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Modelling analysts' target price revisions following good and bad news?[*]

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Modelling analysts' target price revisions following good and bad news

Abstract

We study the relation between analysts' target price revisions and recent market returns, excess stock returns, and other analysts' target price revisions. Empirical results show that, after controlling for earnings forecast and recommendation revisions, target price revisions are associated with each of these information sources. We also find that target price revisions are more sensitive to negative than to positive excess stock returns. We conjecture that firms' tendency to withhold bad news, while releasing good news promptly, drives this effect and, using proxies for firms' withholding of bad news, we report evidence supporting this hypothesis.

Key words: target price revisions; excess stock returns, withholding bad news

JEL: G24, M40

1. Introduction

Analysts' target prices provide a simple information signal that is incrementally informative to investors beyond earnings forecasts and stock recommendations (Brav and Lehavy, 2003; Asquith et al., 2005; Da and Schaumburg, 2011; Bilinski et al. 2013). Nevertheless, research on target prices, and therefore our understanding of them, falls significantly short of the body of research on analysts' earnings forecasts (e.g., Bradshaw, 2011). In this study we explore the relation between analysts' target price revisions and the information in market returns, firm-specific returns, and other analyst forecasts. As private communication with managers is important for analysts (Brown et al., 2015) and managers have a general tendency to withhold bad news (Kothari et al., 2009), we are particularly interested in how the difference between bad and good news conditions this relation.

We examine analysts' target price revisions for 1,104 stocks listed in the UK between January 2003 and December 2014. The UK offers a fertile setting for examining analysts' target prices for several reasons. First, based on Bilinski et al.'s (2013) statistics, the UK has the second largest sample of analysts' target price forecasts after the U.S., and the accuracy of target prices is slightly better in the UK than in the U.S. (see also Bradshaw et al., 2014). The properties of UK target prices, however, are relatively under-researched. Second, UK analysts should have strong incentives to provide high quality information to institutional investors, counterbalancing their incentives to please the companies they follow.[1] Third, the availability of a unique UK corporate disclosure index gives us a valuable proxy for the relative tendencies of UK firms to withhold bad news.

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[1] Brown et al. (2015) suggest that most analysts focus on meeting the demands of large institutional investors rather than those of small, individual investors. Bilinski et al. (2015) find that analysts strategically bias their target prices for stocks associated with high short-term institutional investors and institutional investors reward brokers who cater for their needs. Institutional ownership in the UK is higher than in the U.S. (Short and Keasey, 1999). We therefore expect UK analysts to pay particular attention to the informational needs of UK institutional investors.

We find that, after controlling for earnings forecast and recommendation revisions, analysts' target price revisions are significantly associated with market returns, excess stock returns, and other analysts' target price revisions. We also find that target price revisions are more sensitive to firm-specific bad news than good news in excess stock returns, while the sensitivity to other sources of information does not vary across good and bad news. Using a new UK disclosure index[2] as an information uncertainty proxy, we show that the asymmetric sensitivity of target price revisions to positive and negative excess stock returns is significant for low disclosure quality firms but insignificant for high disclosure quality firms. Using analyst coverage as an alternative information uncertainty proxy yields a similar pattern. Since Kothari et al. (2009) suggest that firms with higher information uncertainty have more opportunities to withhold bad news, we suggest that these findings are consistent with the differential opportunities of firms to withhold and accumulate bad news affecting analysts' target price revisions, although we do not rule out alternative explanations.

Our study contributes to the literature in several ways. It is the first to model the relation between target price revisions and the information in market returns, excess stock returns, and other analysts' target price revisions. Our model has high explanatory power for target price revisions with R-squared values ranging from 52% to 62% for the main analysis and analyses of different subsamples. We extend previous studies examining the association between earnings forecast revisions and information in stock returns and other analysts' forecasts. We show that after controlling for earnings forecast and recommendation revisions, market returns, excess stock returns, and other analysts' target price revisions are incrementally informative for target price revisions. We argue that our

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[2] The disclosure index comes from the Corporate Financial Information Environment (CFIE 2015) Project's web-based annual report scoring tool (http://ucrel.lancs.ac.uk/cfie/).

findings are consistent with analysts using additional information about growth and risk in stock returns and other analysts' forecasts, beyond those in earnings forecast and recommendation revisions, when they revise their target prices. However, as our findings could result from target price revisions, stock returns, other analysts' forecasts, and market returns all responding to the same information source, we acknowledge that the association between these variables does not allow us to establish a causal relation.

A second important contribution of our paper is that we show that firms' strategic disclosure strategies affect analysts' forecasts. Previous studies find evidence of an asymmetric investor reaction to bad and good news and provide conflicting theories for the asymmetric reaction. Skinner (1994) attributes the asymmetric reaction to managers' pre-releasing bad news before mandatory earnings announcements, while Kothari et al. (2009) view the asymmetric pattern as evidence of managers' withholding bad news. We show that analysts react asymmetrically to the bad and good news in excess stock returns when revising their target prices and provide evidence consistent with the withholding bad news argument. This is also the first paper to examine the conditioning effect of corporate disclosure quality on the relation between target price revisions and news.

The paper continues as follows. Section 2 discusses related studies and develops our main hypotheses. Section 3 presents our research design and discusses econometric issues. Section 4 describes the data selection process and presents summary statistics while section 5 reports our empirical results. Section 6 concludes.

2. Literature review and hypotheses

2.1 Analysts' forecasts, stock returns, and other analysts' forecasts

Prior studies show that sell-side analysts incorporate information in stock returns and other analysts' forecasts into their earnings forecast and recommendation revisions (e.g., Lys and Sohn, 1990; Abarbanell, 1991; Conrad et al., 2006; Welch, 2000; Clement et al., 2011). We extend this literature by examining the sensitivity of target price revisions to different information sources. While Clarkson et al. (2013) and Dechow and You (2013) examine the factors affecting target prices and implied expected returns, they do not examine target price revisions. Examining target price revisions rather than levels allows us to examine how analysts use new information to update their forecasts.

Analysts' typically derive their target prices from an underlying valuation model (e.g., Demirakos et al., 2004). Analyst valuation models normally require as inputs an accounting primitive (e.g., future expected earnings, cash flows, dividends) and assumptions about growth and risk. Market, industry, and firm-specific factors affect each of these inputs. Target price revisions should reflect updated views on these inputs between target price revision dates. We also expect market and excess stock returns between target price revision dates to reflect this information.[3] Between target price revision dates, analysts receive news about valuation inputs from direct sources, including management, and from secondary sources such as market and excess stock returns.[4] They also observe the target price revisions of other analysts. Analysts should take news from these information sources into account when revising their target prices. Therefore, we expect to see positive associations between target price revisions and market returns, excess stock returns, and other analysts' target price revisions. We test the following hypotheses.

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[3] Both market and excess stock returns should reflect industry news.

[4] While management forecasts are an important source of information for analysts in the U.S., UK companies do not routinely provide management forecasts. We therefore do not consider management forecasts in our empirical analysis, although we refer to management forecasts below in relation to previous research on U.S. companies.

H1a: *There is a positive association between analysts' target price revisions and recent market returns.*

H1b: *There is a positive association between analysts' target price revisions and recent excess stock returns.*

H1c: *There is a positive association between analysts' target price revisions and other analysts' consensus target price revisions.*

Although we expect to see significant associations between the three sources of analyst information and target price revisions, it is not possible to conclude that such associations imply causality. In all three cases there may be other, unobserved, sources of information that cause analysts to revise their target prices, and this information also causes stock prices to change and other analysts to revise their target prices. Nevertheless, we believe that the strength of the associations we report for these basic relationships and the additional analyses we present are worthy of attention. We leave it to future research to establish the extent to which the strong correlations we report are causal.

2.2 Strategic firm disclosures and analysts' reactions to good and bad news

Several theoretical models and empirical studies suggest that managers withhold bad news. Verrecchia (1983) shows that managers have incentives to withhold bad news when there are disclosure costs. Dye (1985) and Jung and Kwon (1988) show that firms may strategically delay disclosing bad news when investors are uncertain whether managers have received private information. Pae (2005) shows that when firms receive two news signals, they disclose only the favourable signal if it is sufficiently favourable relative to the other. Empirical studies support the predictions of these models. Chambers and Penman (1984) find that firms are more likely to release positive earnings reports earlier than expected and disclose bad news later than expected. Ertimur et al. (2014) find that firms are more likely to delay bad news disclosures in lockup expiry quarters to mitigate

the adverse effect on stock prices. Ge and Lennox (2011) document that firms tend to withhold bad news about future earnings when companies use their own stock to finance acquisitions.

In contrast to the idea that firms withhold bad news, Skinner (1994) argues that managers face an asymmetric loss function when disclosing voluntarily before mandatory earnings announcements, as negative earnings surprises incur large litigation or reputation costs. He finds that stock price reactions to voluntary bad news disclosures are stronger than the reactions to voluntary good news disclosures and concludes that this is consistent with managers' accelerating bad news. Other circumstances in which managers choose to opportunistically disclose bad news are before option grant dates to opportunistically benefit from lower stock prices (Yermack, 1997; Aboody and Kasznik, 2000) and in order to maximise trading profits from insider trading (Cheng and Lo, 2006). While these examples provide settings in which managers have incentives to disclose bad news, they are not inconsistent with the prior withholding of bad news. For managers to have a block of bad news to disclose, they are likely to have accumulated it by withholding bad news over time before eventually disclosing it.

