	0.007	1,423,192
	(2.579)	(2.292)	(0.620)	(-3.957)	(1.082)	
Hoberg-Phillips 50	0.096**	0.263**	-0.016	-0.035***	-0.004	1,271,360
	(2.100)	(2.331)	(-0.402)	(-2.887)	(-0.567)	

Panel B: Forecast errors as the dependent variable

	Table III: (1)	Table III: (2)		Table III: (3)		
	Belief Shock	Negative Shock	Positive Shock	D1	D10	Obs.
Baseline (FF49)	0.156***	0.287***	0.006	-0.050***	0.001	1,423,192
	(3.118)	(2.905)	(0.127)	(-3.521)	(0.168)	
Alternative weight:						
Equal weighting (FF49)	0.157***	0.287***	0.007	-0.050***	0.001	1,423,192
	(3.133)	(2.903)	(0.148)	(-3.525)	(0.198)	
Subperiods:						
Pre-Reg FD: 1993-2000	0.097	0.255*	-0.013	-0.041*	0.002	281,574
	(1.231)	(1.722)	(-0.140)	(-1.750)	(0.181)	
Post-Reg FD: 2001-2006	0.177*	0.420**	-0.104	-0.063**	0.007	344,654
	(1.702)	(2.067)	(-0.912)	(-2.041)	(0.737)	
Financial crisis: 2007-2009	0.117	0.169	-0.004	-0.044*	-0.007	223,218
	(1.362)	(1.254)	(-0.070)	(-1.767)	(-0.685)	
Post-crisis: 2010-2016	0.190**	0.335**	0.084	-0.043***	0.003	573,746
	(2.565)	(2.468)	(1.185)	(-2.647)	(0.486)	
Alternative industry classifications:						
Fama-French 12	0.137***	0.258**	0.005	-0.029***	0.003	1,423,192
	(2.636)	(2.337)	(0.084)	(-2.628)	(0.392)	
GICS industry	0.097***	0.224***	0.008	-0.036***	0.003	1,411,961
	(2.899)	(2.729)	(0.311)	(-3.654)	(0.476)	
Two-digit SIC	0.145***	0.299***	0.038	-0.045***	0.008	1,423,192
	(3.207)	(2.663)	(1.029)	(-4.095)	(1.537)	
Hoberg-Phillips 50	0.106***	0.254**	0.007	-0.038***	-0.003	1,271,360
	(2.514)	(2.386)	(0.193)	(-3.222)	(-0.514)	

Table VII: Heterogeneous effects of negative belief shocks

This table reports the heterogeneous effects of negative belief shocks on analysts' expectations. I divide the sample into firms with different levels of information asymmetry. Specifically, I break down my sample in three ways: firms in high-tech industries (code 3 in Fama-French 5 industries) versus firms in other industries, small firms (with below-median market capitalization) versus big firms, and young firms (with IPO in less than 10 years) versus mature firms. I reestimate the specification of column (5) from Table II in Panel A and column (2) from Table III in Panel B. For brevity, I only report the coefficient estimates of the negative belief shocks, and I suppress the coefficient estimates of the positive shocks and control variables. All of the regression models are estimated with stock × fiscal-year quarter (demeaning variables within firm-quarters), calendar year-quarter, and analyst × stock fixed effects for each subsample. Standard errors are two-way clustered at the calendar year-quarter and analyst × stock level. The corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Adjusted EPS forecast as the dependent variable

	Subsample					
	High Tech	Other	Small	Big	Young	Mature
	(1)	(2)	(3)	(4)	(5)	(6)
Negative Shock	0.417***	0.210**	0.267***	0.260***	0.295***	0.255***
	(3.668)	(2.281)	(2.741)	(2.830)	(2.858)	(2.675)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	324,045	1,099,147	711,424	711,768	450,763	972,429
R^2	0.236	0.182	0.213	0.176	0.252	0.185

Panel B: Forecast errors as the dependent variable

	Subsample					
	High Tech	Other	Small	Big	Young	Mature
	(1)	(2)	(3)	(4)	(5)	(6)
Negative Shock	0.399***	0.225***	0.268***	0.270***	0.352***	0.241***
	(3.202)	(2.603)	(2.794)	(2.967)	(3.210)	(2.594)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	324,045	1,099,147	711,424	711,768	450,763	972,429
R^2	0.228	0.176	0.208	0.168	0.245	0.178

