The Dynamics of Earnings Forecast Management*

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Abstract

This paper examines whether firms manage analyst forecasts and the associated value consequences. We find that earnings forecasts tend to grow pessimistic over the forecast horizon and these forecast changes and their timing are key determinants of whether firms generate positive earnings surprises: Late forecasts that raise (lower) the consensus sharply reduce (raise) the probability of positive surprises. This finding is the *opposite* of that predicted if consensus revisions reflected new information arrival. Investors seem to be "misled": Downward consensus revisions lead to large abnormal returns following the earnings announcement. Paradoxically, downward forecast management reduces post-announcement share price, as the impact of reduced forecasts dominates the gain from generating positive surprises.

Key words: Analysts consensus, forecast errors, earnings management.

JEL classification: D82, D84, and M41.

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1 Introduction

Firms appear to have strong incentives to manage earnings so as to exceed market expectations. Researchers have thoroughly documented that a firm's stock price rises following a 'positive' earnings surprise (i.e., announced earnings exceed the consensus forecast of financial analysts), while stock prices fall sharply following 'negative' earnings surprises. Moreover, the return-surprise relationship is highly non-linear: (i) prices rise less in response to a positive earnings surprise than they fall following a comparably-sized negative earnings surprise; (ii) greater positive earnings surprises have only marginally positive impacts on returns; but (iii) more negative earnings surprises have sharper adverse impacts on stock price.[1]

Firms can generate earnings that exceed the consensus forecast in two ways. One way is by raising earnings. A firm can raise quarterly earnings indirectly via accounting methods by increasing accruals, or directly, for example, by postponing expenses to future quarters. This paper investigates the other way in which firms can generate positive earnings surprises—by inducing analysts to issue lower earnings forecasts. We first show that downward revisions in the consensus forecast are a key determinant of whether firms succeed at generating positive earnings surprises, and that firms experiencing upward consensus revisions that come *very late* in the forecast cycle are likely to generate negative earnings surprises. Similarly-sized revisions earlier in the forecast cycle have minimal impacts on surprise outcomes. We then examine the valuation implications of this apparent forecast management. Among other findings, we uncover evidence that investors are misled by late revisions in the consensus, but—quite interestingly—firms are *hurt* by the downward forecast management.

To illustrate the forecast management dynamics that we study, consider two hypothetical firms in the days preceding their earnings announcements. Firm A privately expects earnings to be twelve cents per share, but faces a consensus forecast of fourteen cents. Firm B is in the opposite situation: it expects earnings of fourteen cents and faces a consensus of twelve cents. What can Firm A do to meet market expectations? One possibility is to manipulate actual earnings, but doing so may be difficult and costly. Alternatively, Firm A can manage forecasts by providing analysts "downward

[1]Papers reporting findings of this type include, among others, Freeman and Tse (1992), Liu and Thomas (2000), Bartov et al. (2002), and Skinner and Sloan (2002).

earnings guidance". If Firm A can influence later forecasts downward then it may be able to reduce the consensus forecast to eleven cents, thereby generating a positive earnings surprise. Firm B, in contrast, has a lesser incentive to alter earnings or influence forecasts, as generating a larger positive earnings surprise should have little impact on B's share price. This suggests that as long as firms' expectations of earnings are close enough to the consensus forecast, firms may want to provide analysts "downward earnings guidance", more often than "upward earnings guidance".

While firms A and B are hypothetical, in the real world many firms face similar situations each forecasting cycle. What then are the consequences of such forecast management? First observe that such forecast management would tend to cause the consensus forecast of earnings to fall as the earnings announcement date approaches. Indeed, this happens in the data. However, one wants further evidence of forecast management, as other stories could underlie this pattern of increasing forecast pessimism. For example, those who issue earlier forecasts may be the more optimistic analysts who want to provide their customers advance notice on which stocks to trade—and analyst compensation rises with the stock trading volume that they generate. Later analysts might issue better-informed forecasts that appear pessimistic only by comparison. Richardson et al. (2004) propose, alternatively, that the managers might have incentives to "walk down" markets expectations to a low estimate that can be beaten, and subsequently sell shares on their own personal accounts (insider trades). The possibility of such alternative rationales for the apparent "growing pessimism" in forecasts suggests that one must back out the *dynamics* of forecast management. Our study does precisely that, looking at daily data on earnings forecasts. Specifically, we use information about the consensus *formation path* to distinguish between the sequence of events and outcomes resulting from (a) possibly superior information content of later forecasts and (b) forecast management by firms.

Two examples illustrate what underlies our approach. Consider the following hypothetical sequence of earnings forecasts. In January, analyst 1 forecasts sixteen cents per share. Subsequently, in February and March, analysts 2 and 3 report forecasts of ten cents per share. Then on April first, one day before the earnings announcement, analyst 1 revises his forecast and reports a forecast of four cents. If the last forecast of four cents reflected new, negative information about the firm, then, even dropping the initial forecast, the outstanding (time-averaged) consensus forecast of eight cents—a measure that, by construction, incorporates stale forecasts—would overstate the market's expectations of earnings. Consequently, following this forecast pattern, on April second, the firm should be likely to report earnings of about four cents per share, and almost certainly below the consensus of eight cents, yielding a negative earnings surprise. Our empirical analysis reveals that the exact *opposite* occurs. In fact, downward revisions to the consensus sharply *raise* the likelihood that earnings will beat the consensus.

Conversely, if we reversed the pattern, with an initial forecast of four cents being revised to sixteen cents, then if the last forecast contained new, positive information, the consensus of twelve cents should understate the market's expectations of earnings, making a positive earnings surprise very likely. Once more, we find that the opposite occurs: small increases in the consensus forecast in the two weeks before the earnings announcement date make negative earnings surprises more likely than positive earnings surprises, while late reductions in the consensus lead to more than twice as many positive as negative earnings surprises. Since some late forecasts do reflect new information, making the consensus stale, the relationship that we uncover between the consensus path and surprise realizations just magnifies the implied intensity with which firms manage analyst forecasts.

Strikingly, we find that the closer the timing of a consensus revision is to the earnings announcement date, the more likely a downward revision is to lead to a positive earnings surprise; and the more likely an upward revision is to lead to a negative earnings surprise. In sharp contrast, earlier consensus revisions, two to three months before the earnings announcement date, have negligible impacts on earnings surprise outcomes.

What accounts for these results? Interpreting the first example in a forecast management context, we see a firm that just learned its earnings will be nine cents per share. While the firm can no longer "cook the books" to meet expectations (see McVay (2006)), its management can still generate a positive earnings surprise by inducing analysts to revise their forecasts. The firm could seek out a new analyst, but it can lower the consensus more effectively if it can convince the most optimistic analyst to issue a sharply lower forecast, thereby enabling its earnings to beat the consensus. In the second example, the firm has earnings of ten cents, on target to beat the consensus of eight cents, when it receives a revised April Fools Day surprise revision of sixteen cents, raising the consensus to twelve cents. Had the surprise, adverse forecast occurred early enough in the forecast cycle, the firms would have had enough time and flexibility to induce new forecasts that unravel adverse forecasts, or to cook the books so as to generate the "right" earnings surprise. However, the firm's accountants had long since signed off on the books, so that manipulating earnings was not possible, and on April 2, the firm had to report earnings that were a penny short of the consensus. This second forecast pattern happens far less frequently than the first, and may reflect failed earnings management: in the real world, firms cannot always induce analysts to issue the desired forecast.

One can understand why a firm's management would want to manage forecasts so as to generate a positive earnings surprise: Matsunaga and Park (2001) document that managers' cash bonuses increase with meeting analyst forecasts, Holthausen et al. (1995) document how the bonus structure influences earnings management, DeGeorge et al. (1999) emphasize that for senior management reaping a bonus or retaining a job may depend on meeting a "bright threshold", such as having earnings beat forecasts, and McVay et al. (2006) "find that the likelihood of just meeting versus just missing the analyst forecast is strongly associated with subsequent managerial stock sales."

At first glance, though, it is less clear why analysts should be willing to oblige, and why the brokerage houses that employ analysts would want them to accede to a firm's wishes. However, in the pre-Reg FD period that we study it was vital for analysts to remain in the good graces of a firm in order to retain access to insiders (see Francis and Philbrick (1993) and Bowen et al. (2003)), so that it was risky for analysts to issue forecasts that upset a firm's management—an analyst who is frozen out by a firm's management[2] is of little value to a brokerage house. To curry favor, analysts may issue late forecasts that are biased down. Ke and Yu (2006, p.1) find evidence for this entire scenario: "Analysts who issue initial optimistic earnings forecasts followed by pessimistic earnings forecasts before the earnings announcement are... less likely to be fired by their employers." They also find that the likelihood that this forecast pattern occurs is greater in firms with heavier insider selling. On the premise that larger brokerage houses have more at stake in terms of underwriting and trading volume and would hence differentially gain from better access to management, we

[2] Solomon and Frank (2003) show that analysts who issue "adverse forecasts" were punished by management in the pre-Reg FD era. Michaely and Womack (1999) argue that analysts' recommendations are biased because of conflicts of interest introduced by underwriting relationships between the firms they follow and the brokerage houses where they work.

search for evidence that larger houses are more willing to issue downward-biased forecasts at a firm's behest. Indeed, we find that the larger brokerage houses are primarily responsible for the preponderance of late pessimistic forecasts.

Because changes in the consensus just before the earnings announcement have a significant impact on whether firms generate positive or negative earnings surprise, we then investigate whether late changes in consensus can predict the share price response following the earnings announcement. If investors naïvely treat late revisions in the consensus as unbiased, then upward revisions will cause them to overestimate earnings, resulting in disappointment when earnings are announced, and hence negative abnormal returns following the announcement. So, too, downward revisions in the consensus will cause investors to underestimate earnings, and hence lead to positive abnormal returns following the earnings announcement.

We find evidence that investors are misled in this way. Firms for which the consensus falls in the last two weeks earn far higher returns around earnings announcements than do firms for which the consensus rise: the difference in annualized returns exceeds 69%. We then "reverse-engineer" the experiment and contrast abnormal returns accruing to firms that manage forecasts down with those firms that do not, conditional on meeting the consensus. That is, we examine whether investors differentiate between firms that meet or beat market expectations only after substantial declines in the consensus prior to the announcement date from those firms that do so without engaging in such forecast management. We find that investors do not differentiate between the two groups. If anything, firms that manage forecasts down have higher returns upon meeting expectations than those firms that do not.

