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# Analyst bias and forecast consistency

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**Abstract**

We contribute to the literature examining inconsistent analyst forecast revisions. While prior research suggests inconsistent analyst forecasts are less accurate, we find this result is sensitive to both the definition and direction of inconsistency. We define consistency relative to each analyst's own forecast error and find the relation between analyst characteristics and the likelihood of issuing an inconsistent forecast differs depending on the direction of the revision. Specifically, less accurate analysts are more likely to issue an inconsistent positive revision and have higher future accuracy than their consistent counterparts. Our results suggest that analysts derive a benefit (better future accuracy) from issuing upward forecast revisions in the period immediately following an earnings announcement regardless of the resulting forecast pattern.

*Key words*: Analyst forecast revision; Forecast accuracy; Forecast optimism; Forecast inconsistency

*JEL classification*: G24

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## 1. Introduction

In this study, we create a new measure of analyst forecast consistency which allows us to consider forecast consistency on an individual analyst basis and explore whether consistency, paired with the direction of the forecast, has consequences vis-à-vis the analyst's future accuracy. Analyst consistency has

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previously been examined principally within three contexts. First, prior research indicates that analysts herd and suggests that forecasts that are inconsistent with those of the analyst's peers are costly (Trueman, 1994; Hong *et al*., 2000; Clement and Tse, 2005; Jegadeesh and Kim, 2010). Second, Dong *et al*. (2015) and Lobo *et al*. (2017) examine analyst consistency relative to other information (stock returns and earnings announcements, respectively) and find evidence that inconsistent forecasts are less accurate and less informative to the market, supporting the concept that inconsistent forecasts are costly. A third body of literature focuses on an analyst's consistency with his/her own other outputs (Trueman, 1994; Raedy *et al*., 2006; Brown and Huang, 2013; Hilary and Hsu, 2013) and finds inconsistent forecasts to be costly in terms of accuracy, reputation and career concerns.

We create a new consistency measure in which we define an inconsistent forecast as one that runs counter to the individual analyst's latest forecast error for the same firm. Specifically, we compare the direction of firm $i$'s earnings surprise for period $t$ (relative to analyst $j$'s last earnings estimate for period $t$) to analyst $j$'s forecast revision for period $t + 1$. For example, if firm $i$ reveals earnings of \$0.12 for which the analyst had previously forecasted earnings of \$0.11 (\$0.13), the news appears to be positive (negative). If the analyst then revises her forecast for firm $i$ for the subsequent period upward (downward) reflecting the positive (negative) news, we consider the analyst's revision to be consistent.[1]

This measure of consistency uses the analyst's own forecast as the benchmark for both earnings surprise and the direction of forecast revision, allowing us to observe the individual analyst's forecast pattern, a growing field of interest. Other papers investigating the importance of individual analyst characteristics include Park and Stice (2000) who observe that capital market participants can recognise differences in analyst forecast ability. Additionally, Hilary and Hsu (2013) find that analysts following a consistent pattern of bias (that is more likely to be unravelled by investors) are more likely to be nominated to the *Institutional Investor* All-Star list and are less likely to be demoted. Additionally, Kirk *et al*. (2014) find that key individual analyst forecasts provide an additional benchmark for investors. Our consistency measure allows us to examine individual forecast patterns and contribute to this stream of research.

Given that much of the prior research finds forecast inconsistency (albeit, defined differently) is costly in terms of career concerns, accuracy and ability to move the market, we are first interested in which analysts choose to issue forecasts that are inconsistent with their own prior forecast. We are agnostic as to the costliness or value of inconsistent forecasts and acknowledge that an analyst's decision to issue an inconsistent forecast is likely not of primary importance to the analyst; we assume that updating his/her forecast based

[1]We discuss other previously used measures of consistency in more detail in Section 2.

on new information is the main goal of a forecast revision. However, given that the majority of forecast revisions are not inconsistent, we conjecture that the analyst does consider the message that an inconsistent forecast sends to the market. On one hand, investors may view inconsistent forecasts as indicative of an analyst's error or lack of knowledge and view them negatively. Alternatively, an analyst willing to issue an inconsistent forecast may be considered bolder or more confident in her knowledge or ability which investors may view positively. Therefore, we view the relation between analyst characteristics and the likelihood of issuing inconsistent forecasts as an empirical question.

In addition to utilising a measure of consistency that allows us to address individual analyst forecasting patterns, we turn another dial relative to the related studies. As mentioned earlier, Dong *et al.* (2015) and Lobo *et al.* (2017) each investigate inconsistent forecasts using different definitions of consistency and conclude that inconsistent forecasts are costly. However, neither study addresses the direction of the inconsistent forecasts. Given that prior literature finds analysts have incentives to provide both optimistically and pessimistically biased forecasts (horizon-dependent), we argue that the direction of an inconsistent revision is likely to play a role in the decision and outcome. In addressing our research question, we investigate whether the direction of the inconsistent forecast is informative.

Using a sample of 87,991 analyst firm-year forecast revisions, we investigate the analyst-specific determinants of issuing a forecast revision that is inconsistent with the analyst's previous forecast and the latest earnings news. Controlling for other factors and information likely to influence the analyst's forecast revision and reflect the information environment, we find that the results differ depending on the direction of the forecast revision. We find evidence that previously less accurate analysts are only more likely to issue an inconsistent upward forecast revision but not an inconsistent downward revision. We also find that more frequent forecasters are more likely to issue inconsistent negative revisions and that 'lead' analysts are less likely to issue inconsistent negative revisions. Those with more firm-specific experience are less likely to issue inconsistent forecasts of either direction. Our results are consistent with the direction of the inconsistency being an important consideration when investigating inconsistent forecasts.

Second, given these results, we investigate whether inconsistent forecasts, conditioned on the direction of the inconsistency, are associated with future analyst accuracy. We find that when the earnings surprise is negative, analysts that issue an inconsistent positive revision have better future accuracy than analysts who issue a consistent negative revision. On the other hand, when the earnings surprise is positive, analysts that issue an inconsistent negative revision are ultimately less accurate than their consistent counterparts (who issue a positive revision). These first two results together suggest that less accurate analysts may issue an inconsistent positive revision in an attempt to curry favour with management as a means to gaining access to better information.

Third, we investigate the relation between inconsistent forecasts and future forecast bias. We find that inconsistent forecasters in both directions tend to have pessimistic biases in the future period, although the relation between inconsistent negative revisions and pessimism is, not surprisingly, more significant. This may suggest that analysts provide an inconsistent negative forecast in order to allow firms to meet-or-beat (MBE) their forecasts (Richardson *et al.*, 2004). However, as mentioned earlier, inconsistent negative forecasts are ultimately less accurate, which suggests that although the forecasts allow for a greater possibility of MBE, they do not appear to result in better information access.

Our results contribute to the literature investigating forecast consistency and individual analyst forecasting patterns. First, we construct a measure of consistency that allows us to focus on an individual analyst's forecast pattern. Second, while prior studies examine the consistency of forecast revisions without examining the direction of inconsistency (Dong *et al.*, 2015; Lobo *et al.*, 2017), our paper joins the concept of consistency with the concept of forecast bias (Hong and Kubik, 2003; Ke and Yu, 2006, among others).

Our results do not provide evidence that analysts issuing inconsistent forecasts are less accurate across the board as suggested by previous studies. Instead, analysts appear to derive a net benefit (in terms of forecast accuracy) from issuing positive revisions even if the revisions are inconsistent with the forecast error. This result suggests that analysts who issue positive revisions in the (+1, +7) window around an earnings announcement are likely to have better access to management. Taken together, these results highlight the multitude of factors analysts likely consider when issuing a forecast. On one hand, analysts may weigh the potential costs and benefits associated with a monotonic forecast revision pattern (Raedy *et al.*, 2006) versus the costs and benefits associated with a positive revision (better access to management) regardless of the resulting forecast pattern. Capital market participants may benefit from these results as they update their expectations based upon individual analyst forecast revisions. Specifically, investors may be able to tease additional information out of forecasts issued by analysts who issue upward revisions in the (+1, +7) window.

The remainder of the paper proceeds as follows: Section 2 describes the background and setting; Section 3 identifies the research question; Section 4 details the sample and model; in Section 5 we present the results of the empirical analyses; and Section 6 concludes.

## 2. Background and setting

### 2.1. *Analyst consistency: alternative meanings in the literature*[2]

Prior studies define consistency in ways that allow the researchers to best address their research questions. For example, Trueman (1994) illustrates analytically and Raedy *et al.* (2006) show empirically that analysts have incentives to under-react to information to issue subsequent revisions that follow a consistent pattern. Raedy *et al.* (2006) use the serial correlation of the forecast errors to illustrate the consistency of forecast revisions as the forecast horizon decreases and argues that an asymmetric loss function explains the forecast under-reaction.

Our paper is most like two recent papers examining consistent forecasts: Dong *et al.* (2015) and Lobo *et al.* (2017). Dong *et al.* (2015) examine analyst forecast revisions that are inconsistent with the stock returns. They define an inconsistent revision as one in which the sign of the analyst revision is inconsistent with that of the prior stock returns, drawing on the literature that finds that prior stock returns are positively associated with analyst forecast revisions (Lys and Sohn, 1990; Cooper *et al.*, 2001; Clement *et al.*, 2011). The direction of the analyst's forecast revision is based on the difference between the individual analyst's forecast and the consensus forecast in the 20–25 days prior. Similar to our study, Dong *et al.* (2015) examine the determinants and accuracy of inconsistent revisions. They find that inconsistent forecasts are more likely to be made by analysts with fewer resources and that the forecasts are less informative to the market.

Lobo *et al.* (2017) investigate the earnings response to 'reinforcing' versus 'contradicting' analyst forecast revisions that occur contemporaneously with the earnings announcement. They identify a 'reinforcing' analyst forecast revision as one that follows the same direction as unexpected earnings. They identify the direction of the analyst forecast revision by comparing the analyst consensus forecast for year $t + 1$ occurring at the year $t$ earnings announcement date (0, +1) to the consensus forecast for year $t + 1$ occurring in the 30 days prior to the year $t$ earnings announcement date. They define the direction of the unexpected earnings based on the difference between the year $t$ earnings per share (EPS) and the most recent analyst forecast occurring prior to the year $t$ earnings announcement date. Thus, their study focuses on the direction of the consensus revision relative to the most recent analyst's forecast. They find that reinforcing revisions are associated with higher market reaction.

[2]In this section we address only alternative meanings of consistency that relate to our research question and design. Other studies examining analyst consistency (i.e., Brown and Huang, 2013; Hilary and Hsu, 2013), are only tangentially related to our research question and are not elaborated on in this paper.

Thus, while our paper investigates the determinants and future accuracy of inconsistent forecasts, our measure allows us to examine analyst-specific forecasting patterns under the assumption that some investors follow individual analysts and attempt to unravel analyst forecasting patterns. Additionally, we turn another dial on the Dong *et al*. (2015) and Lobo *et al*. (2017) studies by investigating differences in the direction of the revision inconsistency.[3]

### 2.2. Costs versus benefits of inconsistent forecasts

The literature on analyst consistency continues to evolve and has yet to provide uniform inferences about the role of consistency in analysts' decision-making processes; however, much of the research suggests inconsistent forecasts are costly in terms of accuracy, market impact and career concerns. As described above, prior literature finds that consistent forecasts are more accurate (Dong *et al*., 2015) and garner a larger market response (Dong *et al*., 2015; Lobo *et al*., 2017); however, these conclusions are based on slightly different measures of consistency.