Table VIII: Analysts with different numbers of coverage industries

This table reports the heterogeneous effects of negative belief shocks on analysts covering different numbers of industries. In both panels, I split the sample based on the number of industries an analyst covers, and I reestimate the specification of column (5) from Table II in Panel A and column (2) from Table III in Panel B. For brevity, I only report the coefficient estimates of the negative belief shocks, and suppress the coefficient estimates of the positive shocks and control variables. I first use the full sample to demean all of the independent variables within each firm-quarter to control for stock × fiscal year-quarter fixed effects and then estimate the regression models with those demeaned variables, calendar year-quarter, and analyst × stock fixed effects for each subsample. Standard errors are two-way clustered at the calendar year-quarter and analyst × stock level. The corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Adjusted EPS forecast as the dependent variable

	Number of industries					
	$n = 2$	$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n \geq 7$
Negative Shock	0.297***	0.386**	0.373***	0.520***	0.282*	0.358**
	(3.473)	(2.564)	(2.880)	(3.464)	(1.823)	(2.174)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	319,300	249,656	203,437	147,843	97,967	160,219
R^2	0.267	0.292	0.300	0.305	0.312	0.244

Panel B: Forecast errors as the dependent variable

	Number of industries					
	$n = 2$	$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n \geq 7$
Negative Shock	0.299***	0.408***	0.352***	0.471***	0.384***	0.349**
	(3.804)	(2.846)	(2.638)	(3.079)	(2.769)	(2.441)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	319,300	249,656	203,437	147,843	97,967	160,219
R^2	0.262	0.286	0.294	0.295	0.306	0.237

Table IX: Belief shocks and earnings surprises

In Panel A of this table, I decompose belief shocks into one component capturing shocks to industries in which the analyst was on average surprised by the actual earnings and another component capturing shocks to industries in which the analyst was not surprised. In Panel B, I contrast industry shocks with firm-level idiosyncratic shocks by including belief shock variables based on firm-level stock market performance as additional control variables to my baseline specifications with belief shock variables based on industry-level performance. In both panels, the dependent variable is the EPS forecast in columns (1) to (3) and forecast errors in columns (4) to (6). The specifications correspond to those in columns (2), (5), and (6) from Table II and those in columns (1) to (3) from III. All of the specifications include the stock × fiscal year-quarter (by demeaning all of the variables within firm-quarters), calendar year-quarter, and analyst × stock fixed effects. Standard errors are two-way clustered at the calendar year-quarter and analyst × stock level, and the corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Industries with and without earnings surprises

	Adjusted EPS Forecast			Forecast Errors		
	(1)	(2)	(3)	(4)	(5)	(6)
Belief Shock (w/ surprise)	0.081***			0.084***		
	(2.956)			(3.308)		
Belief Shock (w/o surprise)	0.076**			0.085***		
	(2.167)			(2.665)		
Negative Shock (w/ surprise)		0.137***			0.141***	
		(2.886)			(2.998)	
Negative Shock (w/o surprise)		0.145**			0.145**	
		(2.203)			(2.369)	
D1 (w/ surprise)			−0.026***			−0.030***
			(−2.829)			(−3.354)
D1 (w/o surprise)			−0.031***			−0.032***
			(−3.084)			(−3.323)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,423,192	1,423,192	1,423,192	1,423,192	1,423,192	1,423,192
R^2	0.194	0.194	0.194	0.187	0.187	0.187

Panel B: Industry shocks versus idiosyncratic firm-level shocks

	Adjusted EPS Forecast			Forecast Errors		
	(1)	(2)	(3)	(4)	(5)	(6)
Belief Shock (industry-level)	0.076			0.095**		
	(1.619)			(2.157)		
Belief Shock (stock-level)	0.063***			0.057***		
	(5.993)			(6.603)		
Negative Shock (industry-level)		0.196**			0.206**	
		(2.238)			(2.335)	
Negative Shock (stock-level)		0.069***			0.067***	
		(4.197)			(4.846)	
D1 (industry-level)			−0.033***			−0.038***
			(−2.903)			(−3.249)
D1 (stock-level)			−0.035***			−0.035***
			(−5.592)			(−6.399)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,423,192	1,423,192	1,423,192	1,423,192	1,423,192	1,423,192
R^2	0.194	0.194	0.194	0.187	0.187	0.187