These patterns in abnormal returns seem to imply that investors reward firms that manage forecasts so as to generate positive earnings surprise, thereby suggesting a rationale for why firms would do so. Our final contribution is to determine whether in fact firms gain from such forecast management. After we control for the extant earnings–consensus forecast gap, and hence for the relevant "information surprise", we find that the way in which firms manage forecasts *does* matter. But, managing forecasts down *lowers*, not raises, post-announcement share price. What happens is that the share price reduction following a downward forecast revision more than offsets the share price appreciation following the earnings announcement. Our results suggest that firms would benefit more from having positive information "leak out" in the form of consensus upward revisions, whether or not actual earnings exceed the consensus. In short, while we uncover evidence that firms manage earnings forecasts (down) and that investors are fooled, we also find that firms are hurt by this practice—the incentives firms provide managers to generate earnings that beat forecasts appear to have adverse consequences.

Several papers have documented that firms appear to manage different aspects accounting earnings (see, e.g., Burgstahler and Dichev (1997), DeGeorge et al. (1999), or Chan et al. (2006)). In contrast to this literature, our paper focuses on firms' attempts to manage earnings expectations (rather than realizations), providing joint evidence on the *dynamics* and the *value consequences* of earnings forecast management. Other papers (e.g., Lim (2001)) document the prevalence of downward forecast revisions, but do not link them to the likelihood of positive and negative earnings surprise. Matsumoto (2002) looks at the different mechanisms used by firms in order to meet the market's earnings expectations. Her study is the first to provide an extensive account of firm characteristics associated with forecast management (avoidance of negative earnings surprises), but it does not examine valuation effects. Bartov et al. (2002) explore whether forecast management pays off, and conclude that it does. We find that they arrive at this conclusion only because their approach does not allow them to disentangle the effects of forecast management from simple information arrival.

We next present our methodology. Section 2 explores the dynamics of forecast management. We document that the pre-announcement path of forecasts consistently influences earnings surprise outcomes. Section 3 examines the value implications of forecast management. Section 4 concludes.

2 Data and Test Design

Our data collection process is standard. Focusing on the period prior to the adoption of Regulation Fair Disclosure ("Reg FD"), we gather quarterly data from the Institutional Brokers Estimate System (I/B/E/S) database from 1989:I to 1999:IV.[3] For each firm in the I/B/E/S *Detail History*

[3] We focus on the period prior to the adoption of Reg FD so as to maximize the sampling of firm-quarters involved in the practice of "selective disclosure" (see Bowen et al. (2003) for a discussion of this practice and its consequences). A growing body of literature discusses the information dissemination effects of Reg FD. While there is no consensus on the real consequences of Reg FD, some researchers argue that Reg FD made it more difficult for firms to engage in selective disclosure of information (see, e.g., Gomes et al. (2004)).

files, we retrieve information on analysts' quarterly forecasts of firm's earnings per share (EPS), the estimate and date of each forecast issued, and actual firm earnings. Data on shares outstanding and earnings announcement dates are taken from COMPUSTAT. Stock prices and returns are obtained from the Center for Research in Security Prices (CRSP). We also use CRSP to adjust the data for stock splits. We filter the data for likely data entry errors, deleting any forecast with an absolute error value exceeding \$10.[4] We discard firm-quarters for which the previous quarter stock price was below \$5. Finally, we also condition the sample on observations of forecasts that are made after the pervious quarter's earnings announcement; this allows for the incorporation of relevant information about past errors in the current forecasts (see O'Brien (1988)). Our sample is restricted to forecasts that target the current quarter EPS.

Central to our analysis of forecast management is how firms influence forecasts given an extant "consensus" forecast. Hence, we only consider firm-quarters in which at least two analysts issue forecasts. Following the prior literature, for each firm-quarter we compute the forecast error in the consensus (FE) as the difference between announced earnings per share (actual EPS) and the consensus (mean) forecast scaled by the stock price at the end of the previous quarter:

$$FE = \frac{EPS \; - \; Consensus\ Forecast}{Previous\ Quarter\ Stock\ Price}. \tag{1}$$

As we have highlighted, firms appear to have an incentive to manage earnings and/or forecasts so that earnings meet or exceed the market consensus forecast. In particular, (i) stock prices are very sensitive to whether the firm exceeded, met or fell short of the consensus, and (ii) stock prices are sensitive to the magnitude of a negative earnings surprise, but relatively insensitive to the magnitude of a positive earnings surprise. This suggests that optimal earnings/forecast management policies may well aim at meeting or slightly exceeding the consensus forecast so as to produce "good news" about the company, while saving financial flexibility for future earnings management. An implication of these earnings management policies is that firms with private good information about earnings relative to the extant consensus will, if anything, manage earnings down and/or forecasts up; while firms with modestly bad private information will manage earnings upwards and/or forecasts down. Of course, as Abarbanell and Lehavy (2003) detail, firms with

[4] Lim (2001) and Bernhardt et al. (2006), among others, use similar rules to remove suspect data-entry errors.

very poor prospects may rationally give up the task of actively managing expectations and take a one-time "earnings bath" to gain future financial flexibility.

We build on these insights to draw inferences about forecast management based on the *ex-post* likelihood of observing earnings surprises (see Burgstahler and Eames (1999) for a related approach). Specifically, such earnings management implies that firms with relatively small *ex-post* forecast errors were likely to have attempted to manage earnings and forecasts to generate positive earnings surprises. Accordingly, we focus on firms with sufficiently small *ex-post* forecast errors, $FE \in [-\phi, \phi]$, where ϕ is the upper bound on the earnings surprise intervals that we consider. That is, we order and partition observed FE's so as to characterize post-managed earnings news according to

Category	Earnings Surprise	FE Partition
1	Large Negative Surprise	$-\infty < FE < -\phi$
2	Small Negative Surprise	$-\phi \leq FE < 0$
3	No Surprise	$FE = 0$
4	Small Positive Surprise	$0 < FE \leq \phi$
5	Large Positive Surprise	$\phi < FE < \infty$

and search for evidence that firms with forecast errors between $[-\phi, \phi]$ manage earnings and forecasts so as to generate "small"earnings surprises.[5] We interpret firms that generate small negative earnings surprises (category 2) as having failed to manage earnings/forecasts successfully; and interpret firms with earnings that slightly exceeded the consensus (category 4) as having successfully managed earnings. Our approach reduces emphasis on firms that report large negative or large positive earnings surprises, because such large forecast errors may indicate that those firms did not try to manage earnings news in the way that we highlight.

– insert Table I here –

The sample average stock price is $20.23, so that a choice of $\phi = j \times 0.001$ allows for forecast errors of up to $2j$ cents around $FE = 0$ for a firm with an average share price. Table I details the number of firm-quarters included for different values of j; i.e., observations for which $j \times -0.001$

[5]We think of the small earnings surprise interval that is relevant for our analysis as symmetrically distributed around zero. We have experimented with slightly asymmetric intervals and found no significant changes in our results. We therefore find it more natural to conduct our analysis with the simple prior of symmetric cut-offs for the positive and negative earnings news categories.

$\leq FE \leq j \times 0.001$. We present results for $\phi \in \{0.001\ , 0.005\ \}$ to highlight that our conclusions do not hinge on particular choices of ϕ. In fact, larger values of ϕ lead to results that even more strongly support our forecast management hypothesis.

3 Do Firms Manage Forecasts to Meet Expectations?

3.1 The evolution of forecasts

Our story implies that active forecast management should manifest itself as a secular decline in the consensus forecast over the forecasting horizon. Before conducting our main investigation, we first document that forecasts evolve over the forecasting cycle exactly in this way. For j days before the earnings announcement, $j = 1, \ldots, 90$, we first compute the distribution of the difference between realized earnings and the date j-outstanding consensus forecast. Figure 1 plots the median of this distribution for each day j using data from firm-quarters for which an initial consensus can be measured at least two months prior to the announcement date. The figure thus depicts the evolution of the median forecast error associated with the running consensus at different points of the forecasting cycle for firms reporting continued analyst coverage.

Figure 1 reveals that forecasts grow systematically more pessimistic over the forecasting cycle. The consensus forecast tends to be "optimistic" (i.e., $FE < 0$) up until three weeks before the announcement day, remain "median-unbiased" for nearly two weeks, but become noticeably "pessimistic" relative to true earnings during the last week of the forecasting cycle.[6] Evidence suggesting that forecasts tend to be too optimistic at the beginning of the forecasting cycle can be found in earlier studies by Abarbanell (1991), Francis and Philbrick (1993), and Lin and McNichols (1998), among others. Only recently, however, have researchers provided more complete evidence consistent with the argument that a pessimistic trend that appears late in the forecasting cycle

[6] Lim (2001) does a similar exercise, but he finds forecast optimism (rather than pessimism) throughout the forecast cycle. Two key reasons account for this starkly different outcome. First, Lim uses I/B/E/S forecasts of earnings, but compares them with Compustat earnings realizations. Compustat earnings correspond with I/B/E/S earnings about 80% of the time, but are systematically lower the other 20% because of differences over what I/B/E/S includes in earnings. Secondly, Lim looks at the average forecast error, rather than the median, despite ample documentation of the left-skewed nature of forecast errors (see, e.g., Abarbanell and Lehavy (2003), who show how outliers influenced previous papers' inferences about forecast optimism).

drive estimates down to "beatable" targets (e.g., Matsumoto (2002) and Richardson et al. (2004)).

– insert Figure 1 here –

A sharper way to illustrate how the consensus tends to evolve downward is to look at *changes* in the consensus throughout the forecasting cycle. Figure 2 presents the empirical distribution for daily (non-zero) changes in the outstanding consensus EPS estimate for firms for two-week intervals that start from the day prior to the EPS announcement date D and go back to 84 days preceding the announcement date. This yields 6 histograms: $\Delta E_{D-14 \to D-1}, \Delta E_{D-28 \to D-14}, ..., \Delta E_{D-84 \to D-70}$.[7] The histograms show that while forecast changes are more symmetric around zero at the beginning of the forecasting cycle, they become substantially biased towards negative revisions a few weeks prior to the EPS announcement date.

– insert Figure 2 here –

3.2 Consensus revisions and the earnings surprise distribution

Figures 1 and 2 show that the market consensus trends downwards as the earnings announcement date approaches, which is consistent with firms managing forecasts to beat/meet earnings expectations. However, they do not shed light on whether the downward forecast corrections *cause* the pattern in the earnings surprise distribution. For example, the pattern of earnings surprise may not differ between those firms for which the consensus fell and those firms for which the consensus remained the same, or rose. This is an important matter for identification. In particular, as our introduction highlights, if late changes in the consensus reflect information arrival (cf., Ivkovich and Jegadeesh (2004)), then the time-averaged nature of the "consensus" should mean that a decline in the consensus make negative earnings surprises *more* likely.