Other studies suggest that consistency is not necessarily beneficial for all analysts. Loh and Stulz (2011) find that analysts who break away from the herd are more likely to issue an 'influential' forecast. In our setting, we do not place any expectation on whether inconsistent forecasts are costly or beneficial.

### 2.3. Directional bias and our setting

Given that a large stream of literature finds that analysts are incentivised to issue biased forecasts (McNichols and O'Brien, 1997; Lin and McNichols, 1998; Gu and Wu, 2003; Hong and Kubik, 2003; Richardson *et al*., 2004; Ke and Yu, 2006), it is likely that analysts consider the direction of the forecast (pessimistic or optimistic relative to their prior forecast for that firm-year), when issuing an inconsistent forecast. We therefore argue that any investigation of analyst forecast patterns needs to control for or separate forecast revisions based on their direction. To our knowledge, no existing study examining analyst forecast revision consistency addresses the direction of the inconsistency.

By design, we examine forecast revisions for year $t + 1$ that occur in the week following the earnings announcement date for year $t$. This point is pertinent given that analysts may be more or less likely to issue optimistic versus pessimistic forecasts at varying points of the forecast period. The literature on

[3]In earlier versions of the paper, we used the same setting as Lobo *et al*. (2017) and Dong *et al*. (2015) wherein we examined forecast revisions only occurring on or immediately after the earnings announcement date (0, +1). In order to increase our sample size and ensure analysts have access and time to process earnings announcement information, we change our sample setting to (+1, +7) following the earnings announcement. Our results are qualitatively similar.

analyst forecast bias suggests that analysts issue optimistically biased forecasts in the long run and pessimistically biased forecasts in the short run (Richardson *et al.*, 2004; Hutton, 2005; Cotter *et al.*, 2006). Skinner and Sloan (2002) find that firms that miss earnings based on earnings forecasts made within a month of the earnings announcement date face larger penalties than the rewards provided to firms that achieve earnings goals. Bartov *et al.* (2002) find evidence that the market provides a premium for firms that meet-or-beat earnings targets even when analysts revise their forecasts late in the period. Therefore, the direction of a forecast revision is also an important consideration to analysts.

Prior literature also finds that analysts tend to issue serially correlated forecasts (i.e., under-reacting to news to move forecasts in a consistent direction) (Raedy *et al.*, 2006), which suggests that the direction of an early revision may likely be the same direction as subsequent forecast revisions for the analyst-firm-year.

## 3. Research question

A large stream of literature relates analyst characteristics to forecast characteristics. For example, several studies examine the link between analyst characteristics and forecast accuracy and find that firm-specific experience, brokerage size, number of firms and industries followed are predictive of analyst forecast accuracy (Mikhail *et al.*, 1997; Clement, 1999; Jacob *et al.*, 1999; among others). Other studies examine the link between analyst characteristics and forecast bias. Lim (2001) finds that analysts employed by smaller brokerage firms or with more experience are more likely to be positively biased, whereas Dugar and Nathan (1995) and Hong and Kubik (2003) find that forecasts issued by analysts working for a firm's underwriter are more likely to issue optimistic forecasts. Another stream examines analyst characteristics and herding behaviour. Hong *et al.* (2000) and Clarke and Subramanian (2006) find analysts with less experience are more likely to herd. These documented relations between analyst characteristics and forecast qualities provide an opportunity for investors to process analyst forecasts more fully. Following this line of research, we are interested in whether analyst characteristics are associated with an analyst's decision to issue a forecast that is inconsistent with other contemporaneously issued news.

Prior literature suggests some associations between analyst characteristics and inconsistent forecasts as a whole. On one hand, prior research suggests that analysts incur costs when issuing inconsistent forecasts. Dong *et al.* (2015) finds that analysts issuing inconsistent forecasts are less accurate, have fewer resources, a greater workload and are less likely to be *Institutional Investor* All-Stars, suggesting that 'better' analysts are less likely to issue inconsistent forecasts. Although Dong *et al.* (2015) define consistency differently, we do not discount this association as a possibility. As such, 'better' analyst characteristics may be negatively associated with inconsistent revisions.

Alternatively, prior studies examine 'bold' forecasts, defined as those that are both above (below) the analyst's own prior forecast and the consensus forecasts, suggesting the analyst has access to new or additional information. Clement and Tse (2005) find that boldness is associated with better past accuracy, larger employing brokerage house, greater experience and a smaller number of firms followed. Additionally, they find that bold forecasts are more accurate than herding forecasts. This suggests that an analyst may be willing to go out 'on a limb' when they have better information than the herd. As such, the characteristics associated with bold forecasts (better past accuracy, larger employing brokerage house, greater experience, smaller number of firms followed) might also be associated with inconsistent forecasts.

Hilary and Hsu (2013) argue that analyst forecasts that are consistently biased are more useful than forecasts that have better stated accuracy because investors can more easily unravel systematic biases. They find that consistently biased analysts are more likely to achieve *Institutional Investor* All-Star status and are less likely to be demoted. If analysts are rewarded for issuing consistently biased forecasts, they may choose to follow the same forecast pattern from period to period for the same firm, regardless of earnings news. If this is the case, we would expect to see a predictable pattern of optimism or pessimism, which might explain an inconsistent forecast revision.

The existing literature also suggests that certain analyst characteristics are associated with directional forecast bias. Therefore, we consider inconsistent forecasts separately by direction, which is one of the innovations of our paper. Therefore, our first research question is:

> *RQ1: Are analyst characteristics associated with the likelihood of issuing an inconsistent forecast when separating inconsistencies by direction?*

### *3.1. Bad news followed by a positive revision*

First, we investigate whether analyst characteristics are associated with an analyst choosing to issue a positive revision when the firm issues 'bad news' (a negative earnings surprise relative to the individual analyst's last forecast for the firm) (Figure 1, Panel A). In examining this issue, we consider and control for other performance-related variables that suggest the overall news in the earnings announcement is more positive than expected, such as: positive stock returns, a positive sales surprise, and whether or not the announced earnings were greater than the consensus forecast. Holding these variables constant, we ask if there are analyst characteristics that might be predictive of an analyst's decision to issue an inconsistent positive forecast revision.

As discussed above, it is *ex ante* unclear what analyst characteristics are predictive of an analyst issuing an upward revision following a negative earnings surprise given the prior literature on inconsistent and bold forecasts.

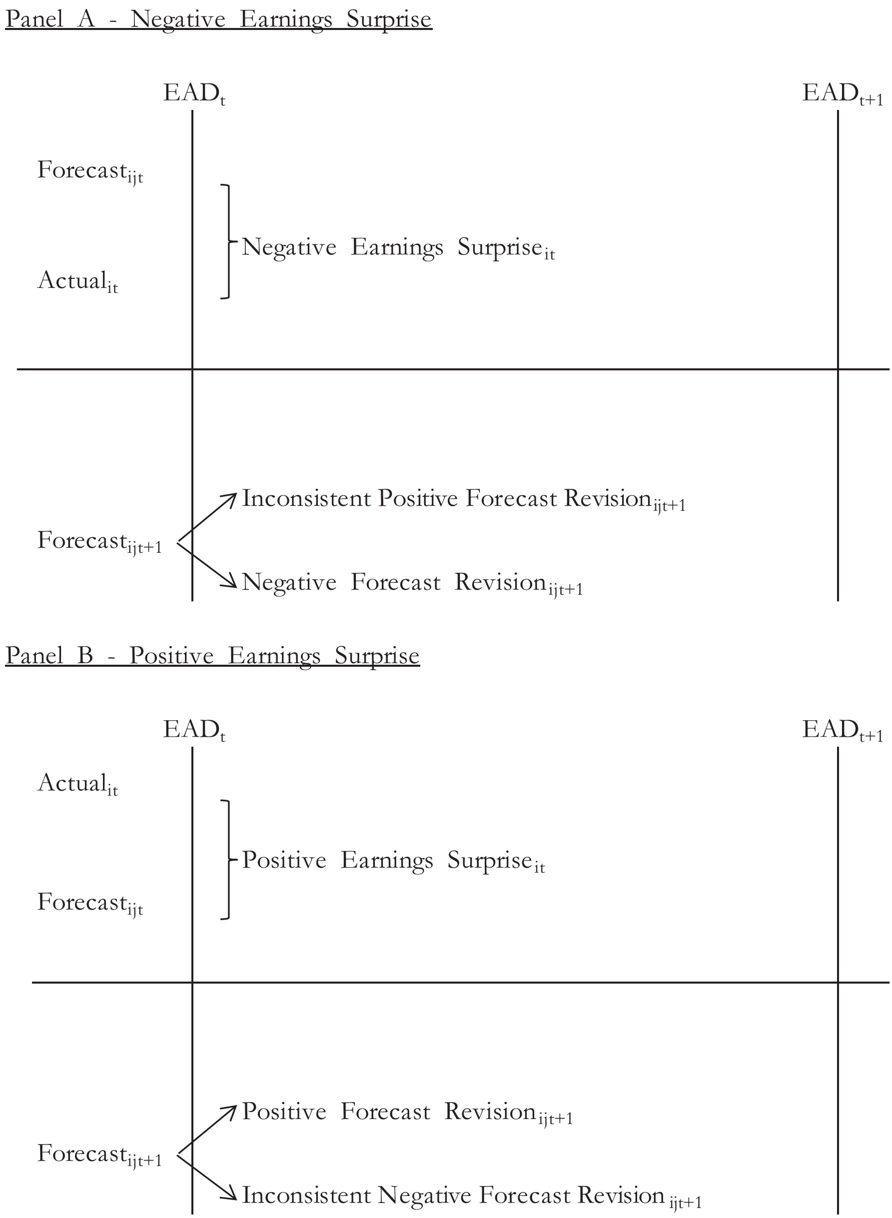


Figure 1 Negative and positive earnings surprises.
*Note:* We examine earnings forecast revisions for year $t$+1 that occur in the window (+1, +7) around the earnings announcement date (EAD) for year $t$.