Table X: Influence of analyst experience and brokerage house

This table shows whether analysts' experience or employers reduces the impact of overgeneralization. The dependent variable is the adjusted EPS forecast in columns (1-3), signed forecast errors in columns (4-6), and the absolute value of forecast errors in columns (7-9). I reestimate the specifications of column (5) from Table II and columns (2) and (5) from Table III, and I additionally interact the negative belief shock variable with, respectively, analysts' overall experience, firm experience, and brokerage firm size. All of the specifications include the stock × fiscal year-quarter (by demeaning all variables within firm-quarters), calendar quarter, and analyst × stock fixed effects. Standard errors are two-way clustered at the calendar year-quarter and analyst × stock level, and the corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Adjusted EPS Forecast			Forecast Errors			PMAFE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Negative Shock	0.230**	0.256***	0.209*	0.270***	0.270***	0.258***	−0.233***	−0.224***	−0.220***
	(2.308)	(2.814)	(1.942)	(2.733)	(2.909)	(2.668)	(−5.148)	(−5.989)	(−3.777)
Negative Shock × Overall experience	0.005			−0.000			0.003		
	(1.301)			(−0.005)			(0.970)		
Negative Shock × Firm experience		0.003			0.000			0.002	
		(0.505)			(0.009)			(0.548)	
Negative Shock × Broker size			0.014			0.003			0.001
			(0.802)			(0.205)			(0.057)
Overall experience	−0.002**	−0.002**	−0.002**	−0.002**	−0.002**	−0.002**	−0.000	−0.001	−0.001
	(−2.334)	(−2.468)	(−2.470)	(−2.227)	(−2.190)	(−2.192)	(−0.669)	(−0.766)	(−0.767)
Firm experience	−0.003*	−0.003*	−0.003*	−0.003**	−0.003**	−0.003**	−0.003***	−0.003***	−0.003***
	(−1.755)	(−1.699)	(−1.760)	(−2.104)	(−2.050)	(−2.107)	(−2.767)	(−2.708)	(−2.767)
Brokerage size	−0.015***	−0.015***	−0.015***	−0.014***	−0.014***	−0.015***	−0.005*	−0.005*	−0.006*
	(−5.181)	(−5.172)	(−4.450)	(−5.654)	(−5.652)	(−5.321)	(−1.945)	(−1.944)	(−1.947)
Number of industries	0.008	0.008	0.008	0.006	0.006	0.006	0.010**	0.010**	0.010**
	(1.121)	(1.123)	(1.122)	(0.797)	(0.797)	(0.798)	(2.044)	(2.049)	(2.045)
Number of stocks	−0.009	−0.009	−0.009	−0.010**	−0.010**	−0.010**	−0.011**	−0.011**	−0.011**
	(−1.595)	(−1.592)	(−1.589)	(−1.981)	(−1.982)	(−1.979)	(−2.405)	(−2.404)	(−2.402)
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,423,192	1,423,192	1,423,192	1,423,192	1,423,192	1,423,192	1,423,192	1,423,192	1,423,192
R^2	0.194	0.194	0.194	0.187	0.187	0.187	0.170	0.170	0.170

Table XI: Impact on analyst disagreement, trading volumes, and return volatilities