To show that forecast revisions are a primary determinant of the realization of earnings surprises, we next compute the likelihood of observing a small negative surprise associated with each of the consensus change histograms displayed in Figure 2. To ease the presentation, we collapse the three earliest bi-weekly time periods into one ($\Delta E_{D-84 \to D-42}$). For each of the seven change-in-consensus

[7] To avoid measuring the consensus as of the announcement date, the first bi-weekly interval has only 13 days, while the other intervals are 14 days long.

bins from Figure 2 that are centered around zero—which contain most of the observations—Table 2 reports the frequencies of small positive, zero, and negative earnings surprises. Panel A presents these frequencies using $\phi = 0.001$ to define a small earnings surprise, while Panel B does so for $\phi = 0.005$ (i.e., using a larger earnings "surprise window").

Late Consensus Revisions. Panels A and B of Table II both reveal that the relative likelihood of a positive earnings surprise is dramatically higher if the consensus fell in the last two weeks prior to announcement than if it rose. Perhaps the most revealing statistic is the ratio of the probabilities of beating and missing the consensus, i.e., the relative likelihoods of positive and negative earnings surprises (see Prob.(Beat)÷Prob.(Miss) in the top portion of both panels). Using the conservative measure $\phi = 0.001$ to define a small earnings surprise, we see that:

- When the consensus falls, positive surprises are about twice as likely as negative surprises.
- When the consensus rises moderately, negative and positive surprises are about equally likely.

Using the larger $\phi = 0.005$ *magnifies* these relationships: following a decline in the consensus, positive earnings surprises are distinctly more than twice as likely as negative ones; but when the consensus rises, negative earnings surprises are more likely than positive earnings surprises. In sum, late changes in the consensus have dramatic impacts on the relative likelihood of positive and negative earnings surprises, in ways consistent with our hypothesis of *dynamic* forecast management.

Early Consensus Revisions. Using $\phi = 0.005$ as a measure of a small earnings surprise, reveals that the impact of earlier changes in the consensus on the relative likelihoods of a positive and negative earnings surprise nearly vanishes. Using the narrower measure, $\phi = 0.001$, going back five to six weeks, decreases (increases) in the consensus still raise (reduce) the relative probability of a positive earnings surprise, but the impacts are weak.

Piecing together our results thus far, the data reveal that late revisions in the consensus seem to drive surprise realizations; while earlier revisions have but slight effects, perhaps because firms enjoy more flexibility in managing earnings surprises earlier in the forecast cycle. We emphasize that—because of the time-averaged feature of the consensus forecast and the fact that analysts revise forecasts only reluctantly—the findings we report are the *opposite* of what would be generated were late forecasts driven solely by new information arrival. Indeed, because late forecasts do reflect some information, our findings *reinforce* the magnitudes of the implied forecast management.[8] Although previous researchers have looked at the (downward) evolution of the consensus over the forecasting cycle and at the relation between earnings surprises and consensus changes (e.g., Matsumoto (2002) and Richardson et al. (2004)), to our knowledge, no prior study establishes a precise connection between the timing of forecast changes over the cycle and the probability of beating the market consensus. Identifying this timing link is a key step towards the notion that managers dynamically manage earnings surprises.

– insert Table II here –

3.3 The frequency of consensus changes

As Table II shows, downward consensus revisions occurring in the last couple of weeks of the forecasting cycle sharply reduce the frequency with which firms meet/beat the consensus. This raises the question: How often are these revisions observed?

Table III shows the frequency with which various degrees of downward and upward revisions occur during different periods of the forecasting cycle. To facilitate discussion (and for consistency), Table III uses the same time and forecast change windows as Table II. The table reveals a number of patterns. Consistent with Figures 1 and 2, there are more downward revisions than upward revisions in the last two weeks of the forecasting cycle. Most importantly, the table reveals that the raw number of late downward revisions both is very high and it rises sharply, increasing by 47% in the last two weeks, while the number of upward revisions drops way off, falling by 29% in the last two weeks, despite the arrival of more information late in the cycle. That is, the pessimistic shift in forecasts is strong in both relative and absolute terms, and the sheer number of times that the consensus drops in the last two weeks—almost 12,000 negative revisions—is remarkable. Given that our data is limited to the 1989-1999 period and that we discard extreme consensus changes (which are predominately negative) our numbers can only underestimate the pervasiveness and the

[8]For example, information arrival probably explains why the relative likelihood of a positive earnings surprise is greatest for a slight decline in the consensus—larger declines likely reflect both the arrival of "bad" news and forecast management, so that the impact of forecast management effect is partially offset by the staleness of the consensus.

impact of earnings forecast management.

– insert Table III here –

3.4 Who is responsible for pessimistic late forecasts?

The striking pattern of increasing pessimism naturally raises questions about the identity of those analysts who are responsible for the prevalence of pessimistic late forecasts. The empirical literature, such as Bernhardt et al. (2006), who find that larger brokerage houses and more experienced analysts tend to be more pessimistic, suggests likely possibilities. Our suspicions from these suggestive empirical findings are reinforced by the stronger economic motives that larger brokerage houses may have at stake in maintaining good relationships with a firm's management (underwriting relations, greater trading volume hinging on information that a firm's management can provide pre-Reg FD, and so on), and hence why larger brokerage houses may be more willing to issue pessimistic forecasts that contribute to the success of earnings management.[9]

We follow Bernhardt et al. (2006) in constructing these measures and in establishing cutoffs for large/small brokerage houses as well as experienced/inexperienced analysts. We measure brokerage house size by the number of analysts issuing forecasts under the same broker code, and classify brokerage houses with at least 60 individual analysts in a given quarter as "large houses" ("small houses" have fewer than 30 individual analysts). We capture analyst experience with the number of years that an analyst appears in the data: analysts appearing for at least 5 years are "more experienced" and those issuing forecasts for less than 3 years are "less experienced" .

Table IV reveals the striking extent to which it is the large brokerage houses and experienced analysts that are responsible for the prevalence of pessimistic forecasts late in the forecasting cycle. In the last two weeks of the cycle, less experienced analysts and small brokerage houses are essentially as likely to submit optimistic as pessimistic forecasts. In remarkable contrast, in the last two weeks, large brokerage houses issue 73% more pessimistic than optimistic forecasts, and

[9] Regarding analyst experience, if experienced analysts are more likely to detect firms' manipulation efforts, their late forecasts may be less pessimistic. Conversely, experienced analysts may issue more pessimistic late forecasts if (i) analysts who help firms produce good surprises are more likely to survive, or (ii) a successful analyst's career path involves moving from smaller to larger brokerage houses, and their forecasts grow more pessimistic as a result.

more experienced analysts issue 46% more pessimistic forecasts than optimistic forecasts.

– insert Table IV here –

To sum up, Tables 2 through 4 indicate that (i) the absolute and relative frequency of pessimistic revisions in the consensus rise dramatically at the end of the forecasting cycle, (ii) it is large brokerage houses and experienced analysts who are responsible for this late rise and (iii) late changes in the consensus have tremendous implications for the odds that firms succeed at managing earnings surprises.

3.5 Probit analysis of forecast management: The relevance of timing

We now employ a multivariate probit analysis at the firm level to shed more light on the details of the dynamics governing forecasts. We confirm the relationships highlighted in Table II and uncover additional evidence of how the size and timing of forecast revisions *drive* earnings surprises. We provide unique evidence that the probability of beating market expectations is a direct function of the timing of forecast revisions.

We formulate an alternative hypothesis against the null of expectations path irrelevance as follows. Conditional on observing a given revision in forecasts, the earlier it is in the forecasting cycle, and hence the more time a firm has to manage expectations (or accounting earnings) in response, the less impact the revision should have on the likelihood of beating the consensus. In other words, the consensus management hypothesis is that the likelihood of observing positive earnings news should *depend systematically* on the path of forecast formation.

To test our hypothesis, we estimate the likelihood of observing a small positive earnings surprise at the end of the forecasting cycle following changes in the consensus that are observed during non-overlapping time windows within the cycle. Specifically, for firm i in quarter s, we estimate a series of probit regressions in which the latent variable equals 1 when $0 < FE \leq \phi$, and is 0 when $-\phi \leq FE \leq 0$, where the independent variables include period-specific expectations changes (ΔE) plus firm controls. The probit model is given by

$$\Pr(0 < FE \leq \phi)_{i,s} = \Phi(\mu + \alpha \Delta E_{i,s} + \mathbf{X}_{i,s}\boldsymbol{\beta}), \tag{2}$$

where $\mathbf{X}$ is a set of control variables and $\boldsymbol{\beta}$ is a conformable vector of coefficients. All models are estimated with a White-Huber variance estimator that adjusts the z-statistics for error heteroskedasticity and allows for contemporaneous (i.e., within-time) residual correlation.[10]

We opt for a parsimonious set of control variables.[11] First, to control for the fact that forecasters may have a harder time achieving a stable consensus for small/growth firms we add firm market capitalization to the model (*Firm Value*). Second, if fewer analysts make forecasts, the consensus may be more unstable and thus, perhaps, more likely to generate "surprises". We therefore add the number of analysts issuing forecasts for the firm-quarter to our control set (*Analyst Coverage*). Finally, we include a dummy variable that equals 1 when the firm reports non-zero special charges to earnings (*Special Charges Dummy*). We do this because Burgstahler and Dichev (1997), among others, provide evidence suggesting that firms are more likely to manipulate accounting earnings if they report such charges to quarterly earnings.

The key regressor in Equation (2) is the change in the daily "running" consensus (ΔE). For each firm-quarter in our sample, we compute changes in the consensus during bi-weekly (14-day) time windows within the forecasting cycle as equal to the change in mean EPS forecast during that time window scaled by the previous quarter-end price.[12] As in previous tests, sampled firms must have at least one forecast issued two months prior to the EPS date. Because there are extreme outliers in each of the resulting variables, we employ a 1% trim of the sample distribution at the bottom and top percentiles. We emphasize, however, that our results are qualitatively unaffected by the trim; varying little if we do not trim the data or if we trim aggressively by as much as 5%.

– insert Table V here –

Panel A of Table V reports the output from probit regressions of positive earnings surprises ($\phi = 0.001$) on changes in the consensus occurring during consecutive bi-weekly intervals preceding the announcement date. In columns 1 through 4, we impose no controls. The results from these estimations show a monotonically increasing time-dependent relationship between increases in the

[10] Using time fixed-effects (instead of random effects) has no implications for our conclusions.

[11] Theory provides little guidance as to the controls one should use in an empirical model that predicts the probability of observing small positive earnings surprises. In unreported regressions, we obtain qualitatively identical results when we include extra controls used in previous empirical work, such as a dummy for the sign of earnings (DeGeorge et al. (1999)) and a dummy for growth firms (Skinner and Sloan (2002)).

