Information Uncertainty and Analyst Forecast Behavior*

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Abstract

Prior literature observes that information uncertainty exacerbates investor underreaction behavior. In this paper, I investigate whether, as professional investment intermediaries, sell-side analysts suffer more behavioral biases in cases of greater information uncertainty. I show that greater information uncertainty predicts more positive (negative) forecast errors and subsequent forecast revisions following good (bad) news, which corroborates previous findings on the post-analyst-revision drift. The opposite effects of information uncertainty on forecast errors and subsequent forecast revisions following good versus bad news support the analyst underreaction hypothesis and are inconsistent with analyst forecast rationality or optimism suggested in prior literature.

Keywords Analyst forecast error; Forecast revision; Information uncertainty; Underreaction

JEL Descriptors G12, G14, M41

Incertitude relative à l'information et comportement prévisionnel des analystes

Condensé

Selon les études récentes (Zhang, 2006 ; Jiang *et al*., 2005), l'incertitude relative à l'information est en relation positive avec le rendement futur des actions à la suite de révisions des prévisions à la hausse, mais en relation négative avec le rendement futur des actions à la suite de révisions des prévisions à la baisse, ce qui donne à penser que la variation postérieure à la révision est attribuable à la réaction mitigée des investisseurs plutôt qu'au risque. Les études antérieures présentent toutefois une limite : la relation entre les révisions des prévisions des analystes et les rendements subséquents des actions pourrait être attribuable à des facteurs de risque non définis ou à des lacunes insoupçonnées des plans de recherche. Étant donné que les prévisions des analystes ne sont pas assujetties au risque ou aux frictions du marché, l'auteur écarte ces éléments en se demandant si les analystes eux-mêmes affichent davantage de distorsion comportementale lorsque l'incertitude relative à l'information est plus grande.

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Il teste plus précisément l'hypothèse mixte suivante : si les analystes ont une réaction mitigée à la nouvelle information lorsqu'ils révisent leurs prévisions, en raison de distorsions comportementales, cette réaction mitigée est plus marquée encore lorsque l'incertitude relative à l'information est grande. En conséquence, les révisions futures des analystes sont susceptibles d'aller dans le même sens, et ces révisions seront plus importantes pour les sociétés dont l'information est plus incertaine. Par incertitude relative à l'information, l'auteur entend l'ambiguïté à l'égard des répercussions de la nouvelle information sur la valeur d'une société, ambiguïté qui peut provenir de deux sources : la volatilité des paramètres fondamentaux sous-jacents à l'entreprise et la piètre qualité de l'information (voir Zhang, 2006). La conséquence vérifiable de cette hypothèse est qu'une incertitude accrue relative à l'information mène à plus d'erreurs prévisionnelles positives (négatives) et à des révisions subséquentes des prévisions à la suite de bonnes (de mauvaises) nouvelles relatives à des entreprises dont l'information est plus certaine, les erreurs prévisionnelles (*forecast errors* — *FE*) étant les écarts entre les résultats réels (*actual earnings* — *E*) de l'I/B/E/S et les prévisions des analystes (*forecasts* — *F*), pondérés en fonction du cours de l'action au début de l'exercice.

L'auteur utilise la dispersion des prévisions de résultats des analystes comme variable de remplacement de l'incertitude relative à l'information, ce qui lui permet de saisir à la fois la volatilité des paramètres fondamentaux sous-jacents à l'entreprise et la piètre qualité de l'information. Il évalue la nouvelle information à l'aide des révisions récentes des prévisions des analystes, les révisions à la hausse étant associées aux bonnes nouvelles et les révisions à la baisse, aux mauvaises nouvelles. Après avoir observé les révisions des prévisions passées des analystes et la dispersion de leurs prévisions, l'auteur formule des prédictions quant au signe et à l'ampleur des erreurs prévisionnelles des analystes et des révisions des prévisions subséquentes.