This table reports the effects of analyst overgeneralization on the differences of opinions about the stock and on stock volatility. In columns (1-2), the dependent variable is the forecast dispersion, which is computed as the standard deviation of EPS forecasts scaled by the absolute value of the mean EPS forecast for each stock j and fiscal year-quarter t. I further define investigation windows as the period between the announcement date of the first analyst forecast and the announcement date of the actual earnings for firm j and fiscal year-quarter t. In columns (3-4), the dependent variable is the trading volume, which is computed as the logarithm of the average daily stock trading volume within the corresponding investigation window. In columns (5-6), the dependent variable is the realized equity volatility as the standard deviation of daily stock returns within the corresponding investigation window. In columns (7-8), the dependent variable is the option-implied volatility from Option Metrics averaged over the corresponding investigation window. Both measures are annualized. All of the specifications include the firm and calendar quarter fixed effects. Calendar quarter is the year-quarter in which the firm announces its realized earnings of fiscal year-quarter t. Detailed definitions of the control variables are presented in Table A1. Standard errors are two-way clustered at the firm and calendar year-quarter level, and the corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Forecast Dispersion		Trading Volume		Realized Volatility		Implied Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief Shock Dispersion	0.332***	0.376***	1.233***	0.725***	0.291***	0.269***	0.250***	0.252***
	(5.089)	(6.375)	(11.302)	(7.682)	(7.134)	(7.702)	(6.662)	(8.097)
Log(MVE)		−0.063***		0.373***		−0.052***		−0.071***
		(−7.586)		(18.615)		(−6.435)		(−10.155)
Book-to-Market		0.219***		−0.050		−0.068***		−0.045***
		(7.686)		(−0.974)		(−5.041)		(−3.654)
ROA		−0.667***		0.220*		−0.343***		−0.326***
		(−6.482)		(1.855)		(−7.590)		(−8.346)
Number of analysts		0.005***		0.028***		0.001***		0.000
		(6.406)		(15.594)		(2.706)		(0.924)
% Multi-Industry		0.103***		0.116***		0.041***		0.014***
		(10.565)		(7.288)		(11.308)		(4.027)
Market volatility						0.013***		0.008***
						(11.616)		(8.578)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	191,726	175,665	191,726	175,665	191,726	175,665	134,541	123,695
R^2	0.202	0.210	0.872	0.899	0.668	0.679	0.746	0.771

Table XII: Impact of negative belief shocks on earnings announcement returns

This table shows the impact of analysts' negative belief shocks on the focal firms' stock returns. The dependent variable is the three-day (-1, +1) market-adjusted cumulative abnormal return around the firm's earnings announcement date. The estimation results in columns (1) and (2) are based on the full sample. Column (2) includes the firm and industry × calendar year-quarter fixed effects. In columns (3) to (5), I focus on the subsample of high-tech firms (code 3 in Fama-French 5 industries), small firms (with below-median market capitalization), and young firms (with IPO in less than 10 years), respectively. Standard errors are two-way clustered at the firm and calendar year-quarter level, and the corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	EA CAR(-1, 1)				
	(1)	(2)	(3)	(4)	(5)
All negative shocks	0.023***	0.019**	0.034**	0.023**	0.026*
	(2.716)	(1.980)	(2.212)	(2.130)	(1.863)
Earnings surprise	0.013***	0.013***	0.013***	0.013***	0.012***
	(33.948)	(32.180)	(19.536)	(27.963)	(19.881)
Log(MVE)	−0.001**	−0.012***	−0.016***	−0.015***	−0.019***
	(−2.511)	(−14.449)	(−8.777)	(−13.037)	(−11.869)
Book-to-Market	0.004**	−0.006**	−0.011**	−0.011***	−0.013***
	(2.284)	(−2.503)	(−1.994)	(−3.221)	(−2.652)
ROA	0.038***	−0.049***	−0.055**	−0.055***	−0.056***
	(5.820)	(−5.167)	(−2.466)	(−4.663)	(−4.225)
Number of analysts	0.000	0.000	0.000	0.000	−0.000
	(1.496)	(0.157)	(0.769)	(1.147)	(−1.153)
% Multi-Industry	−0.003***	−0.002	−0.008**	−0.003*	−0.005**
	(−2.846)	(−1.571)	(−2.292)	(−1.798)	(−2.049)
Industry × Year-Quarter FE	No	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes
Sample	Full	Full	High Tech	Small	Young
Observations	175,031	175,031	36,547	88,501	65,964
R^2	0.030	0.131	0.131	0.170	0.194