[12] The use of monthly time intervals leads to similar conclusions.

consensus forecast of earnings and the likelihood of positive earnings surprises. In columns 5 through 8, the models are augmented to include controls, which only enhances the impact of changes in the consensus on the likelihood of a positive earnings surprise. Specifically, positive shocks to the consensus that occur only a few days prior to the announcement date lead to economically and statistically significant increases in the likelihood that earnings fall short of the consensus. The probit coefficient for $\Delta E_{D-14 \to D-1}$ from column 5 (= –8.00) indicates that the probability earnings exceed the market consensus drops by 5% when the consensus forecast of EPS/Price rises by 1% during the last 13 days of the forecasting cycle, holding other regressors constant at their sample means. In contrast, similar changes in the consensus much earlier in the forecasting cycle have little impact on the likelihood that earnings will beat the consensus. Panel B shows that using the broader definition of a small earnings surprise, $\phi = 0.005$, further magnifies the impact of late consensus changes by more than one third. We emphasize the remarkably monotonic pattern in the relationship between consensus corrections through time and earnings news realizations. Simply put, evidence of a *dynamic form* of forecast management is manifest. We are unaware of any prior studies demonstrating these sorts of dynamics in detail.[13]

4 Valuation Implications of Forecast Management

Presumably, rational investors should be able to perform the same research as the econometrician, and therefore one should not be able to find firms being rewarded for systematically manipulating earnings and forecasts. This leads us to seek the answers to the following questions:

- Are investors misled by firms that manage earnings forecasts?
- Does it pay for firms to manage earnings forecasts?

4.1 Are investors misled?

To uncover whether investors are misled by firms' management of forecasts, we determine whether changes in the consensus forecast at different times in the forecasting cycle systematically predict

[13] Recent studies on public earnings guidance show that firms are likely to (timely) disclose pessimistic news towards the end of the forecasting cycle when analysts are too optimistic in their earlier forecasts. This link between the level of initial forecasts and the timing of information disclosure is consistent with the results we report (see, e.g., Soffer et al. (2000) and Cotter et al. (2004)).

returns following the earnings announcement. For example, if late forecasts are driven down by forecast management, but investors treat late revisions to the consensus as unbiased, then investors will tend to be pleasantly surprised by the earnings when they are announced, and share prices will appreciate. Consequently, if investors treat consensus revisions as unbiased, late downward revisions in the consensus should lead to positive abnormal returns in windows around the announcement.

To investigate this possibility we categorize firm-quarters on the basis of the time path of the consensus forecast of earnings, and compare abnormal returns for different groups of firms following earnings announcements. These differences are estimated via standard OLS, median, and outlier-robust regressions of excess stock returns on indicators for the groups of interest (defined below).

To obtain excess returns for firm-quarters in our sample we first estimate the market model,

$$r_{iD} = \gamma_0 + \gamma_1 r_{mD} + \epsilon_D, \tag{3}$$

where r_{iD} is the daily return on security i and r_{mD} is the return on the value-weighted market index from the CRSP tapes. For each observation, the market model regression uses returns for the $D = -270$ through to $D = -31$, where time $D = 0$ denotes the day when earnings are announced by the firm. The least squares estimates, $\hat{\gamma}_0$ and $\hat{\gamma}_1$, are then used to calculate the cumulative abnormal returns (CAR) around the earnings announcement date for each firm-quarter τ,

$$CAR_{[\underline{D},\overline{D}]} = \sum_{D=\underline{D}}^{\overline{D}} \left[r_{\tau D} - (\hat{\gamma}_0 + \hat{\gamma}_1 r_{mD}) \right], \tag{4}$$

where $\underline{D}$ and $\overline{D}$ are starting and end points of the period over which abnormal returns are cumulated. To ease exposition, we focus on returns cumulated over the 3-day period beginning one day prior to the announcement date through one day after that date, i.e., we present results for which $[\underline{D}, \overline{D}] \equiv [-1, +1]$. Our qualitative findings extend to other windows (e.g., $[-1, +3]$, $[-2, +3]$, $[-2, +2]$).

We first compare abnormal returns for firms that observed significant changes in analysts' consensus during the final days of the forecasting cycle, *prior* to the windows over which returns are cumulated. Our previous results suggest that significant declines in the consensus over the final days of the cycle reflect successful forecast management designed to generate a positive earnings surprise. In contrast, firms observing increases in the consensus may have been unsuccessful in their efforts to manage forecasts. We order firms by the change in the mean-based consensus estimate during the last 14 days of the forecasting cycle, and contrast abnormal returns for firms in the top quartile of the change in the consensus (i.e., those firms witnessing large consensus increases) with those in the bottom quartile of the forecast change ranking in for the same period.[14]

Column 1 of Table VI displays the result from an OLS regression of CARs on an indicator variable for firms with a significant reduction in the consensus in the last 14 days of the forecasting cycle (*Dummy Pessimism*) and another indicator for firms with a significant consensus increase in the same period (*Dummy Optimism*). The regression also includes the difference between true earnings and the earnings consensus as of 14 days prior to announcement ($EPSGap$). The sample consists of firm-quarters in these two categories only and the regression has no constant term. The table displays (at the bottom) a test of the restriction that the returns are similar. Essentially, this regression amounts to a test for differences in means, after the effect of $EPSGap$ is partialled out. However, the test output allows us to see directly the abnormal returns associated with each group of interest, as well as the difference between the two. Moreover, we make the OLS results more conservative than a standard means test by correcting the error structure both for heteroskedasticity and for within-period error correlation using the White-Huber estimator (Rogers (1993)). Column 2 displays results for the analogous median regression estimator; and column 3 reports the results when we use the robust regression technique proposed in Li (1985), which minimizes the influence of outliers on our inferences.[15] Below each coefficient estimate, we report (in square brackets) the associated bootstrapped 95% confidence interval for those estimates. The bootstrapping procedure consists of repeating each of the regressions 500 times with the sampling restricted to one observation per individual firm each time. These confidence bounds are not affected by arguments that within-firm error autocorrelation in panel regressions "too often" reject the null hypothesis (Type I error).

– insert Table VI here –

The regressions in Table VI reveal whether the dynamics of analyst forecasting (i.e., upward or downward forecast revisions over the time leading up to EPS announcement) predicts post-

[14] Our results are qualitatively similar whether we use tirtiles or quintiles (instead of quartiles) of the distribution of consensus changes.

[15] This consists of a series of iterations to detect and assign smaller weights to gross sample outliers.

announcement excess returns. The "strong form of market efficiency" hypothesis suggests this prediction should not be possible *unconditionally*. However, the results in Table VI indicate that investors are "fooled" by late revisions in the consensus. Late changes in the consensus are predictably negatively correlated with earnings announcement returns. In particular, firms for which the consensus rose just prior to the announcement date report statistically significant and economically large negative cumulative returns following the earnings announcement. In contrast, those firms that experienced sharp declines in the consensus in the last two weeks earn statistically significant and economically large positive CARs. Indeed, the OLS estimation in column 2 implies a remarkably large annualized difference return of 69% for firms whose forecasts grew more pessimistic in the final days of the forecasting cycle compared to those whose forecasts become optimistic.

Thus, we see that investors are misled by late, downward revisions to the consensus, driving share prices down excessively prior to the earnings announcement. Most transparently, investors selling at these low prices just prior to the earnings announcement sell "too cheaply"—and, on average, incur large material value losses relative to the alternative of selling just after earnings are announced.

Recall that firms observing significant increases (decreases) in consensus just prior to the announcement date tend to miss (meet/beat) the consensus. To glean further understanding about how investors update following forecast revisions and earnings announcements, we next investigate whether investors differentiate between firms that only meet/beat the consensus (i.e., firms for which $0 \leq FE \leq 0.001$) after the consensus is "talked down" just prior to the EPS announcement from those firms that produce similar earnings news but do not register any such pessimistic trends in late expectations. That is, does the *way* in which firms generate a positive earnings surprise affect returns around the announcement?

Table VII reports results from regressions of CARs around announcement dates on two dummy variables: one indicates that the firm meets or beats the latest available earnings forecast *after* a significant decline in the consensus in the last two weeks (*Meet–Pessimism*); the other indicates if the firm meets or beats the latest forecast *without* such a steep decline in the consensus (*Meet–*

NoPessimism).[16] The results show that returns around the earnings announcement do not depend on *how* the firm beats forecasts (i.e., on whether earnings exceed the latest forecast only because expectations were talked down in the last two weeks). Investors do not appear to unravel firms' strategic management of forecasts, and simply treat them as unbiased. In particular, *all* firms meeting expectations are positively rewarded around the EPS announcement date. Indeed, those firms that manipulate forecasts register even greater excess returns than those that do not.

These results seem to suggest a rationale for firms to actively engage in forecast management, by driving the consensus forecast down so that earnings exceed the final consensus forecast. Of course, for this to be so we must find that direct effect of managing forecasts down on share price (i.e., after lower forecasts are announced) is more than offset by the share price appreciation following the earnings announcement of a positive surprise. We examine this question in turn.

– insert Table VII here –

4.2 Does it pay to manage forecasts?

Our method of determining whether firms profit from manipulating forecasts to meet expectations is straightforward. First, we postulate that a few days prior to the earnings announcement, firms know what their reported earnings will be, as auditors will have signed off on the books and firms are privy to the accounting information. Firms also know the extant consensus forecast. The only remaining control variable at a firm's discretion is the way in which it manages analysts' forecasts of earnings in the days leading up to the announcement date. We first ask: controlling for a firm's net private information relative to the market two weeks prior to the earnings announcement, do subsequent changes in the consensus affect the post-earnings-announcement share price? Market efficiency arguments would suggest that while the evolution of forecasts in the last two weeks may have interim effects on share prices, it should have no impact on the post-announcement share price because all relevant information is revealed by the earnings announcement. We show that

[16] We use the latest available earnings forecast as an up-to-date indicator of the market's expectations of earnings. In a previous version, we used the average consensus at announcement date as an indicator of expectations and obtained similar results. As correctly pointed out by the referee, however, average consensus estimates are affected by the staleness of forecasts that come too early in the forecasting cycle. For robustness, we also constructed tests in which market expectations were computed as the average of the forecasts in the last week (alternatively, last two weeks) preceding EPS announcement. Our results hold in those subsets as well.

the evolution of the consensus forecast *does* matter for post-announcement share price. As a result we then ask: how *should* a firm manage analysts' forecasts to maximize post-announcement share price? In particular, ignoring the private benefits that may accrue to managers, does the forecast management that we document help the firm?