Kothari et al. (2009) find that the magnitude of investors' reactions to bad news announcements such as dividend reductions and pessimistic management forecasts is stronger than that to corresponding good news announcements. Kothari et al. argue that it is managers' tendency to withhold bad news, rather than Skinner's (1994) accelerating bad news explanation, that drives the stronger reaction. They suggest that if their results are due to managers accelerating bad news but disclosing good news gradually, the absolute forecast errors associated with good news management forecasts should be higher than those associated with bad news. But they find that the mean absolute forecast errors associated with good news are smaller, not higher, than those associated with bad

news. Conducting tests to rule out other explanations, Kothari et al. conclude that the asymmetric market reaction to bad news is due to managers' tendency, on average, to withhold bad news while releasing good news as they receive it.

One way that managers release news is by communicating it to analysts. This means that if managers leak good news early to analysts, analysts need to rely less on indirect sources such as public signals in stock returns and other analysts' forecasts to discover good news.[5] In contrast, when managers withhold bad news, analysts have to rely more on other information sources, such as stock returns and other analysts' forecasts, to discover the bad news. As both excess stock returns and other analyst' consensus target price revisions reflect firm-specific news, we predict that the positive associations between analysts' target price revisions and excess stock returns and other analysts' consensus target price revisions are stronger when the firm-specific news is bad. Using negative excess stock returns as an indicator of firm-specific bad news, this leads to the following hypotheses.

H2a: The positive association between target price revisions and recent excess stock returns is stronger for negative than positive excess stock returns.

H2b: The positive association between target price revisions and other analysts' consensus target price revisions is stronger for negative than positive excess stock returns.

As Skinner (1994) and Kothari et al. (2009) discuss, an asymmetric reaction to bad news does not provide definitive evidence of managers' either withholding or

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[5] Recent literature on analysts' access to management indicates the potential for managers to leak good news early to analysts. Greene et al. (2014) note that "brokerage analysts interact with firm management through visits to company headquarters, investor office meetings, and broker-hosted investor conferences." Using a comprehensive record of interactions between executives of a large-cap NYSE-traded firm and sell-side analysts, Soltes (2014) examines the private interactions between managers and analysts and notes 75 private interactions over a one-year sample period. The majority of these interactions are phone conversations but there are also interactions at conferences and office meetings and 43 percent of these interactions occur within 72 hours of some firm-initiated news.

accelerating bad news. If the asymmetric reaction is due to managers' withholding bad news, however, the magnitude of the asymmetric reaction of analysts to bad and good news should be more pronounced for firms that are more likely to withhold bad news. Therefore, the final hypothesis we test is as follows.

H3: The asymmetric sensitivity of analysts' target price revisions to good and bad news is more pronounced for firms that are more likely to withhold bad news.

3. Research design

In this section, we propose an empirical model to examine analysts' target price revisions. We also describe a corporate disclosure quality index, which we use to proxy firms' tendency to withhold bad news in order to test hypothesis *H3*.

3.1 An empirical model of analysts' target price revisions

To test our hypotheses on the relation between target price revisions and market returns, excess stock returns, and other analysts' target price revisions (hypotheses *H1a–c*), we begin by estimating the following model

$$RevTP_{i,j,t} = \beta_0 + \beta_1 RM_t + \beta_2 ExRet_{i,t} + \beta_3 RevCons_{i,j,t} + \varepsilon_{i,j,t} \tag{1}$$

where *i* indexes stocks (firms), *j* indexes analysts, and *t* is the target price revision date, henceforth the target price date. Analyst *j*'s target price revision for stock *i* at time *t*, $RevTP_{i,j,t} = \left(TP_{i,j,t} - TP_{i,j,t-1}\right)\big/P_{i,t-1}$, is the difference between analyst *j*'s target price at time *t* and her target price at time *t*−1, where date *t*−1 is her most recent target price date before *t*, scaled by the closing stock price on the day before the previous target price date; RM_t is the return on the FTSE-All Share Index from *t*−1 to *t*; $ExRet_{i,t}$ is stock *i*'s excess stock return from *t*−1 to *t*, calculated as the difference between stock and market returns from *t*−1 to *t*; and $RevCons_{i,j,t}$ is other analysts' consensus target price revision, calculated as $\left(MeanOTP_{i,j,t} - MeanOTP_{i,j,t-1}\right)\big/P_{i,t-1}$, where $MeanOTP_{i,j,t}$ is the mean target price of

analysts other than *j* for stock *i* between *t*−1 and *t*, taking the latest target price for each analyst.[6] This is consistent with how previous studies calculate consensus forecasts (e.g., Clement et al., 2011; Bernhardt et al., 2006).[7] Figure 1 illustrates the time line of our calculation of variables. We conduct the analysis at the analyst–stock level. According to Bradshaw and Brown (2006),[8] brokerage firms assign an individual analyst or team to follow any one stock, so an analysis at the analyst–stock level should generate similar results to those from an analysis at the broker–stock level.

In estimating model (1) and subsequent extensions of it, we include broker and industry fixed effects to control for common unobserved, but intertemporally constant, broker and industry characteristics. We also include year fixed effects to control factors that affect all forecast revisions in a particular year, e.g., during the financial crisis.

Previous research suggests that analysts' characteristics such as experience, workload, and association with a larger brokerage firm may affect their forecast properties and biases (Mikhail et al., 1997; Clement, 1999; Brown and Hugon, 2009). Research also shows that analysts use information in stock returns and other analysts' forecasts to revise their earnings forecasts (Abarbanell, 1991; Bernhardt et al., 2006; Clement et al., 2011). As earnings forecasts are an important input to target prices, the association between target price revisions and market returns, excess stock returns, and other analysts' forecasts may be due to analysts using these information sources when revising their earnings forecasts. Similarly, the three information sources are likely to influence recommendation revisions. Due to these considerations, we control for analyst

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[6] Appendix 1 defines all the variables in the study.
[7] All of our results are robust to using a variant of *RevCons* where we give greater weight to more recent other analysts' target prices following Chen and Jiang (2006).
[8] This citation is to a working paper version of Bradshaw et al. (2013). Only the working paper version discussed this point.

characteristics and earnings forecast and recommendation revisions in an augmented version of model (1), as follows,

$$RevTP_{i,j,t} = \beta_0 + \beta_1 RM_t + \beta_2 ExRet_{i,t} + \beta_3 RevCons_{i,j,t} + \beta_4 RevEPS_{i,j,t} + \beta_5 RevRecd_{i,j,t}$$
$$+ \beta_6 FExp_{it} + \beta_7 IExp_{i,t} + \beta_8 NFirm_{it} + \beta_9 NInd_{i,t} + \beta_{10} BrSize_{i,t} + \varepsilon_{i,j,t} \quad (2)$$

In model (2), $RevEPS_{i,j,t} = \left(EPS_{i,j,t} - EPS_{i,j,t-1} \right) \big/ P_{i,t-1}$ is the earnings forecast revision, which is the difference between analyst j's earnings forecast at time t and the previous earnings forecast, scaled by the closing stock price on the day before the previous target price date. $RevRecd_{i,j,t} = -\left(Recd_{i,j,t} - Recd_{i,j,t-1} \right) \big/ 4$ is the recommendation revision, calculated as the difference between analyst j's I/B/E/S coded recommendation at time t and the previous recommendation, multiplied by $-1/4$.[9] Analyst characteristics are: firm experience (*FExp*) and industry experience (*IExp*), which equal the number of years the analyst has covered a company and an industry, respectively, up to the year before the target price date; the number of firms (*NFirm*) and industries (*NInd*) the analyst covers in the year before the target price date; and brokerage firm size (*BrSize*), which equals the number of analysts associated with the broker that employs the analyst in the year before the target price date.

Previous studies examining recommendation revisions employ either a continuous measure of recommendation revisions (Feldman et al., 2012) or include dummy variables indicating whether a revision is an upgrade or downgrade from the previous revision (Asquith et al., 2005). Therefore, as an alternative to using *RevRecd*, we substitute three dummy variables: *Upgrade* equals 1 if *RevRecd* > 0, and 0 otherwise; *Dngrade* equals 1 if *RevRecd* < 0, and 0 otherwise; and *Reit* equals 1 if analysts issue recommendations on both the current and previous target price dates, but the recommendation does not change.

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[9] We adopt this measure from Feldman et al. (2012). We recode I/B/E/S analyst recommendations to a rating from 1 to 5, with 1 corresponding to a strong buy and 5 to a strong sell and multiply the recommendation change by $-1/4$ so that positive *RevRecd* indicates an upgrade and negative *RevRecd* indicates a downgrade. This measure not only shows whether the new recommendation is an upgrade or downgrade from the previous one, but also captures the magnitude of the revision.

There are cases where analysts have only one recommendation associated with either the current or the previous target price date. In these cases, we set *RevRecd* to zero and *Reit* to zero instead of 1. In other words, for recommendation revisions, there are four types: upgrade, downgrade, reiteration, and no recommendation at either the current or the previous target price date.