Appendix

A Variable Descriptions

Table A1: Variable descriptions

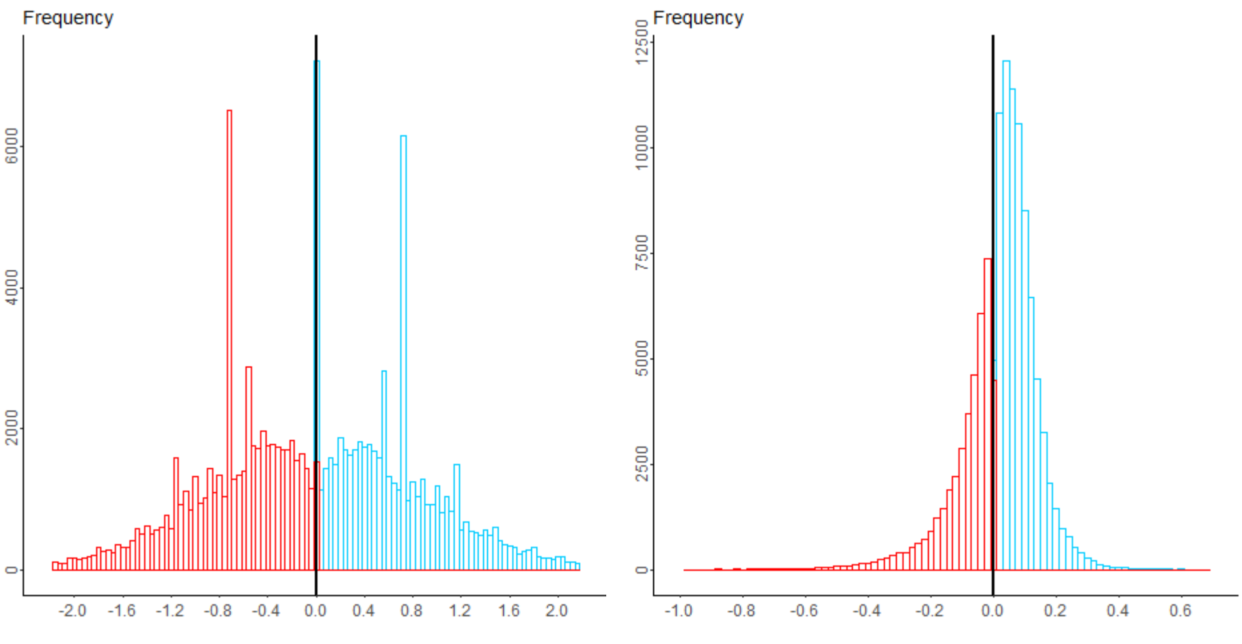
Variable	Description
Dependent variables	
EPS forecast	Earnings per share forecasts demeaned and scaled within each firm-fiscal quarter group, computed as in Equation (1) (winsorized at the 1% and 99% levels).
Forecast errors	Raw eps forecast minus actual earnings, demeaned and scaled within each firm-fiscal quarter group, computed as in Equation (3) (winsorized at the 1% and 99% levels).
PMAFE	Absolute value of forecast errors, demeaned and scaled within each firm-fiscal quarter group, computed as in Equation (2) (winsorized at the 1% and 99% levels).
Number of revisions	Logarithm of one plus the total number of forecasts issued by the same analyst for the same firm and fiscal quarter.
Forecast revision	Magnitude of forecast revision measured as the standardized unexpected forecast (SUF) computed as in (Stickel, 1992) (winsorized at the 1% and 99% levels).
CAR(0, 1)	Market-adjusted cumulative announcement return over the window (0, 1) around the analyst's revision date (winsorized at the 1% and 99% levels).
Explanatory variables	
Belief Shock	Shocks to analyst belief, constructed using Fama-French 49 industries (see Section 3.2).
Belief Shock (EW)	Belief shocks constructed using Fama-French 49 industry and equal-weighting.
Belief Shock (Unrelated)	Belief shocks constructed using three-digit NAICS industries, which are arguably unrelated to the industry of the focal firm, as explained in section 4.2.2.
Belief Shock (Related)	Belief shocks constructed using related three-digit NAICS industries, as explained in section 4.2.2.
Belief Shock (FF12)	Belief shocks constructed using Fama-French 12 industries.
Belief Shock (GICS)	Belief shocks constructed using three-digit GICS industries.
Belief Shock (Sic2)	Belief shocks constructed using two-digit historical SIC industries.
Belief Shock (HP50)	Belief shocks constructed using Hoberg-Phillips 50 industries.
Control variables	
Overall experience	The overall experience computed as the number of years between an analyst's current earnings forecast and his/her first forecast for any firm.
Firm experience	The firm-specific experience computed as the number of years between an analyst's current earnings forecast and his/her first forecast covering a given stock.
Number of stocks	Logarithm of one plus the number of stocks covered by the analyst in a given year.
Broker size	Logarithm of one plus the number of analysts employed by the brokerage house in a calendar year plus one.
Number of industries	Logarithm of one plus the number of Fama-French 49 industries covered by the analyst in a given year.
Number of industries (FF12)	Logarithm of one plus the number of Fama-French 12 industries covered by the analyst in a given year.
Number of industries (GICS)	Logarithm of one plus the number of three-digit GICS industries covered by the analyst in a given year .