Maximizing post-announcement share price given information as of 14 days prior to the announcement date amounts to maximizing cumulated stock excess returns over that entire period. Accordingly, we compute cumulated stock excess returns beginning 14 days prior to the announcement date through the day after the earnings announcement; i.e., we set the CAR window to $[\underline{D}, \overline{D}] \equiv [-14, +1]$. To disentangle the impact of forecast management from that of information arrival, it is crucial to control for the firm's net private information relative to the market two weeks prior to the announcement: we do this by including the difference between true earnings and the earnings consensus as of 14 days prior to announcement ($EPSGap$) in our regressions. Specifically, we estimate a regression of cumulated abnormal returns over the period $[-14, +1]$ on: (a) $EPSGap$, (b) the change in the consensus between days –14 and –2 prior to the earnings announcement day ($\Delta Consensus$), and (c) an interaction term for these two proxies ($EPSGap \times \Delta Consensus$). Note that the inclusion of this interaction term provides for a direct test of our conjecture that the impact of $\Delta Consensus$ should vary with $EPSGap$—we believe that the impact of forecast management on returns will rise as the difference between true and forecasted earnings rises.[17]

To allow for possible decreasing marginal impacts of greater forecast management, we add squares of $\Delta Consensus$. Because $\Delta Consensus^2$ is not a globally monotone function (falling in $\Delta Consensus$ for $\Delta Consensus < 0$, and rising for $\Delta Consensus > 0$), our regressions separate the negative component $((\Delta Consensus < 0)^2)$ from its positive counterpart $(\Delta Consensus \geq 0)^2)$. Finally, we add the number of analysts issuing earnings forecasts for the firm to the specification ($Coverage$) as a "catch all" regressor to control for size and information effects.

[17]The coefficient on the interacted term is the estimated cross partial derivative.

The panel regressions include a constant term and take the form:

$$\begin{aligned} CAR_{[-14,+1]i,t} &= \beta_0 + \beta_1 (EPSGap_{i,t}) + \beta_2 (\Delta Consensus)_{i,t} \\ &+\beta_3 \left((\Delta Consensus < 0)^2\right)_{i,t} + \beta_4 \left((\Delta Consensus \geq 0)^2\right)_{i,t} \\ &+\beta_5 (EPSGap \times \Delta Consensus)_{i,t} + \beta_6 (Analyst\ Coverage)_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{5}$$

where i indexes individual firms and t indexes quarters. As before, we estimate the model via OLS, median, and robust regression techniques. We cannot reject the significance of firm-fixed effects. To control for firm idiosyncratic effects in a consistent manner across all estimation methodologies we "de-mean" the data of firm averages before each estimation.

If managing forecasts in the way that we have uncovered is optimal then the coefficient β_5 will be large, positive, and dominate the impacts of β_2, β_3, and β_4. Put differently, if earnings fall short of the consensus (i.e., $EPSGap < 0$) and downward management implies $\Delta Consensus < 0$, so that this contributes to post-earnings-announcement share price, then we should find that (i) $\beta_5 > 0$, and (ii) this must dominate the direct downward effect on share price realized when investors observe the decline in the consensus ($\beta_2 \Delta Consensus + \beta_3 (\Delta Consensus < 0)^2$).

– insert Table VIII here –

Table VIII reports our results. Estimates are similar across all estimation techniques. The positive coefficient on $EPSGap$ reveals that, as anticipated, firms with private information that earnings will exceed the consensus realize an appreciation in share price once this information is made public. This again highlights the importance of controlling for the net information about earnings relative to the market, $EPSGap$. The coefficient on $EPSGap \times \Delta Consensus$ indicates that firms with earnings that fall short of the consensus prior to the announcement date do better to manage the consensus down than do firms with earnings that exceed the consensus; and firms for which earnings exceed the consensus do better to manage the consensus up than do firms for which earnings fall short of the consensus. On a first pass, these observations seem consistent with the premise that managing forecasts in the way that we document raises firm value.

But, a moment's reflection reveals that this is not so. Specifically, the coefficient on $\Delta Consensus$ is large and positive, and for the overwhelming majority of observations, $|EPSGap| < 0.02$, so that

$EPSGap \times \Delta Consensus << \Delta Consensus$. Ignoring the quadratic terms for the moment, our estimates imply that the direct impact of $\Delta Consensus$ is more than 50 times the offsetting indirect impact of $EPSGap \times \Delta Consensus$. The magnitudes of these coefficients imply that the direct negative impact of a reduction in the consensus (required to switch an earnings surprise from negative to positive) greatly exceeds the impact of a positive earnings surprise on post-announcement share price for post-announcement share price. Post-announcement share price is higher when the consensus is increased than when the consensus is reduced, after controlling for a firm's net private information two weeks before the earnings announcement. The signs on the quadratic components of $\Delta Consensus$ reveal that larger changes (in both directions) have decreasing marginal impacts on returns. Because the vast majority of observations have $|\Delta Consensus| < 0.02$, it follows that $\Delta Consensus^2$ is tiny, so that even though the coefficient on $(\Delta Consensus > 0)^2$ is large and negative, the estimated marginal share price gain from *increasing* the consensus remains positive for *all* reasonable parameter values.

Thus, a key finding of our paper is that we show evidence that firms with earnings below the consensus are hurt when their managers drive down forecasts in the way that we see in the data. In fact, those firms' shareholders would be better off if their managers did the opposite. Of course, as we discussed above, managers often have incentives that differ from those of investors (prior literature documents related effects in the context of earnings management).

Bartov et al. (2002) come to the opposite conclusion with regard to the benefits of forecast management. Those authors compute CARs over the period between the first forecast ($F_{earliest}$) and the actual earnings as well as over the period between the last forecast (F_{last}) and the actual earnings. They find that firms for which both $EPS - F_{earliest} > 0$ and $EPS - F_{last} > 0$ have higher CARs than firms for which $EPS - F_{earliest} > 0$, but $EPS - F_{last} \leq 0$; and that firms for which $EPS - F_{earliest} < 0$ but $EPS - F_{last} > 0$ have higher CARs than firms for which $EPS - F_{earliest} < 0$ and $EPS - F_{last} \geq 0$. This leads Bartov et al. to conclude that forecast management pays off.

What underlies the opposing conclusions is that we control for the firm's net private information relative to the market two weeks prior to the announcement by including the difference between true earnings and the earnings consensus as of 14 days prior to announcement ($EPSGap$) in our regressions. In contrast, Bartov et al. control for this difference at the beginning of the quarter.

A consequence is that Bartov et al. cannot disentangle the effects of forecast management from information arrival. That is, their finding are exactly what one expects to find from information arrival even when there is *no* forecast management: firms for which EPS exceeds both the first and last forecasts have more good earnings news on average than firms for which EPS exceeds only one forecast, and, in turn, firms for which EPS exceeds one forecast have more good news on average than firms for which EPS falls short of both forecasts. Indeed, we obtain results similar to those of Bartov et al. if we, instead, use a measure of $EPSGap$ from sufficiently early in the quarter: information arrival swamps the impact of forecast management.

4.3 Robustness

Thus, forecast management that drives down forecasts by analysts down to beatable levels also appears to drive long-run share price down, hurting investors. Before we reach this conclusion though, we want to ensure that we are not missing a more innocuous explanation. For example, perhaps we just did not consider a long enough window after the earnings announcement to account for post-announcement drift due to delayed market response to the earnings announcement.[18] However, Table IX shows that our estimates are virtually unchanged when we compute excess returns over a longer post-announcement window, $[-14, +5]$: the adverse impact of forecast management does not appear to be due to a failure to allow for a delayed market response to the earnings surprise.

– insert Table IX here –

Another possibility is that the large coefficient on $\Delta Consensus$ is driven by firms with good earnings news. In particular, their share price may be maximized if their good news leaks out gradually over time in the form of consensus revisions, especially since there is evidence that excess returns following the earnings announcement are relatively insensitive to the magnitude of the positive surprise. In contrast, firms whose earnings fall short of the consensus may have more at stake in reducing the consensus than firms with good news have in raising the consensus. Perhaps forecast management just matters more for those firms whose earnings fall short of the prevailing market consensus.

[18] For example, Freeman and Tse (1992) document persistence in post-announcement drift after earnings surprises.

We investigate these possibilities in two ways. We first run our baseline regression model (Equation (5)) solely over the subset of firms for which earnings fall short of the consensus—to ensure that the coefficient estimates are not driven by firms for which earnings exceed the consensus. But, qualitatively similar results (omitted) obtain when we do this. We then provide our baseline model with enough flexibility to distinguish the value effect of forecast revisions that are observed for firms whose earnings come short of the market consensus from those that meet or beat expectations a few days before the earnings announcement. Specifically, we allow $EPSGap$ to attract different slope coefficients, one for realizations that are below zero and another for realizations above or equal zero.

To implement this test, we replace $EPSGap$ in Equation (5) with $EPSGap\ |_{EPSGap<0}$ (denoted by $EPSGap < 0$) and with $EPSGap\ |_{EPSGap\geq 0}$ (denoted by $EPSGap \geq 0$), also allowing for $\Delta Consensus$ to interact with each of those two different segments of $EPSGap$. Taking $EPSGap$ as a spline (with a break around 0) allows to directly gauge whether changes in the consensus in the last few days of the forecasting cycle affect returns differentially according to whether or not the firm is going to meet/beat the consensus ($EPSGap \geq 0$) or miss the consensus ($EPSGap < 0$)—our prior is that the strategic responses of firms (i.e., how they manage forecasts) is likely to depend on the sign of $EPSGap$. Our "spline" regression model can be written as:

$$\begin{aligned} CAR_{[-14,+1]i,t} \quad = \quad & \beta_0 + \beta_1\,(EPSGap < 0)_{i,t} + \beta_2\,(EPSGap \geq 0)_{i,t} + \beta_3\,(\Delta Consensus)_{i,t} \qquad (6) \\ & + \beta_4((EPSGap < 0) \times (\Delta Consensus))_{i,t} \\ & + \beta_5((EPSGap \geq 0) \times (\Delta Consensus))_{i,t} \\ & + \beta_6(Analyst\ Coverage)_{i,t} + \varepsilon_{i,t}. \end{aligned}$$

The regression results are reported in Table X. Again the coefficient on $(EPSGap < 0) \times (\Delta Consensus)$ is large and significant, while that on $(EPSGap \geq 0) \times (\Delta Consensus)$ is, in fact, negative. That is, it clearly is better for a firm to raise the consensus when earnings would otherwise fall short of the consensus than if earnings would already beat the consensus. However, in each case, the direct impact of $\Delta Consensus$ dominates by a factor of fifteen to twenty! Firms appear to do better to have information "leak out" in the form of increases in the consensus, *whether or not* earnings exceed the consensus. That is, even though an increase in the consensus would make the earnings surprise more negative, the direct impact of the increase in the consensus on share price *dominates* the greater magnitude of the negative earnings surprise; the market seems to be more sensitive to the sign of changes in the levels of forecasts and the sign of earnings surprise than they are to the magnitudes of these variables.[19]

The results of this section show that firms that privately hold negative news prior to the announcement of earnings are *hurt* by managing down analysts' forecasts during the days leading up to the announcement. To sum up, we uncover evidence that

- Controlling for a firm's private information about earnings relative to the market, the time path of the consensus does matter for post-announcement share price.
- Firms with earnings that fall short of the consensus two weeks prior to the announcement do better to reduce the consensus than do other firms.
- But, post-announcement share price is highest when firms do not manage the consensus down.