3.2 Analysts' asymmetric reaction to bad and good news

We examine whether target price revisions are more sensitive to bad than good firm-specific news (hypotheses *H2a–b*) using the following augmented version of model (2),[10]

$$
\begin{aligned}
RevTP_{i,j,t} = {} & \beta_0 + \beta_1 RM_t + \beta_2 ExRet_{i,t} + \beta_3 RevCons_{i,j,t} + \beta_4 BadExRet_{i,t} \\
& + \beta_5 BadExRet_{i,t} \times RM_t + \beta_6 BadExRet_{i,t} \times ExRet_{i,t} \\
& + \beta_7 BadExRet_{i,t} \times RevCons_{i,j,t} + \beta_8 RevEPS_{i,j,t} + \beta_9 RevRecd_{i,j,t} \\
& + \beta_{10} BadExRet_{i,t} \times RevEPS_{i,j,t} + \beta_{11} BadExRet_{i,t} \times RevRecd_{i,j,t} \\
& + \beta_{12} FExp_{it} + \beta_{13} IExp_{i,t} + \beta_{14} NFirm_{it} + \beta_{15} NInd_{i,t} + \beta_{16} BrSize_{i,t} + \varepsilon_{i,j,t}
\end{aligned}
\tag{3}
$$

where $BadExRet_{i,t}$ is our indicator of firm-specific bad news and equals 1 if the excess return on stock i between $t-1$ and t is negative, and 0 otherwise.[11] Positive coefficients on *BadExRet × ExRet* and *BadExRet × RevCons* provide support for hypotheses *H2a* and *H2b* respectively. As the tendency of firms to withhold bad news does not provide a clear implication for the case of market return, we have no predictions for the sign of the coefficient on *BadExRet × RM*.

As the interval between consecutive forecasts varies across observations, we deflate all regressions by the square root of the number of calendar days between the previous and current forecasts to address heteroscedasticity arising from varying revision

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[10] We estimate a corresponding model where we replace *RevRecd* with the dummy variables *Upgrade*, *Downgrade*, and *Reit*.

[11] Negative market returns and negative revisions of other analysts' forecasts can imply bad news. But since our main interest is in analysts' reactions to firm-specific bad and good news, we use negative excess stock returns as our main indicator of firm-specific bad news. Repeating the analysis with three different measures of bad news indicated by negative market returns, negative excess stock returns, and negative other analysts' forecast revisions leaves the results qualitatively unchanged.

periods.[12] To control for other forms of heteroscedasticity and correlated regression errors, we report *t*-statistics based on heteroscedasticity-robust standard errors clustered by firm and year following the multi-dimensional clustering suggested by Petersen (2009).

3.3 Withholding bad news and the asymmetric reaction to good and bad news

We predict that analysts' asymmetric reaction to bad and good news is greater for firms that are more likely to withhold bad news. We therefore need to identify firms that are more or less likely to withhold bad news. The main measure we use to identify firms' tendency to withhold bad news is a disclosure quality index, *DiscInd*.[13] A higher *DiscInd* value implies higher disclosure quality. As a measure of disclosure quality, *DiscInd* proxies for information uncertainty surrounding a firm in a particular year and therefore for the opportunities that a firm has to strategically withhold bad news.[14]

After obtaining *DiscInd* for every firm–year in our sample, we sort target price revisions into quintiles based on *DiscInd*. The top quintile includes target price revisions for firms with the highest disclosure quality while the bottom quintile contains revisions for firms with the lowest disclosure quality. We then re-estimate model (3) within these quintiles. As we use *DiscInd* to measure firms' tendency to withhold bad news, we expect the coefficients on *BadExRet × ExRet* and *BadExRet × RevCons* to be higher in the low than in the high disclosure quality quintiles.[15]

4. Sample selection and descriptive statistics

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[12] Our results remain qualitatively unchanged if we do not make this deflation.
[13] Appendix 2 provides a detailed description of *DiscInd*.
[14] Kothari et al. (2009) argue that firms associated with higher information uncertainty have more opportunities to withhold bad news.
[15] An alternative way to test this hypothesis is to interact the disclosure index with the variables of interest and examine the coefficients on *BadExRet × ExRet* and *DiscInd × BadExRet × ExRet.* Conducting this robustness test gives results that are consistent with running separate regression across quintiles. We opt for the separate regression approach because it does not impose identical coefficients on non-interacted variables. We thank an anonymous referee for suggesting this robustness test.

4.1 Sample selection

We obtain target price, earnings forecast, and recommendation data for UK listed firms from the I/B/E/S database.[16] We convert all I/B/E/S foreign currency denominated target prices and earnings forecasts into British currency using the I/B/E/S Daily Currency Exchange Rates file and the Report Currency file. We eliminate multiple intraday target prices, recommendations, and earnings forecasts, and keep the latest forecasts and recommendations by each brokerage firm for each stock on each research report day.[17] We merge these observations with Datastream stock prices and market returns. We initially merge the data using I/B/E/S tickers. Where I/B/E/S and Datastream stock tickers are inconsistent, we use CUSIP codes to merge the data. For any data that we cannot merge, we manually match the data based on company names. We merge the disclosure index data with the merged IBES–Datastream data using Datastream identification codes.

The adjustment factors I/B/E/S and Datastream apply to adjust target prices and earnings forecasts for corporate actions differ for some observations. For these observations, we re-adjust I/B/E/S target prices to make them consistent with Datastream adjusted stock prices by multiplying them by the I/B/E/S adjustment factors and dividing by the Datastream adjustment factors.[18]

The initial sample has 201,200 observations, consisting of 12-month-ahead target prices for UK listed stocks from 1 January 2003 to 31 December 2014. To select our final sample, we apply the following filters.

(1) For each target price observation, there are corresponding Datastream stock price data.

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[16] We select all stocks that have the country code 'EX' in the I/B/E/S Detail Price Targets, I/B/E/S Detail History file and Recommendation file.

[17] We use time-stamps in the I/B/E/S files to identify the latest target prices, recommendations, and earnings forecasts.

[18] The data remain largely the same if we use unadjusted target prices and earnings forecasts from I/B/E/S and adjust using the adjustment factors from Datastream.

(2) For each target price observation, the same analyst issued a target price for the same company between 30 and 360 days earlier.

(3) For each target price observation there is at least one target price from another analyst for the same company between the previous and current target price dates.

(4) Each target price observation is associated with available data for the disclosure index and I/B/E/S data to calculate analyst coverage.

(5) Each target price observation is associated with available data to calculate earnings forecasts and recommendation revisions.

Criterion (2) ensures stale or very short-term target price revisions do not affect our results. The other criteria ensure that observations in the final sample are associated with non-missing data to calculate target price revisions, stock returns, earnings forecast revisions, recommendation revisions, other analyst target price revisions, and other key variables in the study.

For criterion (5), we retain target prices where the accompanying earnings forecasts and recommendations are issued within the past 90 days. When both the current and previous target prices have accompanying earnings forecasts and recommendations, we calculate the earnings forecast revision and recommendation revision as section 3 describes. When the current target price has accompanying earnings forecasts and recommendations but the previous one does not or vice versa, we assume the earnings forecast and recommendation revisions are zero.

Table 1 reports the number of observations lost and remaining after each filter. The final sample comprises 27,288 observations issued by 2,725 analysts working for 201 brokerage firms and following 1,104 stocks. The sample period starts on 1 January 2003

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and ends on 31 December 2014. We winsorize the main variables in our analysis, including *RevTP*, *RM*, *ExRet*, and *RevCons* at the 1st and 99th percentiles.[19]

4.2 Descriptive statistics

This section reports summary statistics and Pearson correlations between the main variables in the analysis. Table 2, panel A reports statistics for the whole sample, panels B and C report statistics for the good news (*ExRet* ≥ 0) and bad news (*ExRet* < 0) subsamples, and panel D reports *p*-values for tests of whether the means of the variables in panels B and C differ.

In panel A, the mean target price to stock price ratio (*TPRatio*) is 1.12, showing that, on average, analysts set target prices about 12 percent higher than current stock prices. In panels B and C the means of this ratio are 1.088 and 1.154, suggesting that analysts set more optimistic target prices following bad news than good news.[20] Recommendation revisions are positive in panels B and C, and panel D shows that they do not differ significantly. These findings are consistent with the conclusions of previous studies that analysts make optimistic forecasts (Lin and Nichols, 1998; Das et al., 1998; Michaely and Womack, 1999; Cowen et al., 2006; Ke and Yu, 2006) and indicate that analysts are reluctant to issue pessimistic target prices and revise recommendations downwards when they receive bad news.

The mean target price revision (*RevTP*) and earnings forecast revision (*RevEPS*) are negative in panel C (−0.105 and −0.004) while they are positive in panel B (0.124 and 0.001), indicating that analysts revise target prices and earnings forecasts in the direction of the news in excess stock returns. Furthermore, the magnitudes of the mean and median target price revisions are smaller than the magnitudes of excess stock returns between the

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[19] Conducting the analysis with corresponding truncated instead of winsorised data leaves the results qualitatively unaffected.
[20] A *t*-test shows that the difference is significant at 1 percent.

previous and current target price dates in panels B and C. This suggests that analysts underreact relative to the information in excess stock returns. This is consistent with the evidence in previous studies that analysts underreact to information in stock returns (Abarbanell, 1991; Clement et al., 2011). These statistics also help to explain why the mean *TPRatio* in panel C exceeds one: analysts tend to move their target prices down when they receive bad news, but the revision is less than the stock price fall.