Number of industries (Sic2)	Logarithm of one plus the number of two-digit historical SIC industries covered by the analyst in a given year.
Number of industries (HP50)	Logarithm of one plus the number of Hoberg-Phillips 50 industries covered by the analyst in a given year.
Number of industries (Naics)	Logarithm of one plus the number of three-digit NAICS industries covered by the analyst in a given year.
Firm-quarter level variables	
Belief shock dispersion	The standard deviation of the belief shock variables within each pair of firm j and fiscal quarter t.
All negative shocks	The sum of the absolute value of negative belief shocks of all analysts covering firm j for fiscal quarter t, scaled by the total number of analysts.
Forecast dispersion	The standard deviation of EPS forecasts scaled by the absolute value of the mean EPS forecast, for each firm j and fiscal quarter t (winsorized at the 1% and 99% levels).
Trading volume	The logarithm of the average daily stock trading volume in the period between the earnings announcement date of fiscal quarter t and that of fiscal quarter $t-1$ (winsorized at the 1% and 99% levels).
Realized volatility	The standard deviation of daily stock returns in the period between the earnings announcement date of fiscal quarter t and that of fiscal quarter $t-1$ (winsorized at the 1% and 99% levels).
Implied volatility	The average daily volatility implied from options with a maturity of 30 days in the OptionMetrics database, over the period between the earnings announcement date of fiscal quarter t and that of fiscal quarter $t-1$ (winsorized at the 1% and 99% levels).
EA CAR(-1, 1)	Market-adjusted cumulative announcement return over the window (-1, 1) around the firm's earnings announcement date (winsorized at the 1% and 99% levels).
Earnings surprise	Actual earnings minus the consensus, divided by the absolute value of the consensus (winsorized at the 1% and 99% levels).
Market value of equity (mln)	The product of total shares outstanding and fiscal quarter closing stock price.
Book-to-market	Book value of equity divided by the current market value of equity (winsorized at the 1% and 99% levels).
ROA	The operating income before depreciation divided by the lagged total assets (winsorized at the 1% and 99% levels).
Number of analysts	Number of analysts following a particular stock in a given quarter
% Multi-industry	The fraction of analysts who follow multiple Fama-French 49 industries for each stock and quarter.
Market volatility	Average daily VIX index in the same period as when realized and implied volatility are computed.

B Initial coverage and belief shocks

This appendix provides evidence supporting the identification assumption that analysts' coverage decisions are not driven by bad performance of the other coverage industries. I first identify coverage initiated as when an analyst issues her first earnings forecast on a particular stock (since 1995), and I then examine the distribution of these initial forecasts adjusted within firm-quarters and the corresponding belief shocks prior to those forecasts. If my results are driven by pessimistic analysts initiating coverage following negative belief shocks, I would observe that (1) analysts' initial forecasts are more pessimistic relative to their peers; and (2) more of the corresponding belief shocks take negative values. Figure A1 depicts the histogram of the forecasts and belief shocks at initial coverage, respectively. As is shown, while there is no obvious bias in the initial forecasts, the corresponding belief shocks are biased towards positive values. In fact, about 48.7% of the initial forecasts are relatively pessimistic, whereas only 34.2% of the belief shocks are negative. This finding suggests that, even though analysts endogenously choose coverage, this selection is unlikely to contaminate my results.