Table 1
Frequency of inconsistent forecasts

| | | *InconPosRev* | | *InconNegRev* | |
|---|---|---|---|---|---|
| Year | Total | *N* | % | *N* | % |
| 1994 | 1,510 | 151 | 10.0% | 285 | 18.9% |
| 1995 | 1,858 | 187 | 10.1% | 352 | 19.0% |
| 1996 | 2,192 | 205 | 9.4 | 515 | 23.5% |
| 1997 | 2,292 | 200 | 8.7 | 516 | 22.5% |
| 1998 | 2,740 | 211 | 7.7 | 693 | 25.3% |
| 1999 | 2,966 | 228 | 7.7 | 748 | 25.2% |
| 2000 | 2,660 | 251 | 9.4 | 535 | 20.1% |
| 2001 | 2,500 | 177 | 7.1 | 739 | 29.5% |
| 2002 | 3,526 | 423 | 12.0% | 976 | 27.7% |
| 2003 | 3,177 | 248 | 7.8 | 1,014 | 31.9% |
| 2004 | 4,010 | 470 | 11.7% | 879 | 21.9% |
| 2005 | 4,070 | 401 | 9.9 | 1,081 | 26.6% |
| 2006 | 4,244 | 358 | 8.4 | 1,245 | 29.3% |
| 2007 | 4,341 | 386 | 8.9 | 1,196 | 27.6% |
| 2008 | 4,120 | 332 | 8.1 | 1,207 | 29.3% |
| 2009 | 4,126 | 253 | 6.1 | 1,568 | 38.0% |
| 2010 | 4,653 | 394 | 8.5 | 1,137 | 24.4% |
| 2011 | 5,351 | 522 | 9.8 | 1,200 | 22.4% |
| 2012 | 4,879 | 441 | 9.0 | 1,355 | 27.8% |
| 2013 | 4,913 | 433 | 8.8 | 1,498 | 30.5% |
| 2014 | 4,923 | 426 | 8.6 | 1,584 | 32.2% |
| 2015 | 4,849 | 339 | 7.0 | 1,678 | 34.6% |
| 2016 | 4,462 | 323 | 7.2 | 1,441 | 32.3% |
| 2017 | 3,629 | 326 | 9.0 | 1,019 | 28.1% |
| Total | 87,991 | 7,684 | 8.7 | 24,464 | 27.8% |

*InconPosRev* = The number and percentage of inconsistent analyst forecast revisions in the year where the firm has a negative earnings surprise for year $t$ (relative to analyst $j$'s last revision for year $t$) and is accompanied by analyst $j$'s upward (relative to analyst $j$'s last revision for firm $i$ for year $t + 1$) revision in the (+1, +7) window around the earnings announcement for year $t$;
*InconNegRev* = The number and percentage of inconsistent analyst forecast revisions in the year where the firm has a positive earnings surprise for year $t$ (relative to analyst $j$'s last revision for year $t$) and is accompanied by analyst $j$'s downward (relative to analyst $j$'s last revision for firm $i$ for year $t + 1$) revision in the (+1, +7) window around the earnings announcement for year $t$.

We also consider the findings in Jackson (2005), which suggest that analysts have incentives to provide optimistically biased forecasts, especially at the beginning of a period. Given that our sample is composed of relatively 'early' forecasts for period $t + 1$, an analyst may issue an upward or optimistic forecast to garner management approval (Francis and Philbrick, 1993; Dechow *et al.*, 2000; Lim, 2001; Ke and Yu, 2006), regardless of the sign of the earnings surprise. It may be that analysts trade off any cost of issuing an inconsistent forecast with the benefits gained by issuing an optimistic forecast when faced with bad news. This action is likely to be constrained, however, if analysts face asymmetric loss functions (Raedy *et al*., 2006) and are likely to under-react to news to allow for serially correlated forecast errors.

As the prior literature provides contradicting expectations regarding whether 'better' analysts issue consistent versus optimistically biased forecasts, we do not place an expectation on the direction of variables generally considered indicative of 'better' analysts.

### 3.2. *Good news followed by a negative revision*

In this scenario, an analyst is faced with 'good' news about a company (the earnings surprise for year $t$ is positive relative to the analyst's last forecast for year $t$), but the analyst chooses to issue a negative revision for the following period (Figure 1, Panel B). As with inconsistent positive revisions, we do not have a clear set of expectations about analyst characteristics and inconsistent negative revisions given the results from prior literature considering inconsistent and bold forecasts.

However, it may be that analysts that revise their forecasts downward at the beginning of the period are doing so to start a negative revision cycle allowing management to meet-or-beat the forecast at the end of the period (Bartov *et al*., 2002; Skinner and Sloan, 2002) and therefore issuing an inconsistent negative revision may not be associated with low-quality analyst characteristics.

## 4. Sample and model

To provide some context for our analyses, Table 1 details the total number of annual analyst forecast revisions made within one week of a firm's earnings announcement in the years 1994–2017. Our sample is similar in nature to that in Lobo *et al*. (2017).[4] We find that 36.5 percent ((7,684 + 24,464)/87,991) of the one-year ahead EPS analyst revisions are inconsistent with the nature of the news revealed in the earnings announcement in our sample period. Lobo *et al*. (2017) find the percentage of 'contradicting' forecast revisions to be 33.8 percent over the period 1994–2014. These percentages are different due to differing time periods, differing definitions of consistent forecasts and the fact

[4]Lobo *et al*. (2017) compare actual earnings to the most recent analyst forecast to determine unexpected earnings, whereas we compare actual earnings to each analyst's most recent forecast to capture unexpected earnings. Lobo *et al*. (2017) compare the consensus analyst forecast in the window (0, +1) to the consensus 30 days prior to the earnings announcement date to determine the forecast revision. We compare each analyst's forecast in the window (+1, +7) to each analyst's prior forecast to determine the forecast revision. We limit the prior forecast to 30 days prior to the earnings announcement date in the robustness section of the paper.

that their sample is at the firm-year level while our sample is at the individual analyst forecast level. However, the fact that inconsistent or contradicting forecasts make up significantly less than half of the forecasts suggests that these are not the norm in either case.

Of the 87,991 forecast revisions, between 6.1 and 12.0 percent (18.9 and 38.0 percent) of the yearly forecast revisions are inconsistent positive (negative) revisions. There does not appear to be a discernible pattern in the percentage of contradicting forecasts; however, the ratio of inconsistent negative revisions to inconsistent positive revisions is significantly higher in 2009 than in all other years in the sample. This coincides with the global financial crisis in 2009 and overall scepticism may account for an increase in negative revisions following positive news; however, further analysis is beyond the scope of this paper.[5]

We use the following logistic regression model (all variables are defined in Appendix A) to answer our research question:

$$\begin{aligned} P(InconPosRev/InconNegRev) = \theta(\alpha &+ \beta_1 AvgFCAcc + \beta_2 FExp + \beta_3 BSize \\ &+ \beta_4 Freq + \beta_5 Follow + \beta_6 LFR + \beta_7 InitPess \\ &+ \beta_8 Ret + \beta_9 PSalesSur + \beta_{10} MBECon \\ &+ \beta_{11} ROA + \beta_{12} Size + \beta_{13} MTB \\ &+ \beta_{14} PDACC + \beta_{15} FCAcc + \beta_{16} FCAge) \end{aligned} \tag{1}$$

### 4.1. Bad news followed by a positive revision

The dependent variable (*InconPosRev*) is equal to one when the analyst issues an inconsistent positive forecast revision when the earnings for year $t$ is less than the analyst's last forecast for year $t$.

We control for other news that may explain why analysts would issue a positive forecast revision. We include one day returns on the earnings announcement date (EAD) (*Ret*), which provides information about how the market perceives the earnings news and other news contained within the earnings announcement following Dong *et al*. (2015). We also include variables to capture whether the firm's actual sales beat the analyst's sales forecast (*PSalesSur*), if the firm meets-or-beats the consensus (*MBECon*), and *ROA*. The expected signs on the control variables differ depending on the direction of the inconsistency. We expect positive coefficients on *Ret*, *PSalesSur*, *MBECon* and *ROA* when the dependent variable is inconsistent positive news because the news may suggest a positive change to expected future cash flows.

Additionally, we control for firm-specific information that is likely to affect the information environment and incentives related to the management of the

[5]As discussed in the robustness section of the paper, we eliminate all observations from 2008 and 2009 with qualitatively similar results.

firm: *Size* (Richardson *et al.*, 2004) and *MTB*. If the size of the company influences the analyst's motives to curry favour with management and issue a positive revision, we expect the coefficient on *Size* to be positive. We include *MTB* as a control variable as growth firms may be more difficult to forecast. We also include the use of positive abnormal accruals (*PDACC*) (Dechow *et al.*, 1995) to allow for timing differences in the recognition of revenue. We expect a negative coefficient on *PDACC* when the dependent variable is an inconsistent positive revision.

We control for the analyst's forecast accuracy for year *t* (*FCAcc*) because the amount of the earnings surprise may affect the likelihood of an analyst issuing an inconsistent revision. We do not hypothesise the direction of this relation. If a larger forecast error signals poor ability or resources, an analyst may not want to draw further attention to himself with an inconsistent forecast. On the other hand, to remedy a larger forecast error, an analyst may need to issue an inconsistent forecast. We also control for the age of the last revision for year *t* (*FCAge*) as more recent forecasts are more accurate (O'Brien, 1988).

Our independent variables of interest are analyst-related factors that have been shown to be associated with other forecast characteristics, as discussed previously. We examine whether these characteristics are associated with the decision to issue an inconsistent positive revision. We include past accuracy (*AvgFCAcc*), firm-specific experience (*FExp*), employer size (*BSize*), forecast frequency (*Freq*), and whether the analyst is a leader (*LFR*). *AvgFCAcc* is defined as the absolute value of analyst *j*'s average forecast error for firm *i* over the past three years. *FExp* is the number of years analyst *j* is associated with the firm as of year *t*. *BSize* is the number of analysts employed at the analyst's brokerage in year *t*. *Freq* is number of forecasts analyst *j* issues for firm *i* in year *t*. We calculate the leader-follower ratio (*LFR)* following Shroff *et al.* (2014) as discussed in Appendix B. Lead analysts issue forecasts earlier and often have better information. These may be bolder analysts so they may be more or less likely to issue inconsistent forecasts. We include the number of firms followed (*Follow*) in year *t* because Drake and Myers (2011) find that analysts who follow fewer firms are better able to understand the role high accruals play in future earnings, suggesting these analysts have more resources to process information or superior access to management.

Positive coefficients on *FExp*, *BSize*, *Freq*, *LFR* and negative coefficients on *Follow* and *AvgFCAcc* would indicate that analysts with better information, ability or resources are more likely to issue inconsistent positive forecasts.

We also include a measure, *InitPess*, to capture whether the analyst considers her initial forecast for year *t* when revising her forecast for year $t + 1$. We assign *InitPess* a value of '1' when the analyst's original forecast for year *t* for firm *i* was pessimistic relative to the revealed actual earnings. We expect a positive coefficient on *InitPess* when the dependent variable is a negative earnings surprise.

### 4.2. Good news followed by a negative revision

Also using Model (1), we set the dependent variable equal to one when the analyst issues an inconsistent negative forecast revision (*InconNegRev*) when the earnings for year $t$ is more than the analyst's last forecast for year $t$. We expect different signs on the control variables. We expect negative coefficients on *Ret*, *PSalesSur*, *MBECon* and *ROA* to reflect that positive changes in these variables may suggest positive changes in the firm's underlying value, reducing the likelihood of issuing a negative revision. Additionally, if analysts are less likely to issue downward revisions for more prestigious firms, we expect a negative coefficient on *Size*. If firms achieve a positive earnings surprise due to use of income-increasing discretionary accruals, analysts may interpret good news in a negative way; therefore, we expect a positive coefficient on *PDACC*.

Again, positive coefficients on *FExp*, *BSize*, *Freq*, *LFR* and negative coefficients on *Follow* and *AvgFCAcc* would indicate that analysts with better information, ability or resources are more likely to issue inconsistent forecasts. We expect a negative coefficient on *InitPess* in this sample.