The mean and median intervals between consecutive forecasts by the same analyst for the same company (*DayInt*) are 111 and 91 days. Mean *DayInt* in the bad news subsample is 112.92, significantly higher than in the good news subsample (109.23). Panel D shows that there are no significant differences in the disclosure index and analyst coverage between the bad and good news subsamples. Although the results in panel D suggest there are differences in analyst characteristics associated with bad and good news, the differences are not economically significant except for broker size.

Table 3 reports Pearson correlations between the variables. There are significant positive correlations of target price revisions with market returns, excess stock returns, and other analysts' consensus target price revisions. Target price revisions are also positively correlated with earnings forecast revisions, consistent with Clement et al., (2011). The bad news indicator (*BadExRet*) is negatively correlated with target price revisions, earnings forecast revisions, market returns, excess stock returns, and other analysts' consensus target price revisions, consistent with the statistics in table 2. The disclosure quality index (*DiscInd*) is positively correlated with analyst coverage (*AnFollow*), consistent with higher disclosure quality reducing information asymmetry and attracting a higher analyst following.

5. Empirical analysis

5.1 Analysts' target price revisions

Table 4 reports the results of regressing target price revisions on market returns, excess stock returns, and other analysts' consensus target price revisions. Columns 1–3 show the results for individual information sources, column 4 reports the results of estimating model (1), and column 5 reports the results for model (2). The coefficients on *RM*, *ExRet*, and *RevCons* in columns 1–3 show that target price revisions are significantly associated with market returns, excess stock returns, and other analysts' consensus target price revisions. The adjusted *R*-squared in column 2 is higher than in columns 1 and 3, suggesting that the firm-specific information in excess stock returns is the most important factor explaining target price revisions.

Column 4 shows that *RM*, *ExRet* and *RevCons* all contribute incrementally to explaining analysts' target price revisions, consistent with hypotheses *H1a–c*. The positive coefficient on *RevCons* implies either that analysts find other analysts' forecasts to be incrementally informative over the information in market and excess stock returns, consistent with Lys and Sohn (1990) and Clement et al. (2011), or that, on average, they respond similarly to information that market and excess stock returns do not capture. Including earnings forecast and recommendation revisions and analyst characteristic as control variables in column 5 shows that the two revision variables are significant, but the results for our main three variables of interest remain essentially unchanged.

5.2 Analysts' asymmetric reaction to bad and good news

We now examine the hypothesis that analysts react more strongly to bad than to good news when revising their target prices by estimating versions of model (3). Table 5, panel A, reports the results. In column 1, which includes control variables for analyst characteristics, the new and important result is that while the positive coefficients on market returns and other analysts' consensus target price revisions are not significantly different for bad and good news, the positive coefficient on firm-specific excess returns

is significantly higher for bad than for good news observations. This supports hypothesis *H2a* that analysts' target price revisions are more sensitive to the information captured by firm-specific excess returns when this indicates bad news. However, we find no support for hypothesis *H2b* that the positive association between target price revision and other analysts' consensus target price revisions is stronger when firm-specific excess returns imply bad news.[21]

Columns 2 and 3, which also control for earnings forecast revisions and the alternative specification of recommendation revisions, show that the coefficients on these controls are significant, but do not change the key result on the incremental sensitivity of target price revisions to bad news in excess stock returns. The positive coefficients on *RevRecd*, *Upgrade*, and *RevEPS* implies that when analysts revise earnings forecasts and recommendations upward, they also revise target prices upward, while the negative coefficient on *Dngrade* implies that analysts revise target prices downward when they downgrade stocks. These results suggest that, on average, analysts are consistent in the way they revise target prices, earnings, and recommendations.

Regarding the rejection of hypothesis *H2b*, we conjecture that although both excess stock returns and other analysts' consensus target price revisions can reflect firm-specific news, other analysts' consensus target price revisions also reflect analysts' private information about firm performance and their own biases. Therefore, when we include both *ExRet* and *RevCons* in the same model, excess stock returns capture more firm-specific publicly available news than do other analysts' forecasts and thus subsume any asymmetric reaction effect in other analysts' forecast revisions. We test this argument by

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[21] While we have no specific predictions or theory for how analysts react to bad and good news in market returns, we examine this in an untabulated analysis. We include indicators of bad market news (*BadRM*) and other analysts' revisions' bad news (*BadRevCons*) and their interactions with *RM* and *RevCons*. *BadRM* equals 1 if *RM* < 0, 0 otherwise; *BadRevCons* equals 1 if *RevCons* < 0, 0 otherwise. The results show that the coefficients on *BadRM* × *RM* and *BadRevCons* × *RevCons* are insignificant, implying that target price revisions react symmetrically to bad and good news in market returns and other analysts' revisions.

re-estimating model (3) without *ExRet* and *BadExRet × ExRet.* Table 5, panel B reports the results. Column 1 shows the results of estimating the complete model (3) while column 2 presents the estimation results without *ExRet* and *BadExRet × ExRet.* Excluding these variables from model (3), *BadExret × RevCons* has a significantly positive coefficient, consistent with hypothesis *H2b*. This supports the conjecture that we reject *H2b* in our main analysis because the asymmetric reaction effect of *ExRet* subsumes that of *RevCons*. The result in column 2 of panel B, Table 5 also shows that if we use *RevCons* as the only source of firm-specific news, we find evidence consistent with target price revisions being more sensitive to the information in firm-specific excess stock returns when this indicates bad news.

5.3 Withholding bad news and the asymmetric reaction to good and bad news

The evidence in table 5 shows that analysts' target price revisions are more sensitive to firm-specific bad news. Nevertheless, this result does not indicate whether the asymmetric reaction of analysts is due to managers' tendency to withhold bad news. Alternative explanations for the asymmetric reaction to bad and good news is managers' accelerating bad news or the higher credibility of bad news. Therefore, we apply the analysis of section 3.3 to examine whether managers' withholding of bad news drives the asymmetric responsiveness of analysts' target price revisions to bad and good news.

For each year in the sample period, we assign each firm its disclosure quality index (*DiscInd*). Firms with a lower value of *DiscInd* have lower disclosure quality. Our argument is that firms with lower disclosure quality are subject to greater information uncertainty and are more likely to withhold and accumulate bad news. We re-estimate model (3) for quintiles ranked by *DiscInd* values. We expect to find a more pronounced asymmetric reaction of analyst target price revisions for firms with lower disclosure quality.

Table 6 reports the result of estimating model (3) for quintiles sorted by *DiscInd*. The first column presents results for the lowest disclosure quality quintile while the final column presents results for the highest disclosure quality quintile. Consistent with our hypothesis, there is no asymmetric reaction of analysts to good and bad news in quintiles 4 and 5, whereas there is a significant asymmetric reaction in quintiles 1–3. A test for the difference between the average coefficients in columns 1–3 versus 4–5 is significant at 5%.[22] This suggests that analysts react symmetrically to bad and good news for firms with high disclosure quality, whereas they react asymmetrically to bad and good news for firms with low disclosure quality.

These results support our hypothesis that the asymmetric reaction of analysts to firm-specific bad and good news in excess stock returns is more pronounced for firms with higher information uncertainty, which have more opportunity and are more likely to withhold bad news. In contrast, if the asymmetric reaction pattern was due to managers' accelerating bad news but revealing good news gradually, we would not observe a stronger asymmetric reaction for firms that are more likely to withhold bad news.[23]

5.4 Robustness check

In section 5.3, we argue that managers' tendency to withhold bad news and disclose good news early drives analysts' asymmetric reaction to bad and good news and present evidence that the asymmetric pattern is more pronounced for low disclosure quality firms. In this section, we employ an alternative proxy for information uncertainty

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[22] A test of the difference between the average coefficients in columns 1–2 versus 4–5 is significant at 1%.
[23] Following a suggestion of an anonymous reviewer, in a supplementary analysis we estimate model (3) conditioning on firms experiencing large changes in *DiscInd*, defined as the 20 percent highest and lowest annual changes in *DiscInd*. This analysis shows that, relative to other firms, firms have no significant change in their asymmetric reaction to bad and good news after large increases in *DiscInd*, but that firms have a stronger asymmetric reaction to bad and good news after large decreases in *DiscInd*. This result is consistent with the asymmetric reaction of analysts to firm-specific bad and good news in excess stock returns becoming more pronounced after large increases in firms' information uncertainty. Details of these results are available on request.

and for firms' tendency to withhold bad news and conduct a similar analysis to section 5.3.

Hong, Lim, and Stein (2000) use analyst coverage as a proxy for information asymmetry.[24] We therefore use analyst coverage (*AnFollow)* as an alternative proxy for firms' tendency to withhold bad news. We examine whether analysts' asymmetric reaction to bad and good news is higher for firms with low analyst coverage. We measure *AnFollow* as the highest number of analysts following the firm in the fiscal year before the target price revision date. We sort observations in each year into quintiles based on *AnFollow* in ascending order. The top quintile includes target price revisions for firms with the highest *AnFollow*, while the bottom quintile includes revisions for firms with the lowest *AnFollow*. We then re-estimate model (3) for these quintiles. Table 7 reports the results.