– insert Table X here –

5 Concluding Remarks

The view that firms manage earnings news is accepted by most researchers and practitioners. Still, little is known about the dynamics of forecast management. This paper first shows that firms manage earnings by "talking down" analysts' forecasts: forecasts of quarterly earnings issued later in the forecasting cycle are systematically more pessimistic than those of earlier forecasters. We then show that successfully managing forecasts is a primary determinant of whether a firm generates a positive earnings surprise. Firms that successfully manage the consensus down in the last two weeks before the earnings announcement generate more than twice as many positive as negative earnings surprises; while firms for which the consensus rises generate more negative earnings surprises than positive surprises. In contrast, changes in consensus earlier in the forecast cycle have minimal

[19] We also verified that sample selection does not drive our findings. In particular, the decision to guide forecasts down is endogenous, leaving open the possibility that firms that did so selected this alternative because they anticipated worse future prospects. Indeed, controlling for *EPSGap*, regression analysis did show that firms with late downward revisions in the consensus tended to have lower EPS the next quarter. However, further tests revealed that controlling for possible selection by adding future EPS changes to our CAR regressions did not affect our conclusions.

effects on the probability that earnings exceed the consensus, possibly because firms have enough time to unwind the impact of these consensus revisions by altering earnings or subsequent forecasts.

We then examine whether firms benefit from actively managing earnings news. We first uncover that changes in the consensus forecast at different times in the forecasting cycle *do* drive returns following the earnings announcement: firms for which the consensus rose significantly just prior to the announcement date report large negative cumulative returns following the earnings announcement, while firms that experienced sharp declines in the consensus earn large positive CARs, with an annualized difference in returns of 69%. We also find that post-announcement returns are higher for firms that managed down the consensus to generate a positive earnings surprise than they are for firms that generated a positive surprise without such management. In short, investors do not appear to unravel the forecast management.

Crucially, while the finding that investors reward firms that successfully manage forecasts down might seem to provide a rationale for downward forecast management, this is not so. Controlling for the extant earnings–consensus forecast differential, the negative impact of downward forecast revisions on stock price dominates the stock price appreciation following the earnings announcement. That is, downward forecast management, on average, hurts firms.

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Table I. Choice of j and raw sample size

This table details the number of sampled firm-quarters for different values of j; i.e., observations for which $j \times -0.001 \leq FE \leq j \times 0.001$, where FE (or forecast error) is defined in Equation (1) in the text. The base sample is comprised of quarterly data on analysts' earnings forecasts taken from the Institutional Brokers Estimate System's (I/B/E/S) *Detail History* files database from 1989:I to 1999:IV. Data on shares outstanding and earnings announcement dates are taken from COMPUSTAT, and stock prices are obtained from CRSP.

Choice of j	Number of Firm-Quarters			% of Total Firm-Quarters
	$j \times -0.001 \leq FE < 0$	$FE = 0$	$0 < FE \leq j \times 0.001$	
$j = 1$	67,337	8,966	97,400	52.3
$j = 2$	89,082	8,966	126,962	67.8
$j = 3$	102,225	8,966	141,345	76.1
$j = 5$	116,226	8,966	155,037	84.4
$j = 10$	130,742	8,966	166,667	92.3
$j = 20$	138,831	8,966	171,628	96.2

Note: The total number of firm-quarters is 332,100.

Table II. Frequency of consensus changes

This table displays earnings news frequencies (in percentage terms) associated with changes in the market earnings forecast consensus at different windows of the forecasting cycle. The consensus forecast is the mean of the forecasts of a firm's quarterly EPS. FE is the forecast error, defined in Equation (1) in the text. The consensus change intervals are analogous to the central bins of Figure 2 in the text. The base sample is comprised of quarterly data on analysts' earnings forecasts taken from the Institutional Brokers Estimate System's (I/B/E/S) *Detail History* files database from 1989:I to 1999:IV. Data on shares outstanding and earnings announcement dates are taken from COMPUSTAT, and stock prices are obtained from CRSP.

Panel A: FE Windows for $\phi = 0.001$

	Consensus Change						
	$[-0.012, -0.008)$	$[-0.008, -0.004)$	$[-0.004, 0)$	0	$(0, 0.004]$	$(0.004, 0.008]$	$(0.008, 0.012]$
	Weeks 1 and 2 prior to EPS						
Earnings News Type	Freq. (%)						
Beat Consensus ($0 < FE \leq 0.001$)	64.56	64.17	69.56	53.26	52.95	51.02	48.22
Meet Consensus ($FE = 0$)	1.67	1.66	1.60	10.82	5.85	4.53	5.69
Miss Consensus ($-0.001 \leq FE < 0$)	33.77	34.17	28.84	35.92	41.20	44.45	46.09
Prob.(Beat)÷Prob.(Miss)	1.9	1.9	2.4	1.5	1.3	1.1	1.0
	Weeks 3 and 4 prior to EPS						
Earnings News Type	Freq. (%)						
Beat Consensus ($0 < FE \leq 0.001$)	58.18	57.39	59.27	55.56	57.56	51.22	48.75
Meet Consensus ($FE = 0$)	7.99	9.37	12.19	9.35	6.21	7.03	10.12
Miss Consensus ($-0.001 \leq FE < 0$)	33.82	33.23	28.55	35.10	36.22	41.75	41.12
Prob.(Beat)÷Prob.(Miss)	1.7	1.7	2.1	1.6	1.6	1.2	1.2
	Weeks 5 and 6 prior to EPS						
Earnings News Type	Freq. (%)						
Beat Consensus ($0 < FE \leq 0.001$)	58.21	58.96	56.20	55.94	57.57	52.76	52.59
Meet Consensus ($FE = 0$)	4.01	7.83	11.51	9.35	6.07	7.63	3.57
Miss Consensus ($-0.001 \leq FE < 0$)	37.77	33.22	32.29	34.71	36.36	39.62	43.84
Prob.(Beat)÷Prob.(Miss)	1.5	1.8	1.7	1.6	1.6	1.3	1.2
	Weeks 7 through 12 prior to EPS						
Earnings News Type	Freq. (%)						
Beat Consensus ($0 < FE \leq 0.001$)	55.56	56.78	59.15	55.71	59.37	56.22	50.20
Meet Consensus ($FE = 0$)	7.69	6.77	7.03	12.02	6.39	7.93	10.18
Miss Consensus ($-0.001 \leq FE < 0$)	36.76	36.44	33.82	32.26	34.24	35.85	39.63
Prob.(Beat)÷Prob.(Miss)	1.5	1.6	1.7	1.7	1.7	1.6	1.3

Table II. – Continued

Panel B: FE Windows for $\phi = 0.005$

	Consensus Change						
	$[-0.012, -0.008)$	$[-0.008, -0.004)$	$[-0.004, 0)$	0	$(0, 0.004]$	$(0.004, 0.008]$	$(0.008, 0.012]$
	Weeks 1 and 2 prior to EPS						
Earnings News Type	Freq. (%)						
Beat Consensus ($0 < FE \leq 0.005$)	67.31	66.57	68.84	54.84	48.11	45.50	43.70
Meet Consensus ($FE = 0$)	1.95	1.57	1.51	13.82	10.90	5.66	5.69
Miss Consensus ($-0.005 \leq FE < 0$)	30.75	31.86	29.65	31.34	40.98	48.84	50.62
Prob.(Beat)÷Prob.(Miss)	2.2	2.1	2.3	1.7	1.2	0.9	0.9
	Weeks 3 and 4 prior to EPS						
Earnings News Type	Freq. (%)						
Beat Consensus ($0 < FE \leq 0.005$)	55.83	58.74	56.57	55.67	54.07	55.09	52.41
Meet Consensus ($FE = 0$)	5.34	4.76	8.23	9.12	10.55	6.16	5.91
Miss Consensus ($-0.005 \leq FE < 0$)	38.83	36.50	35.20	35.20	35.38	38.76	41.69
Prob.(Beat)÷Prob.(Miss)	1.4	1.6	1.6	1.6	1.5	1.4	1.3
	Weeks 5 and 6 prior to EPS						
Earnings News Type	Freq. (%)						
Beat Consensus ($0 < FE \leq 0.005$)	58.52	58.55	57.30	56.07	56.50	55.05	53.04
Meet Consensus ($FE = 0$)	5.12	4.99	9.27	8.98	10.83	6.78	6.66
Miss Consensus ($-0.005 \leq FE < 0$)	36.36	36.46	33.43	34.95	32.66	38.17	40.30
Prob.(Beat)÷Prob.(Miss)	1.6	1.6	1.7	1.6	1.7	1.4	1.3
	Weeks 7 through 12 prior to EPS						
Earnings News Type	Freq. (%)						
Beat Consensus ($0 < FE \leq 0.005$)	59.36	57.47	57.29	56.75	57.32	53.99	54.80
Meet Consensus ($FE = 0$)	6.46	5.88	10.14	10.40	11.01	7.86	7.92
Miss Consensus ($-0.005 \leq FE < 0$)	34.18	36.65	32.57	32.85	31.67	38.15	37.28
Prob.(Beat)÷Prob.(Miss)	1.7	1.6	1.8	1.7	1.8	1.4	1.5

Table III. Frequency of consensus changes

This table displays frequencies (in absolute terms) of changes in the earnings consensus forecast at different windows of the forecasting cycle. The consensus forecast is the mean of the forecasts of a firm's quarterly EPS. The consensus change intervals are analogous to the central bins of Figure 2 in the text. The base sample is comprised of quarterly data on analysts' earnings forecasts taken from the Institutional Brokers Estimate System's (I/B/E/S) *Detail History* files database from 1989:I to 1999:IV. Data on shares outstanding and earnings announcement dates are taken from COMPUSTAT, and stock prices are obtained from CRSP.

Consensus Change						
$[-0.012, -0.008)$	$[-0.008, -0.004)$	$[-0.004, 0)$	0	$(0, 0.004]$	$(0.004, 0.008]$	$(0.008, 0.012]$
Weeks 1 and 2 prior to EPS						
Absolute Freq.						
2,062	3,796	5,930	22,960	2,519	1,414	710
Weeks 3 and 4 prior to EPS						
Absolute Freq.						
1,386	2,294	4,341	23,683	3,831	1,762	892
Weeks 5 and 6 prior to EPS						
Absolute Freq.						
1,448	2,332	4,296	20,252	3,912	1,911	1,056
Weeks 7 through 12 prior to EPS						
Absolute Freq.						
1,956	2,869	6,444	32,100	5,817	3,317	1,889

Table IV. Frequency of forecasts by size of brokerage house and analyst experience

This table displays frequencies (in percentage terms) of forecasts issued in the last 2 weeks of the forecasting cycle that are either below or above the prevailing consensus by the size of the brokerage house (in terms of number of analysts under the same broker code) and the years of experience of analysts (in terms of number of years in the dataset). Each row adds up to 100. The base sample is comprised of quarterly data on analysts' earnings forecasts taken from the Institutional Brokers Estimate System's (I/B/E/S) *Detail History* files database from 1989:I to 1999:IV. Data on shares outstanding and earnings announcement dates are taken from COMPUSTAT, and stock prices are obtained from CRSP.