Concrètement, l'auteur utilise d'abord la méthode du portefeuille et retient la moyenne et la médiane de chaque portefeuille comme base dans la formulation de conclusions. Il procède ensuite à des analyses de régression en testant son hypothèse à l'aide des classements percentiles. Conformément à cette hypothèse, l'auteur constate qu'une plus grande incertitude relative à l'information annonce plus d'erreurs prévisionnelles et de révisions subséquentes positives à la suite de bonnes nouvelles, mais plus d'erreurs prévisionnelles et de révisions subséquentes négatives à la suite de mauvaises nouvelles, ce qui laisse croire que l'incertitude relative à l'information retarde l'intégration de l'information ambiguë dans les prévisions des analystes. L'incidence de l'incertitude relative à l'information sur le comportement des analystes est beaucoup plus marquée à la suite de mauvaises nouvelles qu'à la suite de bonnes nouvelles. En outre, conformément à son hypothèse, l'auteur constate que les analystes ont tendance à diminuer leurs estimations dans le cas des sociétés qui publient de mauvaises nouvelles et à augmenter leurs estimations dans le cas des sociétés qui publient de bonnes nouvelles, lorsque l'horizon prévisionnel raccourcit et que le volume d'information disponible s'accroît. Les effets opposés de l'incertitude relative à l'information sur les erreurs prévisionnelles et les révisions subséquentes des prévisions à la suite de bonnes ou de mauvaises nouvelles confirment l'hypothèse de réaction mitigée des analystes et ne sont pas conformes à la rationalité ou à l'optimisme des prévisions des analystes suggérées dans les études précédentes.

1. Introduction

In recent studies, Zhang (2006) and Jiang, Lee, and Zhang (2005) examine the effect of information uncertainty on investor behavior following analyst forecast revisions. Both papers document that information uncertainty is positively related to future stock returns following upward forecast revisions yet negatively related to future stock returns following downward forecast revisions, suggesting that the post-analyst-revision drift is due to investor underreaction rather than risk. However, a limitation of prior studies is that the relation between analyst forecast revisions and subsequent stock returns could be attributable to unidentified risk factors or unknown research design flaws. For example, Fama (1970) observes that tests of market efficiency are joint tests of mispricing and the underlying asset-pricing model. Thus, the post-analyst-revision drift may be simply due to mismeasured risk or market frictions. Because analyst forecasts are not subject to risk or market frictions, this paper avoids these issues by studying whether analysts themselves exhibit more behavioral biases when there is greater information uncertainty.

Specifically, I test the following joint hypothesis: If analysts, because of behavioral biases, underreact to new information when revising their forecasts, they will underreact even more in cases of greater information uncertainty. As a result, analysts will revise their forecasts in the same direction in the future, and the revision will be stronger for firms with greater information uncertainty. By "information uncertainty", I mean ambiguity with respect to the implications of new information for a firm's value, which potentially stems from two sources: the volatility of a firm's underlying fundamentals and poor information (see Zhang 2006). The testable implication is that greater information uncertainty leads to more positive (negative) forecast errors and subsequent forecast revisions following good (bad) news relative to firms about which there is less information uncertainty, where forecast errors (*FE*) are defined as I/B/E/S actual earnings (*E*) minus analyst forecasts (*F*) scaled by beginning stock price.

I use dispersion in analysts' earnings forecasts as a proxy for information uncertainty, which captures both the volatility of a firm's underlying fundamentals and poor information. I measure new information using analysts' recent forecast revisions, where upward forecast revisions mean good news and downward forecast revisions mean bad news. After observing analysts' past forecast revisions and dispersion in analyst forecasts, I make predictions on the sign and magnitude of analyst forecast errors and subsequent forecast revisions. Consistent with my hypothesis, I find that greater information uncertainty predicts more positive (negative) forecast errors and subsequent forecast revisions following good (bad) news, suggesting that information uncertainty delays the absorption of ambiguous information into analyst forecasts. The effect of information uncertainty on analyst behavior is much stronger following bad news than following good news. Also consistent with my hypothesis, I find that analysts tend to walk down (up) their estimates for bad-news (good-news) firms as the forecast horizon decreases and more information becomes available.

This study contributes to the analyst forecast literature and capital-market research in two ways. First, my evidence complements and extends the literature on post-analyst-revision drift. Stickel (1991) and Gleason and Lee (2003), among others, demonstrate that the stock price reaction to analysts' forecast revisions is incomplete — that is, prices, on average, continue to drift in the same direction for at least three to nine months after the revision. Zhang (2006) and Jiang et al. (2005) further document that information uncertainty is positively related to the post-analyst-revision drift. However, a limitation of prior studies is that they fail to consider that the relation between analyst forecast revisions and subsequent stock returns could be attributable to unidentified risk factors or unknown research design flaws (e.g., Kothari 2001). This study mitigates these concerns by providing direct evidence that, as professional investment intermediaries, sell-side analysts underreact to new information and underreact more when there is greater information uncertainty. My evidence corroborates the hypothesis that investors underreact to analyst forecast revisions.