The first column of table 7 reports results for the lowest analyst following quintile, while the final column reports results for the highest analyst following quintile. The coefficient on *BadExRet* × *ExRet* is again positive for quintiles 1–3, while it is insignificant for quintiles 4–5.[25] These results, though providing weaker evidence than in table 6, also suggest that target price revisions are more sensitive to bad than good news in excess stock returns for firms with a low analyst following, consistent with our argument that firms with low analyst coverage (higher information asymmetry) are more likely to withhold bad news.[26]

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[24] The correlation between analyst coverage and disclosure index in our sample is 0.442, suggesting that these two measures do not capture the same characteristics. In an untabulated two-way frequency table, we find that there are a material numbers of observations in cells with low (high) levels of the disclosure index and high (low) analyst following.

[25] A test for the difference in the average coefficients in quintiles 1–3 versus 4–5 is not significant. The difference in the average coefficients in quintiles 1–3 versus 5, however, is significant at 5 percent.

[26] Adopting the alternative approach of interacting analyst coverage with the variables of interest gives consistent results (cf. fn.15).

The results in tables 6 and 7 are robust to using the alternative specification of recommendation revisions and to replacing *BadExRet* with the indicator *Bad*, which equals 1 when stock return is negative and 0 otherwise.[27] We also replicate the results using standard errors clustered by broker–year-end and analyst–forecast date with the findings remaining qualitatively unchanged.

6. Conclusion

We examine the relation between analysts' target price revisions and market returns, excess stock returns, and other analysts' target price revisions. We find a strong positive correlation between analysts' target price revisions and market returns, excess stock returns, and other analysts' target price revisions, after controlling for earnings forecasts and recommendation revisions. This is consistent with prior studies of earnings forecasts by Clement et al. (2011) and Abarbanell (1991), suggesting that analysts extract information from public signals such as investors' actions and other analysts' reports and incorporate these into their forecasts. However, although the reported associations between target price revisions and our hypothesised indicators of news are strong, we have not established the extent to which they are causal. It is possible that there are other, unobserved, sources of information that cause analysts to revise their target prices, and this information also causes share prices to change and causes other analysts to revise their the target prices.

An important contribution of our study is that we examine whether firms' strategic disclosures of bad and good news drive analysts' asymmetric reaction to bad and good news when revising target prices. We find that when analysts revise their target prices, they rely more heavily on firm-specific information when this information is bad than

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[27] Some studies use negative stock return to represent bad news (e.g. Basu, 1997).

when it is good. Sorting observations into quintiles using a disclosure quality index as a proxy for firm's tendency to withhold bad news, we find that the asymmetric analyst reaction to bad and good news is pronounced among firms with low disclosure quality while the pattern disappears for firms with high disclosure quality. Our findings largely remain when we use analyst coverage as an alternative proxy for firms' tendency to withhold bad news.

These results support our hypothesis that due to firms' tendency to withhold bad news but release good news promptly, analysts react asymmetrically to bad and good news when revising their target prices. These findings are consistent with Kothari et al. (2009), who show that firms' asymmetric reactions to bad and good news disclosures leads to the asymmetric reaction of stock prices to good and bad news disclosures.

Our study has implications for the analyst literature. Our findings suggest that how analysts use information is conditional on how managers disclose this information and that they react asymmetrically to bad and good news, as do general market participants. Therefore, although analysts may gain access to good news early and convey this through their forecasts of future earnings, earnings growth, and positive tone in their reports, they are unlikely to be able to provide such benefits in the case of bad news.

Our paper suggests avenues that future studies should explore. First, we argue that managers' strategic disclosures are the main driver of analysts' asymmetric reaction to bad and good news. Future studies could test alternative explanations for analysts' asymmetric reaction to firm-specific bad and good news. For example, analysts may be subject to loss-aversion and confirmation bias. They may fail to cut their target prices in anticipation of bad news, forcing them to reduce their target prices sharply on the disclosure of bad news. Besides cognitive biases, analysts' economic incentive biases may contribute to this effect. Even when they are aware of bad news, analysts may have

economic incentives to defer downward target price revisions until the news becomes public. These arguments do not exclude our explanation, however, and do not explain why analysts' asymmetric reaction is stronger for firms that are more likely to withhold bad news.

Second, our results suggest that the relation between target price revisions and earnings forecast revisions is lower in firms with higher disclosure quality. The literature provides little insight into how analysts incorporate earnings, growth, and risk into their target prices and whether their reliance on these factors differs depending on the quality of accounting information or non-financial disclosures. Direct engagement with analysts may also help to shed light on these issues. Future studies could explore this avenue.

Third, we employ a disclosure quality index and analyst coverage as two proxies for managers' withholding of bad news. While these measures capture opportunities for managers to withhold bad news and therefore should be correlated with bad news accumulation, they are indirect and noisy proxies for managers' withholding of bad news. Future studies should look for better proxies for managers' withholding of bad news.

Finally, some studies suggest that investor sentiment may affect analyst behaviour. As we do not distinguish sentiment factors from fundamental aspects of information in market returns, excess stock returns, and other analysts' forecasts, future studies can extend our research in this direction.

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Appendix 1. Definitions of key variables

Variable	Definition
AnFollow	Analyst following, equal to the highest number of analysts following the firm in the most recent fiscal year before the target price revision date.
BadExRet	A dummy variable equal to 1 if excess stock return is negative, and 0 otherwise.
BrSize	Brokerage firm size, equal to the number of analysts associated with the broker that employs the analyst in the year before the target price date.
DayInt	The number of days between two consecutive target prices issued by the same analyst for each stock
DiscInd	Disclosure index from the CFIE web-based annual report scoring tool.
Dngrade	Indicator of a downward recommendation revision, equal to 1 if *RecRecd* < 0 and 0 otherwise.
ExRet	Excess stock return, equal to the difference between the stock return and the market return.
FExp	Firm experience, equal to the number of years the analyst has covered a company up to the year before the target price date.
IExp	Industry experience, equal to the number of years the analyst has covered an industry up to the year before the target price date.
NFirm	Number of firms the analyst of interest covers in the year before the target price date.
NInd	Number of industries the analyst of interest covers in the year before the target price date.
Reit	Indicator of a reiteration recommendation revision, equal to 1 if the analyst issues recommendations on both the current and previous target price dates but the recommendation does not change, 0 otherwise.
Return	Return on the stock between the previous and the current target price date.

RevCons	Other analysts' consensus target price revision, equal to $RevCons_{i,j,t} = \left(MeanOTP_{j,t} - MeanOTP_{j,t-1} \right) \big/ P_{i,t-1}$, where $MeanOTP_{j,t}$ is the mean outstanding target price of analysts other than j for stock i between $t-1$ and t, taking the latest target price for each analyst.
RevEPS	Earnings forecast revision, $RevEPS_{i,j,t} = \left(EPS_{i,j,t} - EPS_{i,j,t-1} \right) \big/ P_{i,t-1}$, equal to the difference between analyst j's earnings forecast at time t and the previous earnings forecast, scaled by the closing stock price on the day before the previous target price date.
RevRecd	Recommendation revision, $RevRecd_{i,j,t} = -\left(Recd_{i,j,t} - Recd_{i,j,t-1} \right) \big/ 4$, equal to the difference between analyst j's I/B/E/S coded recommendation at time t and the previous recommendation, multiplied by $-1/4$.
RevTP	Target price revision, $RevTP_{i,j,t} = \left(TP_{i,j,t} - TP_{i,j,t-1} \right) \big/ P_{i,t-1}$, equal to the difference between analyst j's target price at time t and the previous target price, scaled by the closing stock price on the day before the previous target price date.
RM	Market return, equal to the return on the FTSE-All Share Index from $t-1$ to t
TPRatio	Target price over closing stock price on the day before the announcement date of the new target price.
Upgrade	Indicator of an upward recommendation revision, equal to 1 if *RecRecd* > 0 and 0 otherwise.

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Appendix 2. Description of the disclosure index

The disclosure index we use, *DiscInd*, is based on the output of the CFIE web-based annual report scoring tool. The CFIE project uses the web tool to score the linguistic properties of 11,313 annual reports over 2003 to 2013. El Haj et al. (2014, 2015) describe how this tool identifies the main section headings of annual reports and scores their linguistic properties section by section, distinguishing between the front sections (such as highlights, performance commentaries, business strategy, risk, remuneration, and governance) and rear sections (such as accounting policies, the audit report, financial statements, and notes to the accounts).

The disclosure index is an equally weighted sum of eight components, with each component being a percentage ranking of a particular linguistic property of an annual report relative to the 11,313 annual reports in the CFIE (2015) sample. A higher disclosure index implies higher disclosure quality. The eight linguistic components are as follows.

- *Strategic word count*. The relative ranking of the number of times the words and phrases in a list of strategic keywords and phrases appear in the front-end sections of the annual report, excluding the governance and remuneration sections. The list of strategic keywords and phrases is from CFIE (2015).