	Forecasts Issued in Weeks 1 and 2 prior to EPS	
	Forecasts Below Consensus (%)	Forecasts Above Consensus (%)
Brokerage House Size		
$\leq$ 30 analysts	50.8	49.2
$\geq$ 60 analysts	63.4	36.6
Analyst Experience		
$\leq$ 2 years	48.4	51.6
$\geq$ 5 years	59.4	40.6

Table V. Probit regressions: The timing of shocks to expectations and earnings news

This table reports the output from probit regressions of positive earnings surprises on changes in the consensus occurring during consecutive bi-weekly intervals preceding the announcement date (see Equation (2) in the text). In Panel A, the cut-off for positive earnings news, ϕ, is set at 0.001. In Panel B, ϕ is set at 0.005. $\Delta E_{D-x\rightarrow D-y}$ capture changes in the forecast consensus at different time intervals (in days) prior to the EPS announcement date. *Firm Value* is the firm market capitalization. *Analyst Coverage* is the number of analysts issuing forecasts for the firm-quarter. *Special Charges Dummy* is a variable that equals 1 when the firm reports non-zero special charges to earnings. The base sample is comprised of quarterly data on analysts' earnings forecasts taken from the Institutional Brokers Estimate System's (I/B/E/S) *Detail History* files database from 1989:I to 1999:IV. Data on shares outstanding and earnings announcement dates are taken from COMPUSTAT, and stock prices are obtained from CRSP. All models are estimated with a White-Huber variance estimator that adjusts the z-statistics (in parenthesis) for error heteroskedasticity and allows for contemporaneous within-period residual correlation.

Panel A: FE Windows for $\phi = 0.001$

P(Positive News=1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.172	0.168	0.167	0.164	0.153	0.154	0.160	0.156
	(8.58)	(8.31)	(8.08)	(8.19)	(6.31)	(6.26)	(6.21)	(5.98)
$\Delta E_{D-14\rightarrow D-1}$	-7.872				-8.000			
	(-7.35)				(-7.32)			
$\Delta E_{D-28\rightarrow D-14}$		-1.211				-1.248		
		(-2.85)				(-2.95)		
$\Delta E_{D-42\rightarrow D-28}$			-0.849				-0.861	
			(-1.63)				(-1.73)	
$\Delta E_{D-84\rightarrow D-42}$				0.036				0.028
				(0.02)				(0.02)
Firm Value					$3.2e^{-9}$	$3.4e^{-9}$	$3.3e^{-9}$	$2.7e^{-9}$
					(4.09)	(4.22)	(4.08)	(3.51)
Analyst Coverage					0.001	-0.001	-0.002	-0.001
					(0.15)	(-0.37)	(-0.87)	(-0.58)
Special Charges Dummy					0.034	0.035	0.035	0.033
					(1.30)	(1.40)	(1.30)	(1.26)
Pseudo-R^2	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01
Number of Obs.	27,374	26,823	25,513	21,550	27,374	26,823	25,513	21,550

Table V. – Continued

Panel B: FE Windows for $\phi = 0.005$

P(Positive News=1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.163 (6.48)	0.146 (5.90)	0.146 (5.86)	0.142 (5.75)	0.158 (5.44)	0.154 (5.22)	0.156 (5.27)	0.150 (4.89)
$\Delta E_{D-14\rightarrow D-1}$	−12.315 (−14.36)				−12.306 (−14.34)			
$\Delta E_{D-28\rightarrow D-14}$		−0.739 (−1.80)				−0.738 (−1.60)		
$\Delta E_{D-42\rightarrow D-28}$			−0.529 (−2.91)				−0.526 (−1.88)	
$\Delta E_{D-84\rightarrow D-42}$				−0.036 (−0.28)				−0.034 (−0.26)
Firm Value					$4.0e^{-9}$ (4.92)	$4.3e^{-9}$ (5.15)	$4.2e^{-9}$ (5.04)	$3.7e^{-9}$ (4.57)
Analyst Coverage					−0.002 (−1.01)	−0.005 (−2.08)	−0.005 (−2.17)	−0.004 (−1.66)
Special Charges Dummy					0.029 (1.14)	0.026 (1.05)	0.022 (0.90)	0.017 (0.71)
Pseudo-R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Number of Obs.	45,230	44,298	42,047	35,260	45,230	44,298	42,047	35,260

Table VI. Expectations paths and returns around EPS announcement dates

This table displays the result from regressions of 3-day [–1 to +1] CARs on an indicator variable for firms with a significant reduction in the consensus in the last 14 days of the forecasting cycle (*Dummy Pessimism*) and another indicator for firms with a significant consensus increase in the same period (*Dummy Optimism*). The regression also includes the difference between true earnings and the earnings consensus as of 14 days prior to announcement (*EPSGap*). The sample consists of firm-quarters in these two categories only and the regression has no constant term. The base sample is comprised of quarterly data on analysts' earnings forecasts taken from the Institutional Brokers Estimate System's (I/B/E/S) *Detail History* files database from 1989:I to 1999:IV. Data on shares outstanding and earnings announcement dates are taken from COMPUSTAT, and stock returns are obtained from CRSP. The table displays (at the bottom) a test of the restriction that the returns are similar for the two categorical variables. The OLS estimation in column 1 corrects the error structure both for heteroskedasticity and for within-period error correlation using the White-Huber estimator. Column 2 displays results for the analogous median regression estimator; and column 3 reports the results when we use the robust regression technique proposed in Li (1985), which minimizes the influence of outliers on our inferences. The relevant t- and z-statistics are (in parenthesis). Below each coefficient estimate, we also report [in square brackets] the associated bootstrapped 95% confidence interval for those estimates.

Dependent Var. : $CAR_{[-1,+1]}$	OLS Regression	Median Regression	Robust Regression
EPSGap	0.033	0.040	0.107
	(5.18)	(8.28)	(7.05)
	[0.019, 0.047]	[0.028, 0.052]	[0.082, 0.143]
Dummy Pessimism	0.003	0.004	0.004
	(1.99)	(2.90)	(2.17)
	[0.001, 0.006]	[0.001, 0.007]	[0.000, 0.008]
Dummy Optimism	−0.002	−0.002	−0.002
	(−1.88)	(−1.92)	(−1.79)
	[−0.005, 0.001]	[−0.006, 0.002]	[−0.006, 0.002]
F-test (p-value)	0.00	–	0.00
Number of Obs.	4,143	4,143	4,143
Test: $Pessimism - Optimism = 0$	0.006	0.006	0.006
(p-value)	0.01	0.00	0.02

Table VII. Earnings management and returns around EPS announcements

This table displays the result from regressions of 3-day [–1 to +1] CARs on an indicator variable for firms that meet or beat the latest available earnings forecast after a significant decline in the consensus in the last two weeks (*Meet–Pessimism*) and another indicator variable for firms that meet or beat the latest forecast without a steep decline in the consensus (*Meet–NoPessimism*). The sample consists of firm-quarters in these two categories only and the regression has no constant term. The base sample is comprised of quarterly data on analysts' earnings forecasts taken from the Institutional Brokers Estimate System's (I/B/E/S) *Detail History* files database from 1989:I to 1999:IV. Data on shares outstanding and earnings announcement dates are taken from COMPUSTAT, and stock returns are obtained from CRSP. The table displays (at the bottom) a test of the restriction that the returns are similar for the two categorical variables. The OLS estimation in column 1 corrects the error structure both for heteroskedasticity and for within-period error correlation using the White-Huber estimator. Column 2 displays results for the analogous median regression estimator; and column 3 reports the results when we use the robust regression technique proposed in Li (1985), which minimizes the influence of outliers on our inferences. The relevant t- and z-statistics are (in parenthesis). Below each coefficient estimate, we also report [in square brackets] the associated bootstrapped 95% confidence interval for those estimates.

Dependent Var. : $CAR_{[-1,+1]}$	OLS Regression	Median Regression	Robust Regression
Dummy Meet–Pessimism	0.010	0.0010	0.009
	(3.99)	(4.59)	(4.57)
	[0.006, .014]	[0.007, 0.013]	[0.006, 0.012]
Dummy Meet–NoPessimism	0.005	0.005	0.004
	(4.88)	(5.79)	(5.64)
	[0.003, 0.008]	[0.003, 0.006]	[0.002, 0.006]
F-test (p-value)	0.00	–	0.00
Number of Obs.	8,727	8,727	8,727
Test: $Pessimism - NoPessimism = 0$	0.004	0.005	0.005
(p-value)	0.09	0.02	0.01

Table VIII. Private news, expectations path, and returns around EPS announcement dates

This table displays the result from regressions of 16-day [–14 to +1] CARs on the difference between true earnings and the earnings consensus as of 14 days prior to announcement ($EPSGap$) and on the change in the consensus between days –14 and –2 prior to the earnings announcement day ($\Delta Consensus$). The regression also includes quadratic and interaction terms of those two variables (see Equation (5) in the text). *Analyst Coverage* is the number of analysts issuing forecasts for the firm-quarter. The base sample is comprised of quarterly data on analysts' earnings forecasts taken from the Institutional Brokers Estimate System's (I/B/E/S) *Detail History* files database from 1989:I to 1999:IV. Data on shares outstanding and earnings announcement dates are taken from COMPUSTAT, and stock returns are obtained from CRSP. The OLS estimation in column 1 corrects the error structure both for heteroskedasticity and for within-period error correlation using the White-Huber estimator. Column 2 displays results for the analogous median regression estimator; and column 3 reports the results when we use the robust regression technique proposed in Li (1985), which minimizes the influence of outliers on our inferences. The relevant t- and z-statistics are (in parenthesis). Below each coefficient estimate, we also report [in square brackets] the associated bootstrapped 95% confidence interval for those estimates.