## 5. Empirical results

### 5.1. Univariate analyses

Table 2 provides the distribution of the variables used in the study. We truncate all continuous variables at the 1 percent level. In Panel A we provide all of the variable data in which the earnings surprise is negative. There are 27,074 (19,390 + 7,684) analyst-firm-year observations in which the firm had a negative earnings surprise (relative to the analyst's last forecast for year $t$), an analyst issued a revision in the seven days following the earnings announcement, and all data are available to run our regression analyses. Of the observations, 28.4 percent (7,684/27,074) are such that the analyst issued an inconsistent positive revision.

Comparing the subsamples in Panel A of Table 2, we observe the univariate relations between our control variables and the issuance of inconsistent positive forecast revisions. We see that less accurate analysts with more forecasting frequency and those that are less likely to be 'lead' analysts are more likely to issue inconsistent positive forecasts. Additionally, when returns are higher, when the firm meets-or-beats the consensus forecast, and the firm beats the analyst's sales forecast, analysts are more likely to issue inconsistent positive forecasts. Larger firms and growth firms are more likely to garner an inconsistent positive forecast. Newer forecasts are more likely to be inconsistently positive. Future forecast accuracy is better for inconsistent positive revisions than for consistent negative revisions.

Panel B of Table 2 illustrates the variable distribution for positive earnings surprises for consistent and inconsistent revisions. There are a larger number of

Table 2
Descriptive statistics

Distribution of main variables for each sub-sample

| | Consistent forecasts ($N$ = 19,390) | | Inconsistent forecasts ($N$ = 7,684) | | Test statistics | |
|---|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | $t$-test | Wilcoxon test |
| **Panel A: Negative earnings surprise** | | | | | | |
| *AvgFCAcc* | 0.169 | 0.061 | 0.178 | 0.064 | 0.036 | 0.193 |
| *FExp* | 4.331 | 3 | 4.299 | 3 | 0.456 | 0.406 |
| *BSize* | 14.360 | 11 | 14.171 | 12 | 0.347 | 0.439 |
| *Freq* | 2.425 | 2 | 2.533 | 2 | <0.001 | <0.001 |
| *Follow* | 14.696 | 13 | 14.779 | 14 | 0.427 | 0.697 |
| *LFR* | 3.739 | 1.650 | 3.487 | 1.574 | 0.001 | 0.008 |
| *InitPess* | 0.260 | 0 | 0.390 | 0 | <0.001 | <0.001 |
| *Ret* | −0.008 | −0.005 | 0.002 | 0.000 | <0.001 | <0.001 |
| *PSalesSur* | 0.300 | 0 | 0.356 | 0 | <0.001 | <0.001 |
| *MBECon* | 0.213 | 0 | 0.349 | 0 | <0.001 | <0.001 |
| *ROA* | 0.038 | 0.047 | 0.041 | 0.052 | 0.071 | <0.001 |
| *Size* | 7.682 | 7.607 | 8.007 | 7.988 | <0.001 | <0.001 |
| *MTB* | 3.141 | 2.354 | 3.392 | 2.563 | <0.001 | <0.001 |
| *PDACC* | 0.355 | 0 | 0.341 | 0 | 0.035 | 0.035 |
| *FCAcc* | 0.151 | 0.040 | 0.140 | 0.034 | 0.007 | <0.001 |
| *FCAge* | 4.142 | 4.511 | 4.060 | 4.443 | <0.001 | <0.001 |
| *FFCAcc* | 0.213 | 0.053 | 0.165 | 0.039 | <0.001 | <0.001 |
| *FFCErr* | −0.066 | 0.003 | −0.048 | 0.003 | <0.001 | 0.508 |

| | Consistent forecasts ($N$ = 36,453) | | Inconsistent forecasts ($N$ = 24,464) | | Test statistics | |
|---|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | $t$-test | Wilcoxon test |
| **Panel B: Positive earnings surprise** | | | | | | |
| *AvgFCAcc* | 0.126 | 0.045 | 0.135 | 0.049 | <0.001 | <0.001 |
| *FExp* | 4.305 | 3 | 4.410 | 3 | <0.001 | 0.004 |
| *BSize* | 16.025 | 12 | 15.289 | 12 | <0.001 | <0.001 |
| *Freq* | 2.286 | 2 | 2.394 | 2 | <0.001 | <0.001 |
| *Follow* | 14.561 | 13 | 14.268 | 13 | <0.001 | <0.001 |
| *LFR* | 3.860 | 1.628 | 3.681 | 1.600 | <0.001 | 0.183 |
| *InitPess* | 0.699 | 1 | 0.554 | 1 | <0.001 | <0.001 |
| *Ret* | 0.007 | 0.004 | 0.000 | −0.000 | <0.001 | <0.001 |
| *PSalesSur* | 0.482 | 0 | 0.459 | 0 | <0.001 | <0.001 |
| *MBECon* | 0.877 | 1 | 0.865 | 1 | <0.001 | <0.001 |
| *ROA* | 0.069 | 0.071 | 0.052 | 0.061 | <0.001 | <0.001 |

(continued)

Table 2 (continued)

| | Consistent forecasts ($N$ = 36,453) | | Inconsistent forecasts ($N$ = 24,464) | | Test statistics | |
|---|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | $t$-test | Wilcoxon test |
| *Size* | 8.004 | 7.985 | 7.963 | 7.921 | 0.002 | 0.000 |
| *MTB* | 3.863 | 2.953 | 3.335 | 2.512 | <0.001 | <0.001 |
| *PDACC* | 0.312 | 0 | 0.331 | 0 | <0.001 | <0.001 |
| *FCAcc* | 0.068 | 0.024 | 0.088 | 0.030 | <0.001 | <0.001 |
| *FCAge* | 4.173 | 4.522 | 4.097 | 4.511 | <0.001 | <0.001 |
| *FFCAcc* | 0.103 | 0.027 | 0.155 | 0.041 | <0.001 | <0.001 |
| *FFCErr* | −0.001 | 0.011 | −0.003 | 0.014 | <0.001 | <0.001 |

Results of $t$-tests and Wilcoxon tests are presented as $p$-values for two-tailed test.
*AvgFCAcc* = Analyst $j$'s forecast accuracy for firm $i$ calculated over the past 3 years;
*FExp* = Number of years analyst $j$ has a forecast for firm $i$ in the I/B/E/S database;
*BSize* = Number of analysts employed at analyst $j$'s brokerage in year $t$;
*Freq* = Number of forecasts analyst $j$ has for firm $i$ in year $t$;
*Follow* = Number of firms analyst $j$ follows in year $t$;
*LFR* = Leader-follower ratio for analyst $j$ (details in Appendix B);
*InitPess* = 1 if analyst $j$'s earliest forecast for firm $i$ for year $t$ issued on or after year $t-1$'s earnings announcement is lower than the actual EPS for year $t$ as revealed on the earnings announcement date;
*Ret* = One day abnormal returns for firm $i$ on earnings announcement date;
*PSalesSur* = 1 if (actual $\text{sales}_{i,t}$ − analyst sales $\text{forecast}_{i,j,t}$) > 0, 0 otherwise;
*MBECon* = 1 if firm $i$'s actual earnings for year $t$ are greater than the outstanding consensus as calculated by I/B/E/S, 0 otherwise;
*ROA* = Firm industry mean-adjusted ROA;
*Size* = Log of firm $i$'s market cap (stock price × number of outstanding shares);
*MTB* = Market value of equity divided by book value of equity for firm $i$;
*PDACC* = 1 if the firm's annual observation indicates it has positive discretionary accruals using the modified Jones model, 0 otherwise. Additional detail in Appendix B;
*FCAcc* = $|(E_{it} - F_{ijt})|/|E_{it}|$;
*FCAge* = Log of days between earning announcement date and final forecast for analyst $j$ for firm $i$ prior to the earnings announcement date;
*FFCAcc* = $|(E_{it+1} - F_{ijt+1})|/|E_{it+1}|$;
*FFCErr* = $(E_{it+1} - F_{ijt+1})/|E_{it+1}|$.

observations that exhibit positive earnings surprises ($n$ = 36,453 + 24,464 = 60,917), which is expected given the documented increased likelihood of firms meeting or beating expectations (Burgstahler and Dichev, 1997). Some 40.2 percent (24,464/60,917) of the revisions are inconsistent negative revisions.

We find that less accurate forecasters, those with more firm-specific experience, those working for a smaller brokerage firm, those who issue more forecasts, those who follow fewer firms, and those that are less likely to be a lead analyst are more likely to issue inconsistent negative forecasts. We find inconsistent negative forecasts are more associated with lower market returns, less likely to be accompanied by a positive sales surprise, and less likely when the firm meets-or-beats the consensus forecast. Smaller firms and firms that have higher positive discretionary accruals are more likely to be recipients of an inconsistent negative forecast. Older forecast revisions are more likely to be inconsistent. In this univariate setting, it appears that future forecast accuracy tends to be greater for analysts who issue consistent positive forecasts.

It is important to note that these samples may contain the same firms and same analysts in both samples and that many of these explanatory and control variables are correlated. We do not provide Table 2 to answer our research question, but to illustrate that the relation between the explanatory variables and the dependent variables differs based on the direction of the inconsistency. For example, firm experience, brokerage size and number of firms followed are statistically different between the consistent and inconsistent forecasts in the positive news sample, but we find no such difference in the negative news sample. The performance-related control variables (*Ret*, *PSalesSur*, *MBECon*, *ROA*) in each sample are associated with the direction of the forecast in each sample, not with the consistency or inconsistency of the forecast.

In Table 3 we provide the Pearson correlations to further illustrate the point that several of the variables are significantly correlated. We do not interpret the correlations as the table includes both positive and negative earnings surprise observations.

### 5.2. *Multivariate analyses*

In Table 4 we investigate the determinants of inconsistent forecast revisions using Model (1). The dependent variable is an indicator variable equal to 1 if the analyst issued an inconsistent forecast revision in the week following the earnings announcement. The first column details the results for the sample as a whole.

As discussed earlier, one of our paper's contributions to the literature is illustrating that the direction of inconsistency is important to understanding which analyst characteristics are associated with inconsistent forecasting. We mainly provide the first column to illustrate that a further breakdown is necessary and to illustrate that the magnitude of the $R^2$ is significantly higher when we break the sample down based on the direction of the inconsistency. However, it is interesting to note that the coefficients in the first column suggest that analysts with lower past accuracy, less firm experience and more frequent forecasts are more likely to issue inconsistent forecast revisions, mirroring the results in Dong *et al.* (2015).