- *Rear-end word count*. The relative ranking of the number of words in the rear-end sections of the report.

- *Governance and remuneration word count*. The relative ranking of the number of words in the governance and remuneration sections of the annual report.

- *Performance commentary word count*. The relative ranking of the number of words in all front-end performance review sections (i.e., section headings of the

form: Highlights, Chairman's Statement, CEO Review, Financial Review, Business Review, Review of Operations).

- *Causal reasoning word count in performance review sections*. The relative ranking of the number of causal key words appearing in the performance review sections. This proxies for the extent to which the review sections provide an explanation of performance. The list of commonly used causal reasoning key words is from CFIE (2015).

- *Readability (Fog Index)*. The relative ranking of the readability of the performance review sections times minus 1. The Fog index is an estimate of the reading age required to understand a piece of text. Higher values of the Fog index indicate that the text is more difficult to understand. Where an annual report contains more than one performance review section the Fog index is the weighted average Fog score for each section where the weights are the relative number of words in each section.

- *Other front-end word count*. The relative ranking of the number of words in the front-end of the annual report excluding the review, governance, and remuneration sections.

- *Forward looking word count*. The relative ranking of the number of forward looking key words appearing in all sections of the report. The list of forward looking key words is from CFIE (2015).

Figure 1. Illustration of our empirical design

This figure illustrates the main concepts and timeline used in our empirical design. *RevTP* is the target price revision, *RM* is the market return, *ExRet* is excess stock return and *RevCons* is other analysts' target price revisions.
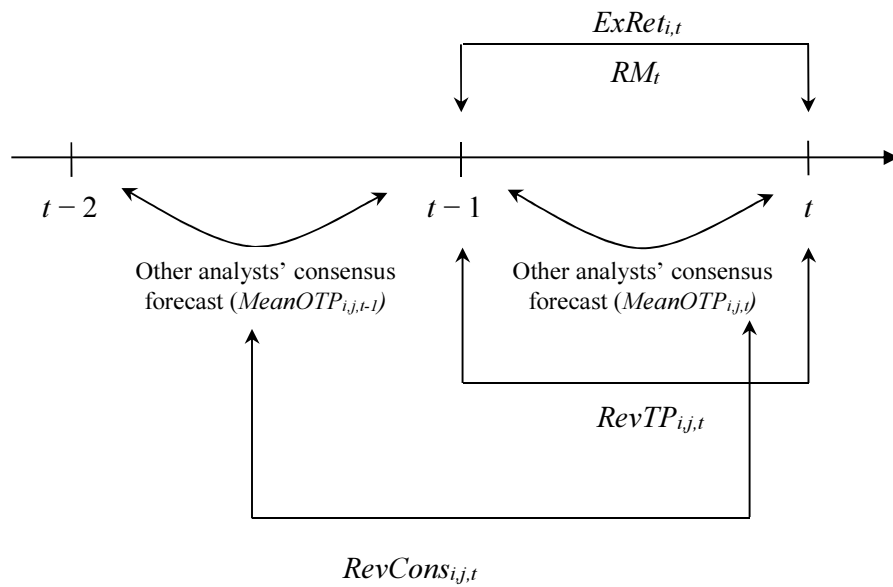
Table 1. Sample selection

This table reports the sample selection steps in our study and the number of observations lost and remaining after each step.

	Observations lost	Remaining observations
Target prices for UK listed companies, from 1 January 2003 to 31 December 2014, with a 12-month forecast horizon. For each analyst, on each target price date, we keep only the latest target price for each company.		201,200
Drop observations without stock price data from Datastream	18,952	182,248
Drop observations without at least one previous target price by the same analyst for the same company	59,237	123,011
Drop observations where the target price forecast horizon differs from 12 months or the interval between consecutive target prices is not between 30 and 360 days.	5,568	117,443
Drop observations without available data to calculate the disclosure quality index	44,470	72,973
Drop observations without available data to calculate analyst coverage	258	72,715
Drop observations without available data to calculate other analyst consensus target prices	18,311	54,404
Drop observations without available data to calculate earnings forecast revisions	5,112	49,292
Drop observations without available data to calculate recommendation revisions	22,004	27,288

Table 2. Summary statistics

This table reports summary statistics for selected variables in the study. Panel A reports summary statistics for the full sample, panel B for observations with non-negative excess stock returns (the good news sample), and panel C for observations with negative excess stock returns (the bad news sample). The summary statistics are the mean, the median, the 1st and 99th percentile values, the maximum and minimum values, and the standard deviation. Panel D reports the results of tests of differences in means in panels B and C. *TPRatio* is target price over stock price, *RevTP* is the target price revision, *Return* denotes stock return, *RM* is market return, *ExRet* is excess stock return, *RevCons* is consensus target price revisions of other analysts, *RevEPS* is earnings forecast revision; *RevRecd* is recommendation revision; *DayInt* is the days between consecutive forecasts; *AnFollow* is analyst coverage; *NFirm* is the number of firms covered by the analyst of interest; *NInd* is the number of industries covered by the analyst of interest; *IExp* is analyst's industry experience; *FExp* is analyst' firm experience; *BrSize* is brokerage firm size; and *BadExRet* is an indicator of firm-specific bad news (*ExRet* < 0). Appendix 1 gives a detailed explanation of the variables.

Panel A. Full sample (N = 27,288)

	Mean	Median	P1	P99	Max	Min	Std
TPRratio	1.120	1.095	0.685	1.951	2.738	0.685	0.222
RevTP	0.014	0.030	−0.830	0.777	0.777	−0.920	0.246
Return	0.032	0.036	−0.540	0.714	0.714	−0.540	0.208
RM	0.026	0.029	−0.250	0.251	0.251	−0.250	0.084
ExRet	0.006	0.006	−0.501	0.613	0.613	−0.501	0.182
RevCons	−0.002	0.024	−0.921	0.572	0.572	−0.921	0.234
RevEPS	−0.001	0.000	−0.130	0.064	0.086	−0.130	0.023
RevRecd	0.005	0.000	−0.500	0.500	1.000	−1.000	0.171
NFirm	9.156	8.000	1.000	33.000	33.000	1.000	6.573
NInd	4.324	4.000	1.000	14.000	19.000	1.000	2.886
IExp	5.964	4.000	0.000	19.000	21.000	0.000	5.522
FExp	3.221	2.000	0.000	16.000	21.000	0.000	3.974
BrSize	42.701	40.000	2.000	134.000	161.000	1.000	25.473
DiscInd	492.531	514.660	165.623	627.751	627.751	121.816	97.906
AnFollow	17.008	17.000	3.000	34.000	34.000	2.000	7.347
DayInt	111.008	91.000	31.000	326.000	360.000	30.000	69.686

Panel B. Good news sample, ExRet ≥ 0 (N = 14,155)

	Mean	Median	P1	P99	Max	Min	Std
TPRratio	1.088	1.081	0.685	1.626	2.738	0.685	0.175
RevTP	0.124	0.094	−0.391	0.777	0.777	−0.920	0.207
Return	0.163	0.128	−0.133	0.714	0.714	−0.335	0.162
RM	0.030	0.033	−0.242	0.251	0.251	−0.250	0.080
ExRet	0.132	0.094	0.002	0.613	0.613	0.000	0.131
RevCons	0.070	0.077	−0.715	0.572	0.572	−0.921	0.208
RevEPS	0.001	0.000	−0.125	0.064	0.086	−0.130	0.021
RevRecd	0.004	0.000	−0.500	0.500	1.000	−1.000	0.165
NFirm	9.001	8.000	1.000	33.000	33.000	1.000	6.522
NInd	4.291	4.000	1.000	14.000	19.000	1.000	2.908
IExp	5.978	4.000	0.000	19.000	21.000	0.000	5.505
FExp	3.265	2.000	0.000	16.000	21.000	0.000	3.976
BrSize	43.594	40.000	2.000	134.000	161.000	1.000	25.914
DiscInd	492.666	514.713	180.027	627.751	627.751	121.816	96.500
AnFollow	17.019	17.000	3.000	34.000	34.000	2.000	7.331
DayInt	109.230	89.000	31.000	323.000	360.000	30.000	68.633

Panel C. Bad news sample, Exret < 0 (N = 13,133)

	Mean	Median	P1	P99	Max	Min	Std
TPRratio	1.154	1.111	0.685	2.180	2.738	0.685	0.259
RevTP	−0.105	−0.064	−0.920	0.377	0.777	−0.920	0.230
Return	−0.110	−0.078	−0.540	0.171	0.552	−0.540	0.153
RM	0.021	0.024	−0.250	0.251	0.251	−0.250	0.087
ExRet	−0.131	−0.094	−0.501	−0.002	0.000	−0.501	0.120
RevCons	−0.079	−0.037	−0.921	0.408	0.572	−0.921	0.235
RevEPS	−0.004	0.000	−0.130	0.062	0.086	−0.130	0.024
RevRecd	0.006	0.000	−0.500	0.500	1.000	−1.000	0.177
NFirm	9.323	8.000	1.000	33.000	33.000	1.000	6.624
NInd	4.360	4.000	1.000	14.000	19.000	1.000	2.861