Dep. Var. : $CAR_{[-14,+1]}$	OLS Regression	Quantile Regression	Robust Regression
$EPSGap$	0.187	0.197	0.236
	(3.98)	(11.88)	(12.22)
$\Delta Consensus$	1.329	1.038	1.602
	(2.66)	(2.26)	(5.21)
$(\Delta Consensus < 0)^2$	7.152	2.970	17.529
	(1.63)	(1.08)	(3.21)
$(\Delta Consensus \geq 0)^2$	−24.627	−18.769	−40.943
	(−3.39)	(−5.30)	(−5.67)
$EPSGap \times \Delta Consensus$	1.152	1.322	1.054
	(3.48)	(11.57)	(6.40)
Analyst Coverage	0.001	0.001	0.001
	(2.54)	(2.99)	(2.73)
F-test (p-value)	0.00	–	0.00
Number of Obs.	42,057	42,057	42,057

Table IX. Private news, expectations path, and returns around EPS announcement dates: Longer CARs

This table displays the result from regressions of 20-day [–14 to +5] CARs on the difference between true earnings and the earnings consensus as of 14 days prior to announcement ($EPSGap$) and on the change in the consensus between days –14 and –2 prior to the earnings announcement day ($\Delta Consensus$). The regression also includes quadratic and interaction terms of those two variables (see Equation (5) in the text). *Analyst Coverage* is the number of analysts issuing forecasts for the firm-quarter. The base sample is comprised of quarterly data on analysts' earnings forecasts taken from the Institutional Brokers Estimate System's (I/B/E/S) *Detail History* files database from 1989:I to 1999:IV. Data on shares outstanding and earnings announcement dates are taken from COMPUSTAT, and stock returns are obtained from CRSP. The OLS estimation in column 1 corrects the error structure both for heteroskedasticity and for within-period error correlation using the White-Huber estimator. Column 2 displays results for the analogous median regression estimator; and column 3 reports the results when we use the robust regression technique proposed in Li (1985), which minimizes the influence of outliers on our inferences. The relevant t- and z-statistics are (in parenthesis). Below each coefficient estimate, we also report [in square brackets] the associated bootstrapped 95% confidence interval for those estimates.

Dep. Var. : $CAR_{[-14,+5]}$	OLS Regression	Quantile Regression	Robust Regression
$EPSGap$	0.142	0.185	0.169
	(3.38)	(9.44)	(7.82)
$\Delta Consensus$	1.144	1.437	1.466
	(2.18)	(4.56)	(4.26)
$(\Delta Consensus < 0)^2$	2.953	11.170	20.956
	(0.48)	(3.44)	(3.43)
$(\Delta Consensus \geq 0)^2$	-18.765	-21.706	-29.107
	(-2.52)	(-5.03)	(-3.60)
$EPSGap \times \Delta Consensus$	0.828	1.198	0.794
	(2.98)	(8.76)	(4.30)
Analyst Coverage	0.001	0.001	0.001
	(3.95)	(4.46)	(4.31)
F-test (p-value)	0.00	–	0.00
Number of Obs.	42,046	42,046	42,046

Table X. Asymmetric effects of private news around EPS announcement dates

This table displays the result from regressions of 16-day [–14 to +1] CARs on the difference between true earnings and the earnings consensus as of 14 days prior to announcement ($EPSGap$) and on the change in the consensus between days –14 and –2 prior to the earnings announcement day ($\Delta Consensus$). The regression also includes spline and interaction terms of those two variables (see Equation (6) in the text). *Analyst Coverage* is the number of analysts issuing forecasts for the firm-quarter. The base sample is comprised of quarterly data on analysts' earnings forecasts taken from the Institutional Brokers Estimate System's (I/B/E/S) *Detail History* files database from 1989:I to 1999:IV. Data on shares outstanding and earnings announcement dates are taken from COMPUSTAT, and stock returns are obtained from CRSP. The OLS estimation in column 1 corrects the error structure both for heteroskedasticity and for within-period error correlation using the White-Huber estimator. Column 2 displays results for the analogous median regression estimator; and column 3 reports the results when we use the robust regression technique proposed in Li (1985), which minimizes the influence of outliers on our inferences. The relevant t- and z-statistics are (in parenthesis). Below each coefficient estimate, we also report [in square brackets] the associated bootstrapped 95% confidence interval for those estimates.

Dep. Var. : $CAR_{[-14,+1]}$	OLS Regression	Quantile Regression	Robust Regression
$EPSGap < 0$	0.194	0.252	0.247
	(3.10)	(12.40)	(11.20)
$EPSGap \geq 0$	0.066	0.067	0.319
	(1.01)	(2.58)	(6.33)
$\Delta Consensus$	1.280	1.372	1.374
	(3.77)	(7.16)	(6.27)
$(EPSGap < 0) \times (\Delta Consensus)$	3.703	4.778	4.669
	(3.17)	(12.22)	(10.02)
$(EPSGap \geq 0) \times (\Delta Consensus)$	−0.315	−0.387	−30.915
	(−0.61)	(−1.93)	(−4.77)
Analyst Coverage	0.001	0.001	0.001
	(2.48)	(2.78)	(2.78)
F-test (p-value)	0.00	–	0.00
Number of Obs.	42,057	42,057	42,057

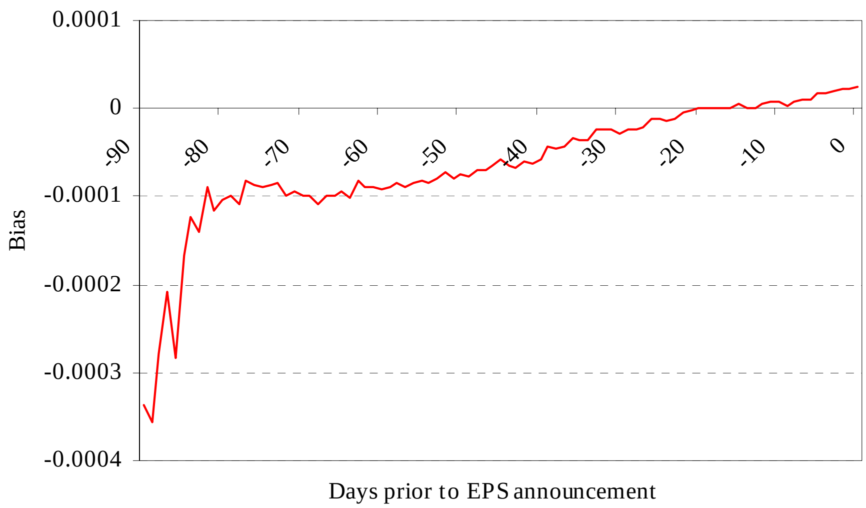

Figure 1: Daily evolution of the median forecast bias over the forecasting cycle. For j days before the earnings announcement, $j = 1, \ldots, 90$, we first compute the distribution of the difference between realized earnings and the date j-outstanding consensus forecast. The figure plots the median of this distribution for each day j using data from firm-quarters for which an initial consensus can be measured at least two months prior to the announcement date.

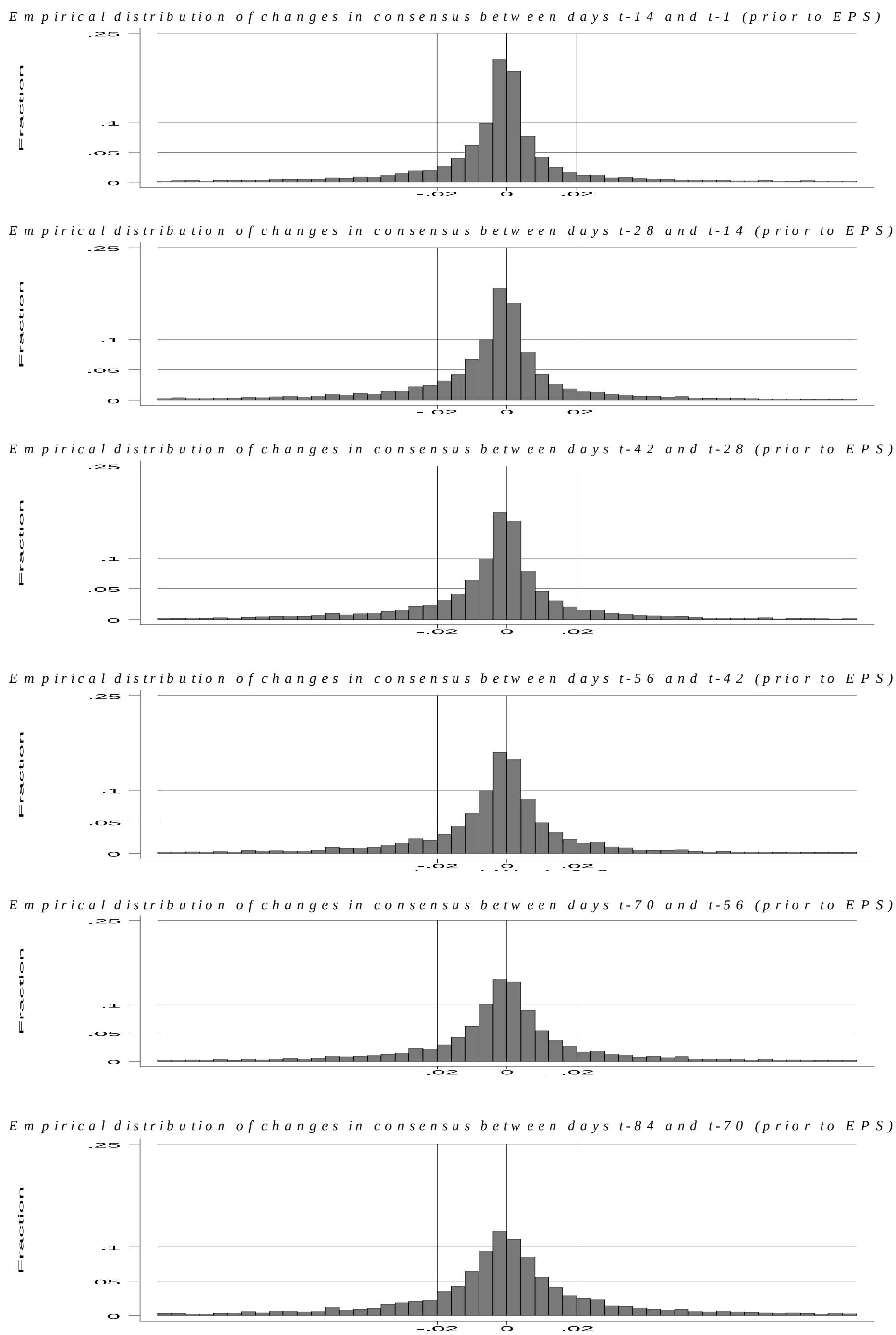

Figure 2: Empirical distribution of bi-weekly changes in the consensus. The figure presents the empirical distribution for daily (non-zero) changes in the outstanding consensus EPS estimate for firms for two-week intervals that start from the day prior to the EPS announcement date D and go back to 84 days preceding the announcement date. This yields 6 histograms: $\Delta E_{D-14\to D-1}, \Delta E_{D-28\to D-14}, ..., \Delta E_{D-84\to D-70}$.