Table 3
Pearson correlations

| Variable | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *InconFC (A)* | 1.000 | **0.008** | **0.010** | **−0.013** | **0.030** | **−0.014** | **−0.016** | **−0.030** | **−0.018** | **0.016** | **0.099** | **−0.041** | **0.025** | **−0.038** | **0.007** | **0.008** | **−0.039** | **0.008** | **0.009** |
| *AvgFCAcc (B)* | | 1.000 | **−0.136** | **−0.046** | **0.007** | **−0.027** | **−0.008** | **−0.044** | −0.003 | **−0.012** | **−0.067** | **−0.144** | **−0.165** | **−0.046** | **0.039** | **0.421** | 0.004 | **0.052** | **−0.007** |
| *FExp (C)* | | | 1.000 | **0.050** | **0.040** | **0.125** | −0.001 | **−0.026** | −0.001 | 0.001 | 0.004 | **0.046** | **0.199** | **−0.032** | **−0.012** | **−0.049** | **−0.009** | **−0.012** | 0.001 |
| *BSize (D)* | | | | 1.000 | **−0.026** | **0.113** | **0.062** | **0.008** | **0.024** | **−0.038** | **0.025** | **0.056** | **0.038** | **0.027** | 0.003 | **−0.033** | **−0.013** | **−0.011** | 0.003 |
| *Freq (E)* | | | | | 1.000 | **0.062** | **−0.065** | **−0.024** | **−0.007** | **−0.018** | **−0.030** | **0.017** | **0.154** | **−0.051** | **0.007** | **0.013** | **−0.140** | **−0.013** | **0.014** |
| *Follow (F)* | | | | | | 1.000 | **−0.007** | **−0.019** | 0.001 | **−0.168** | **−0.009** | **0.061** | **−0.011** | **−0.018** | **0.021** | **−0.015** | **0.050** | 0.003 | −0.003 |
| *LFR (G)* | | | | | | | 1.000 | 0.001 | **0.010** | **0.018** | 0.001 | **−0.009** | **−0.121** | **−0.007** | **−0.010** | **−0.011** | **0.047** | −0.003 | −0.000 |
| *InitPess (H)* | | | | | | | | 1.000 | **0.050** | **0.102** | **0.318** | **0.212** | **0.136** | **0.134** | **−0.065** | **−0.128** | **0.036** | **−0.033** | **0.018** |
| *Ret (I)* | | | | | | | | | 1.000 | **0.043** | **0.139** | **0.018** | **−0.014** | 0.004 | **−0.009** | **−0.016** | 0.005 | **−0.010** | 0.001 |
| *PSalesSur (J)* | | | | | | | | | | 1.000 | **0.128** | **−0.016** | **0.031** | **0.032** | **−0.031** | **−0.017** | **−0.026** | **−0.015** | **0.010** |
| *MBECon (K)* | | | | | | | | | | | 1.000 | **0.099** | **0.076** | **0.057** | **−0.036** | **−0.123** | **0.032** | **−0.038** | **0.025** |
| *ROA (L)* | | | | | | | | | | | | 1.000 | **0.260** | **0.169** | **−0.123** | **−0.245** | **−0.006** | **−0.038** | −0.004 |
| *Size (M)* | | | | | | | | | | | | | 1.000 | **0.258** | **−0.105** | **−0.178** | **−0.152** | **−0.048** | **0.022** |
| *MTB (N)* | | | | | | | | | | | | | | 1.000 | **−0.133** | **−0.075** | **0.014** | **−0.025** | **0.007** |
| *PDACC (O)* | | | | | | | | | | | | | | | 1.000 | **0.047** | 0.005 | **0.011** | **−0.012** |
| *FCAcc (P)* | | | | | | | | | | | | | | | | 1.000 | −0.000 | **0.072** | **−0.016** |
| *FCAge (Q)* | | | | | | | | | | | | | | | | | 1.000 | **−0.009** | −0.003 |
| *FFCAcc (R)* | | | | | | | | | | | | | | | | | | 1.000 | **−0.109** |
| *FFCErr (S)* | | | | | | | | | | | | | | | | | | | 1.000 |

Numbers in bold indicate statistical significance at 5 percent. All variable definitions can be found in Appendix A.

### 5.3. Bad news followed by a positive revision

The second column provides the coefficient estimates for the negative earnings surprise sample. The performance-related characteristics (*Ret*, *PSalesSur* and *MBECon*) all load in the expected direction except *ROA*. We attribute this to *ROA* being highly correlated with the other performance-related variables. Firm size is significant and positive suggesting that an analyst is more likely to issue an inconsistent positive revision when the firm is larger.

Table 4
Determinants of inconsistent forecast revisions

| Variables | Whole sample | Expected sign | Negative ES sample | Expected sign | Positive ES sample |
|---|---|---|---|---|---|
| Intercept | $-1.065^{***}$ | | $-1.664^{***}$ | | $-0.355^{***}$ |
| | (0.086) | | (0.154) | | (0.110) |
| **Analyst-related factors** | | | | | |
| *AvgFCAcc* | $0.082^{***}$ | ? | $0.151^{***}$ | ? | 0.031 |
| | (0.031) | | (0.054) | | (0.039) |
| *FExp* | $-0.004^{*}$ | ? | $-0.009^{*}$ | ? | $-0.008^{***}$ |
| | (0.002) | | (0.005) | | (0.003) |
| *BSize* | 0.000 | ? | −0.001 | ? | 0.000 |
| | (0.000) | | (0.001) | | (0.001) |
| *Freq* | $0.016^{***}$ | ? | 0.010 | ? | $0.015^{**}$ |
| | (0.005) | | (0.009) | | (0.006) |
| *Follow* | 0.001 | ? | 0.002 | ? | 0.001 |
| | (0.001) | | (0.002) | | (0.001) |
| *LFR* | $-0.003^{**}$ | ? | −0.001 | ? | $-0.005^{***}$ |
| | (0.001) | | (0.003) | | (0.002) |
| **Control variables** | | | | | |
| *InitPess* | $-0.234^{***}$ | + | $0.482^{***}$ | | −0.548*** |
| | (0.016) | | (0.031) | | (0.019) |
| *Ret* | $-1.807^{***}$ | + | $6.730^{***}$ | − | $-5.968^{***}$ |
| | (0.201) | | (0.388) | | (0.254) |
| *PSalesSur* | $-0.041^{**}$ | + | $0.219^{***}$ | − | $-0.199^{***}$ |
| | (0.016) | | (0.032) | | (0.019) |
| *MBECon* | $0.619^{***}$ | + | $0.548^{***}$ | − | $0.102^{***}$ |
| | (0.018) | | (0.032) | | (0.027) |
| *ROA* | $-0.599^{***}$ | + | $-0.591^{***}$ | − | $-0.550^{***}$ |
| | (0.077) | | (0.147) | | (0.098) |
| *Size* | $0.027^{***}$ | + | $0.106^{***}$ | − | 0.001 |
| | (0.005) | | (0.011) | | (0.007) |
| *MTB* | $-0.019^{***}$ | | $0.015^{***}$ | | $-0.028^{***}$ |
| | (0.003) | | (0.005) | | (0.003) |
| *PDACC* | 0.016 | − | −0.028 | + | $0.036^{*}$ |
| | (0.016) | | (0.031) | | (0.019) |

(continued)

Table 4 (continued)

| Variables | Whole sample | Expected sign | Negative ES sample | Expected sign | Positive ES sample |
|---|---|---|---|---|---|
| *FCAcc* | 0.000 | | $0.106^{**}$ | | $0.446^{***}$ |
| | (0.036) | | (0.054) | | (0.057) |
| *FCAge* | $-0.048^{***}$ | | $-0.058^{***}$ | | $-0.029^{***}$ |
| | (0.008) | | (0.016) | | (0.010) |
| Industry dummies | Included | | Included | | Included |
| Year dummies | Included | | Included | | Included |
| Sample size | 87,991 | | 27,074 | | 60,917 |
| Adj. $R^2$ | 0.044 | | 0.096 | | 0.097 |

*, **, *** indicates significance of coefficient estimates at the $p < 0.10$, $p < 0.05$ and $p < 0.01$ levels, respectively (two-tailed). The continuous variables are truncated at the 1% level. Standard errors were adjusted for both cross-sectional and serial correlation following Petersen (2009).

Model (1):

$$P(InconPosRev/InconNegRev) = \theta(\alpha + \beta_1 AvgFCAcc + \beta_2 FExp + \beta_3 BSize + \beta_4 Freq + \beta_5 Follow + \beta_6 LFR + \beta_7 InitPess + \beta_8 Ret + \beta_9 PSalesSur + \beta_{10} MBECon + \beta_{11} ROA + \beta_{12} Size + \beta_{13}\mathrm{MTB} + \beta_{14} PDACC + \beta_{15} FCAcc + \beta_{16} FCAge)$$

where the variables are defined as follows:

*InconFC* = 1 if firm *i*'s positive (negative) earnings surprise for year *t* (relative to analyst *j*'s last revision for year *t*) is accompanied by analyst *j*'s downward (relative to analyst *j*'s last revision for firm *i* for year $t + 1$) revision in the (+1, +7) window around the earnings announcement for year *t*;

*AvgFCAcc* = Analyst *j*'s forecast accuracy for firm *i* calculated over the past 3 years;

*FExp* = Number of years analyst *j* has a forecast for firm *i* in the I/B/E/S database;

*BSize* = Number of analysts employed at analyst *j*'s brokerage in year *t*;

*Freq* = Number of forecasts analyst *j* has for firm *i* in year *t*;

*Follow* = Number of firms analyst *j* follows in year *t*;

*LFR* = Leader-follower ratio for analyst *j* (details in Appendix B);

*InitPess* = 1 if analyst *j*'s earliest forecast for firm *i* for year *t* issued on or after year $t - 1$'s earnings announcement is lower than the actual EPS for year *t* as revealed on the earnings announcement date;

*Ret* = One day abnormal returns for firm *i* on earnings announcement date;

*PSalesSur* = 1 if (actual $\text{sales}_{i,t}$ − analyst sales $\text{forecast}_{i,j,t}$) > 0, 0 otherwise;

*MBECon* = 1 if firm *i*'s actual earnings for year *t* are greater than the outstanding consensus as calculated by I/B/E/S, 0 otherwise;

*ROA* = Firm industry mean-adjusted ROA;

*PDACC* = 1 if the firm's annual observation indicates it has positive discretionary accruals using the modified Jones model, 0 otherwise. Additional detail in Appendix B;

*Size* = Log of firm *i*'s market cap (stock price × number of outstanding shares);

*MTB* = Market value of equity divided by book value of equity for firm *i*;

*FCAcc* = $|(E_{it} - F_{ijt})|/|E_{it}|$;

*FCAge* = Log of days between earning announcement date and final forecast for analyst *j* for firm *i* prior to the earnings announcement date.

The coefficient on *FCAcc* is a positive 0.106 which signifies that an analyst whose forecast is less accurate is more likely to issue an inconsistent forecast than an analyst whose forecast missed the mark by a smaller amount. More recent final forecasts for year *t* are associated with a higher likelihood of an inconsistent positive forecast revision. The positive coefficient on *InitPess* is as expected.

Most analyst-specific characteristics are not associated with the likelihood of an analyst issuing a positive revision following a negative earnings surprise; however, analysts with less firm-specific experience are marginally less likely to issue an inconsistent positive revision. The strongest relation appears to be that less accurate analysts are more likely to issue inconsistent positive revisions.

### 5.4. Good news followed by a negative revision

We present the results for the positive earnings surprise sample in the third column. Again, the performance-related variables of *Ret*, *PSalesSur* and *ROA* load as expected as they suggest positive unexpected news that might steer an analyst away from issuing an inconsistent negative revision. However, the coefficient on *MBECon* is positive, which is not as expected. *Size* does not load in this regression. The use of income-increasing accruals management (*PDACC*) is marginally associated with issuing a negative revision, as expected.

A larger error for period *t* is associated with an increased likelihood of issuing an inconsistent revision. Younger final forecasts for period *t* are associated with a higher likelihood of issuing an inconsistent revision. The negative coefficient on *InitPess* is again consistent with our expectation.