Figure A1: Histogram of the adjusted earnings forecasts and belief shocks at initial coverage



Panel A: Adjusted earnings forecasts

Panel B: Value of belief shocks

C Effects of lagged belief shocks

The results in Table III suggest that analysts make less accurate forecasts, which is more in line with the noise channel than with the information channel. However, it may be that the information that analysts acquire takes time to influence focal firms, which will help analysts make forecasts in the future. In this case, even though their current forecasts are inaccurate (which is the analysts' mistake for using the information too soon), their future forecasts would be more accurate. To test this possibility, I examine the effects of lagged belief shocks on analysts' EPS forecasts and forecast errors in Table A2. As is shown, lagged belief shocks have no significant impact on analysts' forecasts or their accuracy, which is inconsistent with the notion that analysts learn information from industry shocks that is useful in the future.

Table A2: Lagged belief shocks

This table reports the effects of lagged belief shocks on analysts' EPS forecasts and forecast errors. The dependent variables are the EPS forecast in columns (1-4), signed forecast errors in columns (4-8), and PMAFE columns (9-12). I reestimate specification (5) from Table II, and columns (2) and (5) from Table III by replacing current belief shocks with lagged belief shock variables. For brevity, I only report the coefficients on the lagged negative shock variables, as those on the positive shocks are negligible. All of the specifications control for the stock × fiscal year-quarter (by demeaning all variables), calendar year-quarter, and analyst × stock fixed effects. Standard errors are two-way clustered at the calendar year-quarter and analyst × stock level, and the corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Adjusted EPS Forecast				Forecast Errors				PMAFE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Negative Shock (Lag 1)	−0.005			−0.048	−0.021			−0.053	−0.002			0.007
	(−0.238)			(−1.268)	(−1.092)			(−1.601)	(−0.085)			(0.277)
Negative Shock (Lag 2)		0.051		0.053		0.043		0.036		0.018		−0.004
		(1.345)		(1.369)		(1.295)		(0.979)		(0.769)		(−0.137)
Negative Shock (Lag 3)			−0.023	−0.021			−0.026	−0.025			−0.004	−0.001
			(−0.703)	(−0.583)			(−0.935)	(−0.827)			(−0.215)	(−0.065)
Overall experience	−0.001	−0.001	−0.000	−0.001	−0.001	−0.001	−0.000	−0.000	0.000	−0.000	0.001	0.001
	(−0.649)	(−0.579)	(−0.283)	(−0.281)	(−0.569)	(−0.476)	(−0.015)	(−0.020)	(0.048)	(−0.076)	(0.802)	(0.747)
Firm experience	−0.004**	−0.004**	−0.005**	−0.005**	−0.003**	−0.004**	−0.004**	−0.004*	−0.003***	−0.004***	−0.004***	−0.004***
	(−2.166)	(−2.003)	(−2.124)	(−2.038)	(−2.262)	(−2.143)	(−1.984)	(−1.951)	(−2.770)	(−2.905)	(−2.630)	(−2.587)
Number of industries	0.003	−0.001	−0.007	−0.010	−0.001	−0.007	−0.011	−0.013	0.007	0.007	0.012	0.011
	(0.403)	(−0.113)	(−0.620)	(−0.721)	(−0.195)	(−0.785)	(−1.087)	(−1.085)	(1.248)	(0.983)	(1.330)	(1.092)
Number of stocks	−0.018**	−0.019**	−0.022**	−0.021**	−0.014**	−0.015**	−0.019**	−0.018**	−0.017***	−0.021***	−0.020**	−0.020**
	(−2.387)	(−2.136)	(−2.155)	(−1.966)	(−2.259)	(−2.062)	(−2.233)	(−2.052)	(−2.714)	(−2.912)	(−2.435)	(−2.321)
Brokerage size	−0.015***	−0.012***	−0.013***	−0.013***	−0.013***	−0.012***	−0.012***	−0.012***	−0.002	−0.003	−0.001	−0.001
	(−4.277)	(−3.188)	(−2.879)	(−2.659)	(−4.319)	(−3.252)	(−2.871)	(−2.639)	(−0.606)	(−0.802)	(−0.277)	(−0.224)
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,032,928	779,799	602,726	602,726	1,032,928	779,799	602,726	602,726	1,032,928	779,799	602,726	602,726
R^2	0.213	0.224	0.232	0.232	0.206	0.217	0.224	0.224	0.186	0.195	0.202	0.202