IExp	5.949	4.000	0.000	19.000	21.000	0.000	5.540
FExp	3.172	2.000	0.000	16.000	21.000	0.000	3.971
BrSize	41.737	38.000	2.000	125.000	161.000	1.000	24.955
DiscInd	492.386	514.661	133.099	627.318	627.751	121.815	99.403
AnFollow	16.998	17.000	3.000	34.000	34.000	2.000	7.365
DayInt	112.924	92.000	31.000	328.000	360.000	30.000	70.756

Panel D. Mean comparison between bad and good news subsamples

	Good	Bad	Bad − Good	*p*-value
TPRratio	1.088	1.154	0.065***	0.000
RevTP	0.124	−0.105	−0.228***	0.000
Return	0.163	−0.110	−0.273***	0.000
RM	0.030	0.021	−0.009***	0.000
ExRet	0.132	−0.131	−0.264***	0.000
RevCons	0.070	−0.079	−0.150***	0.000
RevEPS	0.001	−0.004	−0.005***	0.000
RevRecd	0.004	0.006	0.002	0.240
NFirm	9.001	9.323	0.322***	0.000
NInd	4.291	4.360	0.069**	0.048
IExp	5.978	5.949	−0.028	0.670
FExp	3.265	3.172	−0.093*	0.054
BrSize	43.594	41.737	−1.857***	0.000
DiscInd	492.666	492.386	−0.280	0.813
AnFollow	17.019	16.998	−0.021	0.811
DayInt	109.230	112.924	3.694***	0.000

Table 3. Pearson correlations of selected variables

This table reports Pearson correlations between selected variables. *RevTP* is the target price revision; *RM* is market return; *ExRet* is excess stock return; *RevCons* is consensus target price revisions of other analysts; *RevEPS* is earnings forecast revision; *RevRecd* is recommendation revision; *BadExRet* is an indicator of firm-specific bad news (*ExRet* < 0); *DiscInd* is the disclosure index; *AnFollow* is analyst coverage; *DayInt* is the days between consecutive forecasts; *NFirm* is the number of firms covered by the analyst of interest; *NInd* is the number of industries covered by the analyst of interest; *IExp* is analyst industry experience; *FExp* is analyst firm experience; and *BrSize* is brokerage firm size. Appendix 1 gives a detailed explanation of the variables. An asterisk (*) denotes significance at 5 percent.

	RevTP	RM	ExRet	RevCons	RevEPS	Rev-Recd	Bad-ExRet	DiscInd	An-Follow	DayInt	NFirm	NInd	IExp	FExp
RM	0.302*													
ExRet	0.632*	0.091*												
RevCons	0.521*	0.227*	0.432*											
RevEPS	0.300*	0.035*	0.195*	0.259*										
RevRecd	0.216*	−0.023*	−0.008	0.004	0.046*									
BadExRet	−0.452*	−0.058*	−0.722*	−0.318*	−0.149*	0.012*								
DiscInd	0.016*	−0.020*	0.001	0.001	0.001	0.012*	−0.004							
AnFollow	−0.006	−0.023*	−0.011*	0.020*	0.007	0.005	0.006	0.442*						
DayInt	0.008*	0.173*	−0.020*	0.040*	0.033*	−0.009	0.023*	−0.042*	−0.059*					
NFirm	−0.001	−0.004	−0.004	−0.008	−0.020*	−0.001	0.006	−0.134*	−0.191*	0.008*				
NInd	0.013*	−0.005	0.013*	−0.006	−0.022*	0.004	−0.010*	−0.132*	−0.260*	0.039*	0.456*			
IExp	0.017*	0.004	0.012*	0.018*	0.000	0.000	−0.015*	0.107*	0.126*	0.045*	0.019*	0.160*		
FExp	0.026*	0.011*	0.021*	0.038*	0.019*	0.001	−0.026*	0.150*	0.217*	0.045*	−0.035*	0.084*	0.635*	
BrSize	0.024*	−0.001	0.023*	0.020*	0.034*	−0.009	−0.031*	0.072*	0.049*	−0.078*	−0.213*	−0.208*	−0.033*	0.016*

Table 4. Analysts' use of information when revising target prices

The table shows the results of a regression of target price revisions on market returns (column 1), excess stock returns (column 2), and other analysts' target price revisions (column 3). Column (4) reports the results of estimating model (1). *RevTP* is the target price revision; *RM* is market return; *ExRet* is excess stock return; *RevCons* is consensus target price revisions of other analysts; *RevEPS* is earnings forecast revision; *RevRecd* is recommendation revision; *NFirm* is the number of firms covered by the analyst of interest; *NInd* is the number of industries covered by the analyst of interest; *IExp* is analyst's industry experience; *FExp* is analyst' firm experience; and *BrSize* is brokerage firm size. Appendix 1 gives a detailed explanation of the variables. All coefficients are estimated controlling for broker, industry, and year fixed effects; all regressions include a constant (unreported); reported *t*-statistics use cluster-robust standard errors with two-way firm–year clustering; *, **, and *** denote significance at 10, 5, and 1 percent.

RevTP	1	2	3	4	5
RM	0.992***			0.576***	0.599***
	(10.11)			(7.07)	(8.30)
ExRet		0.885***		0.733***	0.721***
		(31.45)		(37.40)	(62.74)
RevCons			0.491***	0.202***	0.184***
			(18.76)	(15.51)	(15.38)
RevEPS					1.004***
					(11.79)
RevRecd					0.324***
					(20.61)
FExp					0.001
					(1.63)
IExp					−0.000
					(−0.25)
NFirm					0.000
					(0.07)
NInd					0.000
					(0.32)
BrSize					−0.001
					(−0.96)
Broker FE	No	No	No	Yes	Yes
Industry FE	No	No	No	Yes	Yes
Year FE	No	No	No	Yes	Yes
Adj *R*-squared	0.099	0.418	0.229	0.519	0.582
N	27,288	27,288	27,288	27,288	27,288

Table 5. Analysts' asymmetric reaction to bad and good news

The table shows the results of estimating model (3). Column (1) includes analyst characteristics control variables, while columns (2) and (3) also include earnings forecast revisions and alternative specifications of recommendation revisions. Panel A report the results of estimating versions of model (3) while Panel B reports the results of estimating the complete model (3) and re-estimating the model without *ExRet* and *BadExret×ExRet*. *RevTP* is the target price revision; *RM* is market return; *ExRet* is excess stock return; *RevCons* is consensus target price revisions of other analysts; *BadExret* is an indicator of firm-specific bad news (*ExRet* < 0); *RevEPS* is earnings forecast revision; *RevRecd* is recommendation revision; *Upgrade* equals 1 if *RevRecd* > 0, 0 otherwise; *Dngrade* equals 1 if *RevRecd* < 0, 0 otherwise; *Reit* equals 1 if analysts issue recommendations on the previous and current target price forecast dates, but the recommendation does not change; *FExp* is analyst firm experience; *IExp* is analyst industry experience; *NFirm* is the number of firms the analyst covers; *NInd* is the number of industries the analyst covers; and *BrSize* is brokerage firm size. Appendix 1 gives a detailed explanation of all the variables. All coefficients are estimated controlling for broker, industry, and year fixed effects; all regressions include a constant (unreported); reported *t*-statistics use cluster-robust standard errors with two-way firm–year clustering; *, **, and *** denote significance at 10, 5, and 1 percent.

Panel A

RevTP	1	2	3
RM	0.582***	0.600***	0.599***
	(7.74)	(8.16)	(8.12)
ExRet	0.652***	0.674***	0.674***
	(34.27)	(38.50)	(37.91)
RevCons	0.198***	0.187***	0.184***
	(11.38)	(13.68)	(13.45)
BadExRet	0.001**	0.001*	0.001*
	(2.37)	(1.85)	(1.77)
BadExRet × RM	−0.010	0.001	0.008
	(−0.302)	(0.024)	(0.307)
BadExRet × ExRet	0.242***	0.158***	0.173***
	(17.46)	(31.19)	(18.78)
BadExRet × RevCons	−0.013	−0.017	−0.017
	(−0.85)	(−1.36)	(−1.46)
RevEPS		0.991***	1.012***
		(10.79)	(11.19)
RevRecd		0.323***	
		(16.29)	
BadExRet × RevEPS		−0.084	−0.073
		(−0.69)	(−0.67)
BadExRet × RevRecd		0.000	
		(0.01)	
Upgrade			0.016***
			(12.30)
Dngrade			−0.010***
			(−12.91)

Reit			0.001
			(1.53)
BadExRet × Upgrade			−0.002**
			(−2.06)
BadexRet × Dngrade			−0.002***
			(−3.72)
BadExRet × Reit			0.002***
			(4.01)
NFirm	0.000	0.000	0.000
	(0.37)	(0.21)	(0.29)
NInd	−0.000	0.000	0.000
	(−0.11)	(0.24)	(0.09)
IExp	−0.001	−0.001	−0.001
	(−0.95)	(−0.22)	(−0.28)
FExp	0.000	0.000	0.000
	(1.18)	(1.17)	(1.16)
BrSize	−0.000	−0.000	−0.000
	(−0.90)	(−1.07)	(−1.19)
Broker FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. *R*-squared	0.522	0.584	0.579
N	27,288	27,288	27,288