Several analyst-related factors play a role in an analyst choosing to issue a negative revision following a positive earnings surprise. First, analysts with more firm-specific experience and leaders are less likely to issue a negative inconsistent revision. More frequent forecasters are more likely to issue a negative inconsistent revision.

Taken together with the results from column (2), it appears that, controlling for economic reasons for an analyst to issue a revision in a certain direction, differences in determinants to issue inconsistent forecasts do appear. While analysts with more firm-specific experience are less likely to issue inconsistent forecasts of both directions, past analyst accuracy only appears to be related to the likelihood of issuing an inconsistent positive revision. Additionally, frequency of forecasts and being a leader are associated with an increased likelihood of issuing a negative inconsistent revision and a decreased likelihood of issuing an inconsistent negative revision, respectively, while neither appear to be related to the likelihood of issuing an inconsistent positive revision.

Two takeaways of this analysis are: (1) the determinants of inconsistent forecasts differ depending on the direction of the inconsistent forecast, and (2) less accurate analysts are more likely to issue inconsistent positive revisions. This leads us to ask whether less accurate analysts believe they can improve their forecast performance by issuing positive revisions in an attempt to garner favour with management. This suggests our second research question:

*RQ2: Are inconsistent forecasts, segregated by direction, associated with future forecast accuracy?*

### 5.5. Analyst forecast accuracy

In Table 5 we examine whether there is a relation between forecast consistency and future forecast accuracy. We define future accuracy based on the analyst's final forecast revision for period $t + 1$. Model (2) is as follows[6]:

$$\begin{aligned} FFCAcc = {} & \alpha_0 + \beta_1 InconFC + \beta_2 BSize + \beta_3 FExp + \beta_4 Freq + \beta_5 LFR \\ & + \beta_6 Follow + \beta_7 AvgFCAcc + \beta_8 Size + \beta_9 MTB \\ & + \beta_{10} ROA + \beta_{11} LagDacc + \varepsilon \end{aligned} \tag{2}$$

Based on prior research, we expect *BSize and FExp* to load negatively as size of brokerage firm and firm-specific experience are associated with greater accuracy (Clement, 1999). We expect a positive coefficient on *AvgFCAcc* and *Follow* as less accurate analysts and those following more firms are likely to exhibit greater forecast errors (Sinha *et al*., 1997; Clement, 1999). Larger firms and those with higher performance are easier to forecast; therefore, we expect negative coefficients on *Size* and *ROA*.[7] We expect negative coefficients on *Freq* and *LFR* as more recent forecasts and leaders are expected to be more accurate. We include a measure of lagged discretionary accruals as some analysts are better able to see through discretionary accruals and have lower forecast errors.

The variable of interest is *InconFC*. We again separate the sample into analyst firm-year observations in which the analyst faces a negative earnings surprise in the first column and a positive earnings surprise in the second column.

Table 5 provides the empirical results of our analysis of forecast accuracy. Most of the control variables load as expected. More frequent forecasters, those with better past accuracy, those from larger brokerages and leaders are more likely to have smaller forecast errors going forward. However, analysts with more firm experience are likely to have larger forecast errors.

In the first column, we find that analysts that issue inconsistent positive revisions are more accurate than their counterparts that issued consistent,

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[6]The estimators and significance levels remain qualitatively similar using either an OLS or Tobit regression model.

[7]We also included a *Loss* variable in all regressions and the results are qualitatively similar. We removed the variable due to multicollinearity issues and to obtain the most parsimonious model possible with no loss of inference.

negative revisions. One explanation is that analysts that attempt to please management by issuing higher forecasts are more accurate, possibly as a result of better access to management. Moving to the second column, analysts that issue inconsistent negative revisions following a positive earnings surprise are ultimately less accurate than analysts that follow positive earnings surprises with consistent positive revisions. The results of the two columns taken together confirm the inference taken from the determinants model; inconsistent forecasts, and specifically the accuracy thereof, should not be examined without analysing the direction of the inconsistency.

## 5.6. Future forecast bias

In Table 6 we examine whether the analysts who issue inconsistent forecasts are more or less biased in their final forecast for year $t + 1$. Our dependent variable is *FFCErr*, the signed measure of forecast accuracy used in earlier models. We find, not surprisingly, that analysts who issue an inconsistent negative forecast are significantly more likely to be pessimistic when the

Table 5
Future forecast accuracy of analysts with inconsistent forecast revisions

| Variables | Negative ES sample | Positive ES sample |
|---|---|---|
| *Intercept* | 0.131*** | 0.169*** |
| | (0.020) | (0.012) |
| *InconFC* | −0.024*** | 0.016*** |
| | (0.004) | (0.002) |
| *BSize* | 0.000 | 0.000*** |
| | (0.000) | (0.000) |
| *FExp* | 0.003*** | 0.003*** |
| | (0.001) | (0.000) |
| *Freq* | −0.004*** | −0.004*** |
| | (0.000) | (0.000) |
| *LFR* | −0.001*** | −0.001*** |
| | (0.000) | (0.000) |
| *Follow* | −0.000 | −0.001*** |
| | (0.000) | (0.000) |
| *AvgFCAcc* | 0.724*** | 0.670*** |
| | (0.021) | (0.018) |
| *Size* | −0.008*** | −0.011*** |
| | (0.002) | (0.001) |
| *MTB* | −0.003*** | −0.000 |
| | (0.001) | (0.000) |
| *ROA* | −0.373*** | −0.416*** |
| | (0.023) | (0.015) |
| *LagDacc* | −0.034*** | −0.033*** |
| | (0.012) | (0.006) |

(continued)

Table 5 (continued)

| Variables | Negative ES sample | Positive ES sample |
|---|---|---|
| Industry dummies | Included | Included |
| Year dummies | Included | Included |
| Sample size | 28,452 | 63,165 |
| Adj. $R^2$ | 0.367 | 0.351 |

*, **, *** indicates significance of coefficient estimates at the $p < 0.10$, $p < 0.05$ and $p < 0.01$ levels, respectively (two-tailed). The continuous variables are truncated at the 1% level. Standard errors were adjusted for both cross-sectional and serial correlation following Petersen (2009).

Model (2):

$$FFCAcc = \alpha_0 + \beta_1 InconFC + \beta_2 BSize + \beta_3 FExp + \beta_4 Freq + \beta_5 LFR + \beta_6 Follow + \beta_7 AvgFCAcc + \beta_8 Size + \beta_9 MTB + \beta_{10} ROA + \beta_{11} LagDacc + \epsilon$$

where the variables are defined as:

$FFCAcc = |(E_{it+1} - F_{ijt+1})|/|E_{it+1}|$;

$InconFC = 1$ if firm $i$'s positive (negative) earnings surprise for year $t$ (relative to analyst $j$'s last revision for year $t$) is accompanied by analyst $j$'s downward (relative to analyst $j$'s last revision for firm $i$ for year $t + 1$) revision in the (+1, +7) window around the earnings announcement for year $t$;

$BSize$ = Number of analysts employed at analyst $j$'s brokerage in year $t$;

$FExp$ = Number of years analyst $j$ has a forecast for firm $i$ in the I/B/E/S database;

$Freq$ = Number of forecasts analyst $j$ has for firm $i$ in year $t$;

$LFR$ = Leader-follower ratio for analyst $j$ (details in Appendix B);

$Follow$ = Number of firms analyst $j$ follows in year $t$;

$AvgFCAcc$ = Analyst $j$'s forecast accuracy for firm $i$ calculated over the past 3 years;

$Size$ = Log of firm $i$'s market cap (stock price × number of outstanding shares);

$MTB$ = Market value of equity divided by book value of equity for firm $i$;

$ROA$ = Firm industry mean-adjusted ROA;

$LagDacc$ = Discretionary accruals measured from the modified Jones model in year $t - 1$.

Table 6
Future forecast bias of analysts with inconsistent forecast revisions

| Variables | Negative ES sample | Positive ES sample |
|---|---|---|
| *Intercept* | $-0.073^{***}$ | $-0.046^{***}$ |
| | (0.019) | (0.011) |
| *InconFC* | $0.007^{*}$ | $0.006^{***}$ |
| | (0.004) | (0.002) |
| *BSize* | $-0.000^{*}$ | 0.000 |
| | (0.000) | (0.000) |
| *FExp* | $-0.003^{***}$ | $-0.001^{***}$ |
| | (0.001) | (0.000) |
| *Freq* | $0.006^{***}$ | $0.002^{***}$ |
| | (0.000) | (0.000) |

(continued)

Table 6 (continued)

| Variables | Negative ES sample | Positive ES sample |
|---|---|---|
| *LFR* | 0.001*** | 0.000** |
| | (0.000) | (0.000) |
| *Follow* | 0.000 | 0.000 |
| | (0.000) | (0.000) |
| *AvgFCAcc* | −0.363*** | −0.211*** |
| | (0.016) | (0.013) |
| *Size* | 0.004** | 0.000 |
| | (0.002) | (0.001) |
| *MTB* | 0.003*** | 0.003*** |
| | (0.001) | (0.000) |
| *ROA* | 0.218*** | 0.168*** |
| | (0.023) | (0.014) |
| *LagDacc* | 0.039*** | 0.028*** |
| | (0.012) | (0.006) |
| Industry dummies | Included | Included |
| Year dummies | Included | Included |
| Sample size | 28,041 | 62,670 |
| Adj. $R^2$ | 0.135 | 0.055 |

*, **, *** indicates significance of coefficient estimates at the $p < 0.10$, $p < 0.05$ and $p < 0.01$ levels, respectively (two-tailed). The continuous variables are truncated at the 1% level. Standard errors were adjusted for both cross-sectional and serial correlation following Petersen (2009).

Model (2):

$FFCErr = \alpha_0 + \beta_1 InconFC + \beta_2 BSize + \beta_3 FExp + \beta_4 Freq + \beta_5 LFR + \beta_6 Follow$
$+ \beta_7 AvgFCAcc + \beta_8 Size + \beta_9 MTB + \beta_{10} ROA + \beta_{11} LagDacc + \epsilon$

where the variables are defined as:

$FFCErr = (E_{it+1} - F_{ijt+1})/|E_{it+1}|$;

*InconFC* = 1 if firm *i*'s positive (negative) earnings surprise for year $t$ (relative to analyst *j*'s last revision for year $t$) is accompanied by analyst *j*'s downward (relative to analyst *j*'s last revision for firm $i$ for year $t + 1$) revision in the (+1, +7) window around the earnings announcement for year $t$;

*BSize* = Number of analysts employed at analyst *j*'s brokerage in year $t$;

*FExp* = Number of years analyst $j$ has a forecast for firm $i$ in the I/B/E/S database;

*Freq* = Number of forecasts analyst $j$ has for firm $i$ in year $t$;

*LFR* = Leader-follower ratio for analyst $j$ (details in Appendix B);

*Follow* = Number of firms analyst $j$ follows in year $t$;

*AvgFCAcc* = Analyst *j*'s forecast accuracy for firm $i$ calculated over the past 3 years;

*Size* = Log of firm *i*'s market cap (stock price × number of outstanding shares);

*MTB* = Market value of equity divided by book value of equity for firm $i$;

*ROA* = Firm industry mean-adjusted ROA;

*LagDacc* = Discretionary accruals measured from the modified Jones model in year $t - 1$.