D Overreaction to past forecast errors

The results in Tables II and III imply that negative shocks to other industries lead analysts to make incorrectly pessimistic forecasts for the focal firms. However, one potential concern is that this finding is driven by analysts who overreact to their past forecast errors. Specifically, recall the example from the introduction. If the negative shock to the transportation industry also disrupts the earnings of COAL Corp in 2011Q2, which surprises analyst A who is overoptimistic about COAL (assuming analyst B not surprised), analyst A might overreact to this individual signal and become subsequently overpessimistic about COAL in 2011Q3. This overcorrection could for example happen if analyst A forms a diagnostic expectation (Bordalo et al., 2018a,b). As a result, his forecast error is negatively correlated with his forecast error at the first lag, and my results might capture this correlation.

To address this concern, I additional control for the forecast errors from the previous fiscal quarter in columns (2,5-6) from Table II and in columns (1-3) from Table III. The results are shown in Table A3. The estimated coefficients on one-quarter lagged forecast errors are significantly negative, implying that analysts make more pessimistic forecasts if their forecasts for the previous fiscal quarters are overoptimistic, and vice versa. This is consistent with the implications of diagnostic expectations that analysts overcorrect their past forecast errors. Nevertheless, after controlling for the analyst overcorrection, the magnitude and statistical significance of the coefficients on belief shock variables are virtually the same as those in the baseline, which mitigates the concern that my main results are driven by analysts' overcorrection for past errors.

Table A3: Controlling for the effects of past forecast errors

This table reports the effects of belief shocks on adjusted EPS forecast in columns (1-3) and on signed forecast errors, after controlling for the effects of past forecast errors. Standard errors are two-way clustered at the calendar year-quarter and analyst × stock level, and the corresponding t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Adjusted EPS Forecast			Forecast Errors		
	(1)	(2)	(3)	(4)	(5)	(6)
Belief Shock	0.132***			0.139***		
	(2.662)			(2.969)		
Negative Shock		0.268***			0.265***	
		(2.830)			(2.831)	
Positive Shock		−0.025			−0.005	
		(−0.509)			(−0.117)	
D1			−0.047***			−0.049***
			(−3.788)			(−3.873)
D10			0.001			−0.000
			(0.127)			(−0.006)
Forecast errors (Lag 1)	0.012***	0.012***	0.012***	−0.009**	−0.009**	−0.009**
	(2.902)	(2.898)	(2.902)	(−2.218)	(−2.221)	(−2.219)
Overall experience	−0.002**	−0.002**	−0.002**	−0.002*	−0.002*	−0.002*
	(−2.079)	(−2.080)	(−2.079)	(−1.835)	(−1.837)	(−1.837)
Firm experience	−0.003*	−0.003*	−0.003*	−0.003**	−0.003**	−0.003**
	(−1.758)	(−1.772)	(−1.766)	(−2.160)	(−2.182)	(−2.169)
Number of industries	−0.002	0.007	0.003	−0.006	0.001	−0.001
	(−0.254)	(0.839)	(0.436)	(−0.954)	(0.199)	(−0.160)
Number of stocks	−0.012*	−0.013**	−0.012**	−0.011*	−0.011*	−0.011*
	(−1.910)	(−1.998)	(−1.968)	(−1.869)	(−1.959)	(−1.938)
Brokerage size	−0.015***	−0.015***	−0.015***	−0.014***	−0.014***	−0.014***
	(−4.848)	(−4.827)	(−4.862)	(−5.187)	(−5.168)	(−5.197)
Stock × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,254,215	1,254,215	1,254,215	1,254,215	1,254,215	1,254,215
R^2	0.195	0.195	0.195	0.187	0.187	0.187