Panel B

RevTP	1	2
RM	0.600***	0.630***
	(8.16)	(8.19)
ExRet	0.674***	
	(38.50)	
RevCons	0.187***	0.255***
	(13.68)	(29.30)
BadExRet	0.001*	−0.017***
	(1.85)	(−18.98)
BadExRet × RM	0.001	−0.034
	(0.02)	(−0.542)
BadExRet × ExRet	0.158***	
	(31.19)	
BadExRet × RevCons	−0.017	0.085***
	(−1.36)	(5.22)
RevEps	0.991***	0.561***
	(10.79)	(2.62)
RevRecd	0.323***	0.320***
	(16.29)	(13.94)
BadExRet × RevEps	−0.084	1.097***
	(−0.69)	(5.72)

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BadExRet × *RevRecd*	0.000	0.017
	(0.01)	(0.85)
NFirm	0.000	0.000
	(0.21)	(0.34)
NInd	0.000	0.000
	(0.24)	(0.22)
IExp	−0.001	0.000
	(−0.22)	(0.01)
FExp	0.000	0.000*
	(1.17)	(1.78)
BrSize	−0.000	−0.000
	(−1.07)	(−0.06)
Broker FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adj. *R*-squared	0.584	0.462
N	27,288	27,288

Table 6. Withholding bad news and the asymmetric reaction to bad and good news: subsamples ranked by disclosure quality

The table shows the OLS estimation of model (3) on five quintiles based on firms' disclosure index. Each year, we rank observations into quintiles based on firms' disclosure index (*DiscInd*) values in ascending order. The top quintile includes target price revisions for firms with the highest *DiscInd* (column 5) and the bottom quintile contains revisions for firms with the lowest *DiscInd* (column 1). *RevTP* is the target price revision; *RM* is market return; *ExRet* is excess stock return; *RevCons* is consensus target price revision of other analysts; *BadExRet* is an indicator of firm-specific bad news (*ExRet* < 0); *RevEPS* is the earnings forecast revision, *RevRecd* is the recommendation revision; *FExp* is analyst firm experience; *IExp* is analyst industry experience; *NFirm* is the number of firms the analyst covers; *NInd* is the number of industries the analyst covers; and *BrSize* is brokerage firm size. All coefficients are estimated controlling for broker, industry, and year fixed effects; all regressions include a constant (unreported); reported *t*-statistics use cluster-robust standard errors with two-way firm–year clustering; *, **, and *** denote significance at 10, 5, and 1 percent.

RevTP	Rank *DiscInd* = 1	Rank *DiscInd* = 2	Rank *DiscInd* = 3	Rank *DiscInd* = 4	Rank *DiscInd* = 5
RM	0.509***	0.578***	0.577***	0.604***	0.678***
	(6.68)	(9.64)	(6.69)	(7.20)	(7.70)
ExRet	0.649***	0.603***	0.704***	0.686***	0.675***
	(10.71)	(10.48)	(27.29)	(13.60)	(29.94)
RevCons	0.168***	0.204***	0.169***	0.206***	0.163***
	(3.64)	(5.84)	(5.02)	(5.69)	(6.35)
BadExRet	0.001	0.002	0.002***	0.001	−0.001
	(0.62)	(1.50)	(2.58)	(1.09)	(−0.67)
BadExRet × RM	0.053	0.017	0.008	−0.008	0.005
	(0.86)	(0.39)	(0.16)	(−0.15)	(0.06)
BadExRet × Exret	0.228***	0.327***	0.136***	0.104	0.046
	(3.09)	(7.38)	(3.23)	(1.22)	(0.87)
BadExRet × RevCons	0.009	−0.039	−0.018	−0.056	0.030
	(0.17)	(−1.34)	(−0.39)	(−1.49)	(0.69)
RevEPS	1.196***	1.402**	0.981***	1.003***	0.659***
	(3.97)	(2.40)	(4.33)	(5.57)	(6.02)

RevRecd	0.337***	0.279***	0.342***	0.365***	0.286***
	(12.46)	(18.01)	(9.55)	(9.86)	(7.49)
BadExRet × RevEPS	−0.325	−0.514	0.221	−0.015	0.012
	(−1.121)	(−0.801)	(0.821)	(−0.058)	(0.001)
BadExRet × RevRecd	−0.004	0.045*	−0.025	−0.051	0.045**
	(−0.107)	(1.78)	(−0.58)	(−1.50)	(2.81)
FExp	−0.000	0.000*	0.000	0.000	0.000
	(−0.99)	(1.69)	(0.33)	(0.92)	(0.34)
IExp	0.001**	−0.000	−0.000	−0.000	0.000
	(2.45)	(−0.90)	(−1.28)	(−0.67)	(0.10)
NFirm	0.000	0.000	0.000	0.000	−0.000
	(1.06)	(0.01)	(0.77)	(0.86)	(−0.97)
NInd	−0.000	0.000	−0.000	−0.001	0.000
	(−0.74)	(1.22)	(−0.05)	(−1.29)	(1.05)
BrSize	0.000	−0.001*	0.000	−0.000	−0.000
	(0.79)	(−1.80)	(0.82)	(−0.22)	(−0.93)
Broker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj. *R*-squared	0.589	0.601	0.605	0.596	0.579
N	4,050	5,258	5,611	6,211	6,158

Table 7. Withholding bad news and the asymmetric reaction to bad and good news: subsamples ranked by analyst following

The table shows the OLS estimation of model (3) on five quintiles based on firms' analyst following. Each year, we rank observations into quintiles based on analyst following (*AnFollow*) in ascending order. The top quintile includes target price revisions for firms with the highest *AnFollow* (column 5) and the bottom quintile contains revisions for firms with the lowest *AnFollow* (column 1). *RevTP* is the target price revision; *RM* is market return; *ExRet* is excess stock return; *RevCons* is consensus target price revision of other analysts; *BadExRet* is an indicator of firm-specific bad news (*ExRet* < 0); *RevEPS* is the earnings forecast revision, *RevRecd* is the recommendation revision; *FExp* is analyst firm experience; *IExp* is analyst industry experience; *NFirm* is the number of firms the analyst covers; *NInd* is the number of industries the analyst covers; and *BrSize* is brokerage firm size. All coefficients are estimated controlling for broker, industry, and year fixed effects; all regressions include a constant (unreported); reported *t*-statistics use cluster-robust standard errors with two-way firm–year clustering; *, **, and *** denote significance at 10, 5, and 1 percent.

RevTP	Rank *AnFollow* = 1	Rank *AnFollow* = 2	Rank *AnFollow* = 3	Rank *AnFollow* = 4	Rank *AnFollow* = 5
RM	0.632***	0.573***	0.712***	0.519***	0.576***
	(5.82)	(8.59)	(6.55)	(8.23)	(8.60)
ExRet	0.692***	0.709***	0.661***	0.651***	0.596***
	(26.82)	(19.09)	(42.22)	(12.21)	(8.37)
RevCons	0.150***	0.131***	0.213***	0.245***	0.201***
	(6.62)	(6.03)	(8.17)	(11.77)	(12.72)
BadExRet	0.001*	0.002	0.001***	0.001	−0.001
	(1.75)	(1.58)	(30.39)	(0.96)	(−0.40)
BadExRet × *RM*	0.006	0.031	−0.127**	0.058	0.036
	(0.05)	(0.02)	(−2.11)	(1.33)	(0.63)
BadExRet × *Exret*	0.239***	0.166***	0.167***	0.128	0.047
	(5.34)	(5.71)	(6.17)	(1.56)	(0.59)
BadExRet × *RevCons*	−0.020	0.020	−0.058***	−0.067**	0.098***
	(−0.59)	(0.59)	(−4.34)	(−1.99)	(2.89)
RevEPS	1.648***	1.031***	0.829***	0.690***	1.160***
	(3.61)	(5.88)	(6.68)	(3.86)	(3.88)
RevRecd	0.323***	0.343***	0.334***	0.338***	0.252***

	(6.92)	(14.91)	(8.44)	(16.27)	(9.15)
BadExRet × RevEPS	−0.298	−0.309	−0.328	0.285	−0.095
	(−0.61)	(−1.40)	(−0.93)	(1.05)	(−0.25)
BadExRet × RevRecd	0.029	0.004	−0.035	−0.006	0.019
	(1.05)	(0.15)	(−0.95)	(−0.29)	(1.44)
FExp	−0.000	0.000**	0.000	0.001	−0.000
	(−0.43)	(2.48)	(0.14)	(1.33)	(−0.47)
IExp	0.000	−0.000	0.000	−0.000*	−0.000
	(0.48)	(−0.76)	(0.99)	(−1.80)	(−0.70)
NFirm	0.000	−0.000	0.000	0.000	−0.000
	(0.86)	(−0.45)	(0.17)	(1.22)	(−0.54)
NInd	−0.000	0.000	−0.000	−0.000	0.000***
	(−0.39)	(0.22)	(−1.088)	(−0.248)	(2.12)
BrSize	0.000	0.000	−0.000	−0.000	−0.000
	(1.24)	(0.61)	(−0.35)	(−1.02)	(−1.24)
Broker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj. *R*-squared	0.623	0.609	0.584	0.598	0.539
N	3,232	5,632	5,847	6,716	5,861

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