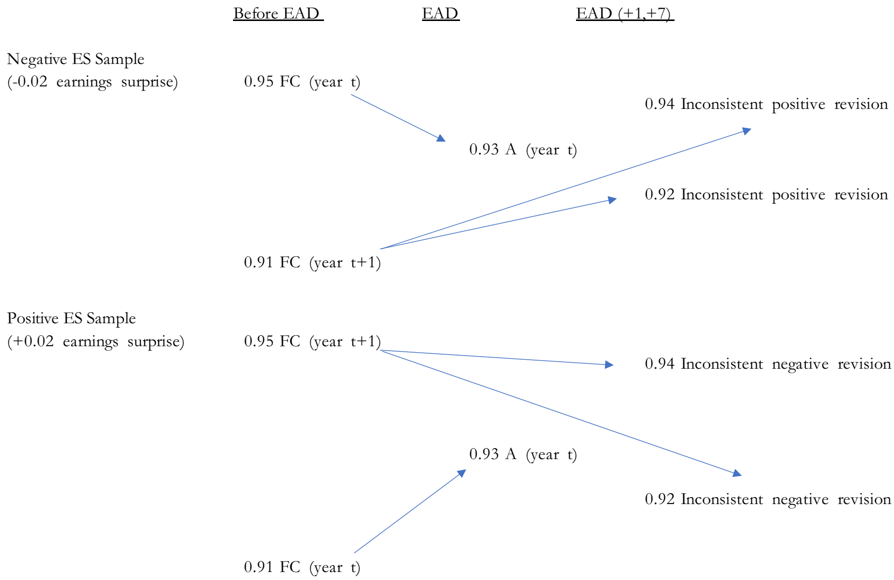


Figure 2 Inconsistent forecast revisions - additional specification. [Colour figure can be viewed at wileyonlinelibrary.com]

earnings for year $t + 1$ are revealed. Alternatively, analysts who issue an inconsistent positive forecast appear to be marginally more pessimistic than their consistent counterparts.

## 5.7. *Robustness checks*

### 5.7.1. *Inconsistent forecast revisions – additional specification*

In Figure 2 we add more specificity to our definition of inconsistent forecasts.[8] In the case of a negative earnings surprise, we suggest a scenario in which the analyst has a final forecast for period $t$ of $0.95 and a forecast for period $t + 1$ of $0.91 prior to the period $t$ earnings announcement date. The revealed actual earnings for period $t$ are $0.93. The analyst may issue an inconsistent positive forecast revision for period $t + 1$ at either below the revealed actual earnings (e.g., $0.92) for period $t$ or equal to or above the actual earnings (e.g., $0.94) for period $t$. The implications of these two revisions may differ even though they are both considered inconsistent positive revisions in our study. One might argue that in the case of the $0.92 revision ($forecast_{t+1} < actual_t$), the analyst appears to be updating his forecast based on current earnings news and to classify it as ‘inconsistent’ may be problematic.

[8]We thank an anonymous reviewer for this suggestion.

On the other hand, the \$0.94 revision ($forecast_{t+1} > actual_t$), appears to be overly optimistic holding all other information constant. As discussed previously, this forecast may be an attempt to garner favour with management.

In Table 7 we run Model (1) again, segregating our negative earnings surprise sample by forecast revisions greater than or equal to actual and forecast

Table 7
Determinants of inconsistent forecast revisions – split by relation of revision to actual

| Variables | Negative ES sample | | Positive ES sample | |
|---|---|---|---|---|
| | $Forecast_{t+1} \geq Actual_t$ | $Forecast_{t+1} < Actual_t$ | $Forecast_{t+1} \geq Actual_t$ | $Forecast_{t+1} < Actual_t$ |
| Intercept | −1.426*** | −1.892*** | −0.615*** | −0.625** |
| | (0.166) | (0.679) | (0.128) | (0.284) |
| **Analyst-related factors** | | | | |
| *AvgFCAcc* | 0.194*** | 0.073 | −0.014 | −0.003 |
| | (0.060) | (0.146) | (0.047) | (0.079) |
| *FExp* | −0.008 | −0.008 | −0.011*** | −0.000 |
| | (0.005) | (0.013) | (0.003) | (0.006) |
| *BSize* | −0.001 | −0.001 | −0.001* | −0.000 |
| | (0.001) | (0.004) | (0.001) | (0.001) |
| *Freq* | 0.012 | 0.013 | 0.022*** | −0.022* |
| | (0.010) | (0.025) | (0.007) | (0.013) |
| *Follow* | 0.002 | −0.001 | −0.001 | 0.006* |
| | (0.002) | (0.006) | (0.002) | (0.003) |
| *LFR* | −0.000 | −0.012 | −0.005*** | 0.001 |
| | (0.003) | (0.009) | (0.002) | (0.003) |
| **Control variables** | | | | |
| *InitPess* | 0.495*** | 0.533*** | −0.600*** | −0.192*** |
| | (0.035) | (0.087) | (0.023) | (0.040) |
| *Ret* | 6.764*** | 5.388*** | −5.632*** | −5.591*** |
| | (0.441) | (1.091) | (0.312) | (0.524) |
| *PSalesSur* | 0.194*** | 0.116 | −0.167*** | −0.145*** |
| | (0.035) | (0.088) | (0.023) | (0.040) |
| *MBECon* | 0.579*** | 0.559*** | −0.032 | 0.519*** |
| | (0.035) | (0.088) | (0.032) | (0.054) |
| *ROA* | −0.471*** | −0.807** | −0.937*** | −0.120 |
| | (0.169) | (0.378) | (0.121) | (0.181) |
| *Size* | 0.095*** | 0.050* | 0.029*** | 0.039*** |
| | (0.011) | (0.030) | (0.008) | (0.014) |
| *MTB* | 0.002 | −0.003 | −0.011*** | 0.006 |
| | (0.005) | (0.019) | (0.003) | (0.008) |
| *PDACC* | −0.016 | −0.046 | 0.007 | 0.049 |
| | (0.035) | (0.092) | (0.023) | (0.042) |
| *FCAcc* | −0.006 | 0.049 | 0.242*** | 0.311*** |
| | (0.059) | (0.178) | (0.067) | (0.115) |

(continued)

Table 7 (continued)

| | Negative ES sample | | Positive ES sample | |
|---|---|---|---|---|
| Variables | $Forecast_{t+1} \geq Actual_t$ | $Forecast_{t+1} < Actual_t$ | $Forecast_{t+1} \geq Actual_t$ | $Forecast_{t+1} < Actual_t$ |
| *FCAge* | −0.081*** | −0.215*** | −0.010 | 0.086*** |
| | (0.017) | (0.043) | (0.012) | (0.021) |
| Industry dummies | Included | Included | Included | Included |
| Year dummies | Included | Included | Included | Included |
| Sample size | 20,483 | 6,591 | 46,931 | 13,986 |
| Adj. $R^2$ | 0.100 | 0.141 | 0.083 | 0.063 |

*, **, *** indicates significance of coefficient estimates at the $p < 0.10$, $p < 0.05$ and $p < 0.01$ levels, respectively (two-tailed). The continuous variables are truncated at the 1% level. Standard errors were adjusted for both cross-sectional and serial correlation following Petersen (2009).

Model (1):

$P(InconPosRev/InconNegRev) = \theta(\alpha + \beta_1 AvgFCAcc + \beta_2 FExp + \beta_3 BSize + \beta_4 Freq + \beta_5 Follow + \beta_6 LFR + \beta_7 InitPess + \beta_8 Ret + \beta_9 PSalesSur + \beta_{10} MBECon + \beta_{11} ROA + \beta_{12} Size + \beta_{13}\mathrm{MTB} + \beta_{14} PDACC + \beta_{15} FCAcc + \beta_{16} FCAge)$

where the variables are defined as follows:

*InconFC* = 1 if firm *i*'s positive (negative) earnings surprise for year *t* (relative to analyst *j*'s last revision for year *t*) is accompanied by analyst *j*'s downward (relative to analyst *j*'s last revision for firm *i* for year $t + 1$) revision in the (+1, +7) window around the earnings announcement for year *t*;

*AvgFCAcc* = Analyst *j*'s forecast accuracy for firm *i* calculated over the past 3 years;

*FExp* = Number of years analyst *j* has a forecast for firm *i* in the I/B/E/S database;

*BSize* = Number of analysts employed at analyst *j*'s brokerage in year *t*;

*Freq* = Number of forecasts analyst *j* has for firm *i* in year *t*;

*Follow* = Number of firms analyst *j* follows in year *t*;

*LFR* = Leader-follower ratio for analyst *j* (details in Appendix B);

*InitPess* = 1 if analyst *j*'s earliest forecast for firm *i* for year *t* issued on or after year $t - 1$'s earnings announcement is lower (higher) than the actual EPS for year *t* as revealed on the earnings announcement date;

*Ret* = One day abnormal returns for firm *i* on earnings announcement date;

*PSalesSur* = 1 if (actual $\text{sales}_{i,t}$ – analyst sales $\text{forecast}_{i,j,t}$) > 0, 0 otherwise;

*MBECon* = 1 if firm *i*'s actual earnings for year *t* are greater than the outstanding consensus as calculated by I/B/E/S, 0 otherwise;

*ROA* = Firm industry mean-adjusted ROA;

*PDACC* = 1 if the firm's annual observation indicates it has positive discretionary accruals using the modified Jones model, 0 otherwise. Additional detail in Appendix B;

*Size* = Log of firm *i*'s market cap (stock price × number of outstanding shares);

*MTB* = Market value of equity divided by book value of equity for firm *i*;

$FCAcc = |(E_{it} - F_{ijt})|/|E_{it}|$;

*FCAge* = Log of days between earning announcement date and final forecast for analyst *j* for firm *i* prior to the earnings announcement date.

revisions that are less than actual. We find the control variables load as before, but we find that the significance of the past accuracy is driven by the case in which the forecast revision is greater than actual. The coefficient on *AvgFCAcc* is 0.194 when the forecast revision is greater than the revealed actual, whereas the coefficient on forecast accuracy does not load when the revision is less than actual. With regard to the positive earnings surprise sample, we find no difference between the two subsamples.

In Table 8, we run the accuracy Model (2) again using this split sample and continue to find that forecast accuracy is greater for analysts issuing inconsistent positive forecast revisions and less for analysts issuing inconsistent negative forecasts. We do not find different inferences when splitting the sample further.

Table 8
Future forecast accuracy of analysts with inconsistent forecast revisions – split by relation of revision to actual

| | Negative ES sample | | Positive ES sample | |
|---|---|---|---|---|
| Variables | $Forecast_{t+1} \geq Actual_t$ | $Forecast_{t+1} < Actual_t$ | $Forecast_{t+1} \geq Actual_t$ | $Forecast_{t+1} < Actual_t$ |
| *Intercept* | 0.220*** | 0.106*** | 0.201*** | 0.142*** |
| | (0.018) | (0.036) | (0.010) | (0.026) |
| *InconFC* | −0.009*** | −0.021** | 0.009*** | 0.011*** |
| | (0.003) | (0.010) | (0.002) | (0.004) |
| *BSize* | 0.000 | 0.000 | 0.000*** | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| *FExp* | 0.001* | 0.003*** | 0.002*** | 0.002*** |
| | (0.005) | (0.001) | (0.000) | (0.001) |
| *Freq* | −0.005*** | −0.006*** | −0.003*** | −0.004*** |
| | (0.000) | (0.001) | (0.000) | (0.001) |
| *LFR* | −0.001*** | −0.001** | −0.001*** | −0.001*** |
| | (0.000) | (0.001) | (0.000) | (0.000) |
| *Follow* | −0.001* | −0.001 | −0.001*** | −0.000 |
| | (0.000) | (0.001) | (0.000) | (0.000) |
| *AvgFCAcc* | 0.457*** | 0.686*** | 0.400*** | 0.636*** |
| | (0.016) | (0.045) | (0.015) | (0.030) |
| *Size* | −0.013*** | −0.005* | −0.013*** | −0.011*** |
| | (0.001) | (0.003) | (0.001) | (0.002) |
| *MTB* | −0.002*** | −0.005*** | 0.000 | −0.002*** |
| | (0.001) | (0.001) | (0.000) | (0.001) |
| *ROA* | −0.419*** | −0.107*** | −0.408*** | −0.191*** |
| | (0.024) | (0.034) | (0.014) | (0.023) |
| *LagDacc* | −0.022** | −0.040** | −0.021*** | −0.045*** |
| | (0.011) | (0.030) | (0.005) | (0.011) |

(continued)

Table 8 (continued)

| | Negative ES sample | | Positive ES sample | |
|---|---|---|---|---|
| Variables | $Forecast_{t+1} \geq Actual_t$ | $Forecast_{t+1} < Actual_t$ | $Forecast_{t+1} \geq Actual_t$ | $Forecast_{t+1} < Actual_t$ |
| Industry dummies | Included | Included | Included | Included |
| Year dummies | Included | Included | Included | Included |
| Sample size | 21,294 | 6,757 | 48,243 | 14,427 |
| Adj. $R^2$ | 0.321 | 0.335 | 0.277 | 0.341 |

*, **, *** indicates significance of coefficient estimates at the $p < 0.10$, $p < 0.05$ and $p < 0.01$ levels, respectively (two-tailed). The continuous variables are truncated at the 1% level. Standard errors were adjusted for both cross-sectional and serial correlation following Petersen (2009).

Model (2):

$FFCAcc = \alpha_0 + \beta_1 InconFC + \beta_2 BSize + \beta_3 FExp + \beta_4 Freq + \beta_5 LFR + \beta_6 Follow$
$+ \beta_7 AvgFCAcc + \beta_8 Size + \beta_9 MTB + \beta_{10} ROA + \beta_{11} LagDacc + \epsilon$

where the variables are defined as:

$FFCAcc = |(E_{it+1} - F_{ijt+1})|/|E_{it+1}|$;

*InconFC* = 1 if firm *i*'s positive (negative) earnings surprise for year *t* (relative to analyst *j*'s last revision for year *t*) is accompanied by analyst *j*'s downward (relative to analyst *j*'s last revision for firm *i* for year $t + 1$) revision in the (+1, +7) window around the earnings announcement for year *t*;

*BSize* = Number of analysts employed at analyst *j*'s brokerage in year *t*;

*FExp* = Number of years analyst *j* has a forecast for firm *i* in the I/B/E/S database;

*Freq* = Number of forecasts analyst *j* has for firm *i* in year *t*;

*LFR* = Leader-follower ratio for analyst *j* (details in Appendix B);

*Follow* = Number of firms analyst *j* follows in year *t*;

*AvgFCAcc* = Analyst *j*'s forecast accuracy for firm *i* calculated over the past 3 years;

*Size* = Log of firm *i*'s market cap (stock price × number of outstanding shares);

*MTB* = Market value of equity divided by book value of equity for firm *i*;

*ROA* = Firm industry mean-adjusted ROA;

*LagDacc* = Discretionary accruals measured from the modified Jones model in year $t - 1$.

### 5.7.2. *Removal of 2009 forecast revisions*

As discussed in the empirical results, the frequency of inconsistent forecasts in 2009 is different than in the rest of the sample; the relative number of inconsistent negative revisions is much greater than the number of inconsistent positive revisions, likely as a result of the financial crisis. We perform the analyses again, removing all observations occurring only in 2009 and in both 2008 and 2009 to determine if our results are driven or confounded by those years. Our results remain qualitatively similar when adopting both new specifications.

### 5.7.3. Alternative window specifications

We adopt different forecast revision windows, including (0, +1), (0, +2) and (+1, +1), and find qualitatively similar results. Additionally, we limit the prior analyst forecast to the window 30 days prior to the earnings announcement date as in Lobo *et al.* (2017). Our sample size is reduced by 78 percent, to a total of 19,209 analyst forecasts. In untabulated results, our results related to future accuracy are qualitatively similar. In the determinants model, we no longer find that prior accuracy is related to the likelihood of issuing an inconsistent forecast. This result does not change the tenor of our main results.

## 6. Conclusion

First, we create a measure of inconsistent forecasts that allows us to examine individual analyst forecasting patterns and which recent literature has suggested is meaningful to investors. Using this measure, we examine the characteristics, future accuracy and future bias of analysts who issue inconsistent forecast revisions occurring within a week of a firm's earnings announcement date. While prior literature has examined inconsistent forecasts, there are no papers of which we are aware that also consider the direction of the inconsistent revision, an extension that we illustrate is meaningful.

Prior literature on inconsistent forecasting behaviour generalises inconsistency into one category, ignoring the direction of bias, and finds that less accurate analysts are more likely to issue inconsistent or contradicting forecasts. By segregating the sample, we find that less accurate analysts are more likely to issue inconsistent positive forecasts but not inconsistent negative forecasts. Additionally, we find that analysts who issue positive forecasts (both consistent and inconsistent) are ultimately more accurate for the period, suggesting that analysts who issue positive forecasts (relative to their own prior forecast) in the week following an earnings announcement might have better access to management as a result.

These results should be of interest to researchers and market participants as further insight into analyst behaviour. If investors can identify predictable differences in analyst behaviour, they can revise their own expectations more fully. Additionally, our study provides rationale as to why future studies on forecast inconsistency should consider both the direction of bias as well as the nature of the inconsistency.

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# APPENDIX A

| | |
|---|---|
| *InconFC* | 1 if firm *i*'s positive (negative) earnings surprise for year *t* (relative to analyst *j*'s last revision for year *t*) is accompanied by analyst *j*'s downward (relative to analyst *j*'s last revision for firm *i* for year $t + 1$) revision in the (+1, +7) window around the earnings announcement for year *t* |
| *AvgFCAcc* | Analyst *j*'s forecast accuracy for firm *i* calculated over the past 3 years |
| *FExp* | Number of years analyst *j* has a forecast for firm *i* in the I/B/E/S database |
| *BSize* | Number of analysts employed at analyst *j*'s brokerage in year *t* |
| *Freq* | Number of forecasts analyst *j* has for firm *i* in year *t* |
| *Follow* | Number of firms analyst *j* follows in year *t* |
| *LFR* | Leader-follower ratio for analyst *j* (details in Appendix B) |
| *InitPess* | 1 if analyst *j*'s earliest forecast for firm *i* for year *t* issued on or after year $t - 1$'s earnings announcement is lower (higher) than the actual EPS for year *t* as revealed on the earnings announcement date |
| *Ret* | One day abnormal returns for firm *i* on earnings announcement date |
| *PSalesSur* | 1 if (actual $\text{sales}_{i,t}$ – analyst sales $\text{forecast}_{i,j,t}$) > 0, 0 otherwise |
| *MBECon* | 1 if firm *i*'s actual earnings for year *t* are greater than the outstanding consensus as calculated by I/B/E/S, 0 otherwise |
| *PDACC* | 1 if the firm's annual observation indicates it has positive discretionary accruals using the modified Jones model, 0 otherwise. Additional detail in Appendix B |
| *ROA* | Firm industry mean-adjusted ROA |
| *Size* | Log of firm *i*'s market cap (stock price × number of outstanding shares) |
| *MTB* | Market value of equity divided by book value of equity for firm *i* |
| *FCAcc* | $\lvert(E_{it} - F_{ijt})\rvert / \lvert E_{jt}\rvert$ |
| *FCAge* | Log of days between earning announcement date and final forecast for analyst *j* for firm *i* prior to the earnings announcement date |
| *A* | Total assets [Compustat data item *atq*] |
| *ΔRev* | Change in revenue [Compustat data items $saleq_q - saleq_{q\text{-}4}$] |
| *PPE* | Gross property, plant and equipment [Compustat data item *ppegt*] |
| *ROA* | Income before extraordinary items divided by average assets [Compustat data items *ibcy* divided by $(atq_q + atq_{q\text{-}1})/2$] |
| *TA* | Total accruals, defined as income before extraordinary items [Compustat data item *ibcy*] minus cash flow from operations [Compustat data item *oancy*] |
| *ΔAR* | Change in accounts receivable from the same quarter in the prior year [Compustat data item *rectqq-rectqq-4*] |

Compustat quarterly data items *oancy* and *ibcy* are provided on a year-to-date basis. Therefore, in order to calculate the value of the total accruals and return on assets for each quarter, we subtract the prior quarter value from the current quarter's year-to-date value.

## APPENDIX B

### Measuring earnings management

We define earnings management using the modified Jones model (Jones, 1991; Dechow *et al*., 1995), controlling for contemporaneous ROA as suggested by Kothari *et al*. (2005), to calculate discretionary accruals as our measure of accruals management. We calculate total accruals following Hribar and Collins (2002) using the cash flow statement approach. The model is:

$$\frac{TA_q}{A_{q-1}} = \alpha\left[\frac{1}{A_{q-1}}\right] + \beta_1\left[\frac{\Delta REV_q}{A_{q-1}}\right] + \beta_2\left[\frac{PPE_q}{A_{q-1}}\right] + \beta_3 ROA_q + \varepsilon_q \tag{A1}$$

where $q$ indicates the quarter. We omit industry and firm subscripts for readability.

We run the above regression for each quarter by industry as defined by two-digit SIC code. Following prior literature, we exclude industry-quarters that contain less than 10 observations. We truncate total accruals at the top and bottom 1 percent to eliminate the effect of outliers and errors in the data. We take the coefficient estimates and obtain the fitted values for each firm-quarter to obtain the expected normal accruals ($NA$) as shown in the equation below:

We subtract the estimated normal accruals from the firm's actual total accruals to find the discretionary accruals by firm, which we define as *Daccps*. If the firm-quarter reflects a positive earnings surprise due to a positive amount of *Daccps*, we set $PDACC = 1$. We use the one-year lagged discretionary accruals to find the value for the variable *LagDacc*.

### Measuring leader-follower ratio

We calculate the leader-follower ratio (*LFR*) following Shroff *et al*. (2014). For each forecast that is not issued within 2 days of an earnings announcement, we identify the two preceding forecasts and two subsequent forecasts issued by other analysts. Leader-follower ratio is defined as $T_0/T_1$, where $T_0$ is the cumulative number of days by which the preceding forecasts lead the forecast of interest and $T_1$ is the cumulative number of days by which the subsequent forecasts lag the forecast of interest. We calculate the average leader-follower ratio for each analyst-year.