I also extend the literature on post-analyst-revision drift by documenting that information uncertainty has asymmetric effects on analyst forecasts following good versus bad news. Both Zhang (2006) and Jiang et al. (2005) find that information uncertainty has a stronger effect on future stock returns following bad news than following good news. Zhang (2006) conjectures that this might be due to short-sale restrictions. Jiang et al. (2005) and Diether, Malloy, and Scherbina (2002) suggest that this is consistent with Miller's 1977 model that high-information-uncertainty stocks are overpriced because pessimistic investors are kept out of the market as a result of market frictions and, therefore, stock price reflects the excess optimism of the investors with the highest private valuation. Because analyst forecasts are not subject to short-sale restrictions or other market frictions, a similar finding on analyst forecast behavior suggests that asymmetric effects of information uncertainty on expected returns are rooted in underlying investor behavior and/or the flow of information to the market rather than in market frictions. For example, it is possible that managers tend to fully disclose good news but, to some degree, withhold bad news. Hence, bad news is more autocorrelated, and market participants, such as investors and analysts, underestimate the autocorrelation.

Second, my evidence contributes to the analyst forecast literature by shedding new light on analysts' forecast efficiency from an information perspective. A number of theories have been advanced to explain observed analysts' forecast errors, such as economic incentive–based explanations, behavioral cognitive-bias explanations, and earnings-management arguments (see Kothari 2001 for a review). The evidence that information uncertainty leads to more positive forecast errors and subsequent forecast revisions following good news yet more negative ones following bad news supports the underreaction hypothesis (e.g., Mendenhall 1991). On the contrary, the evidence is inconsistent with analyst forecast rationality or optimism suggested in prior literature.[1]

This paper is organized as follows. Section 2 discusses related literature and develops a testable hypothesis. Section 3 describes the sample data and provides descriptive statistics. Section 4 presents empirical evidence using portfolio and regression approaches. Section 5 examines some alternative explanations, and section 6 concludes.

2. Prior literature and hypothesis development

Prior work and hypothesis development

This paper is related to two lines of research. The first line of research examines stock prices following analyst forecast revisions. Stickel (1991) and Gleason and Lee (2003), among others, demonstrate that the stock price reaction to analysts' forecast revisions is incomplete — that is, prices, on average, continue to drift in the same direction for at least three to nine months after the revision, which is the well-known post-analyst-revision drift. In more recent studies, Zhang (2006) and Jiang et al. (2005) document that the post-analyst-revision drift and price momentum are stronger for firms with greater information uncertainty, which is consistent with the notion that information uncertainty exacerbates investors' underreaction behavior. A common criticism of market-efficiency tests is that observed mispricing evidence is simply due to risk mismeasurement and/or market frictions. To avoid such issues, this paper examines whether, as professional investment intermediaries, sell-side analysts suffer similar problems. A comparison of investor behavior and analyst behavior provides additional insights on the post-revision drift and other market anomalies.

The second line of research examines analyst forecast behavior. There is substantial evidence in the prior literature that analysts underreact to some information. Mendenhall (1991), Abarbanell and Bernard (1992), and Ali, Klein, and Rosenfeld (1992) document evidence of analysts underreacting to the information in prior-period earnings. Lys and Sohn (1990), Abarbanell (1991), and Ali et al. (1992) document evidence of analysts underreacting to the information in prior-period returns. The underreaction to new information is often attributed to analysts' judgement heuristics and biases under uncertainty, such as conservatism (Edwards 1968) or overconfidence (Daniel, Hirshleifer, and Subrahmanyam 1998). Hirshleifer (2001) posits that greater uncertainty about a set of stocks and a lack of accurate feedback about their fundamentals leave more room for psychological biases. Therefore, the misvaluation effects of almost any mistaken-beliefs model should be strongest among firms for which there is high uncertainty and poor information.

In this paper, I test the following joint hypothesis: If analysts underreact to new information because of behavioral biases such as conservatism, they should underreact to a higher degree when there is greater uncertainty about a firm's fundamentals. As a result, forecast errors and subsequent forecast revisions exhibit a predictable pattern. The testable implication is that greater information uncertainty produces more positive (negative) forecast errors and subsequent revisions following analysts' initial upward (downward) revisions.

Following Zhang 2006, information uncertainty captures both the volatility of a firm's underlying fundamentals and poor information. Theoretically, an observed signal (s) is characterized as a firm's fundamental value (v) plus a noise term (e) — that is, $s = v + e$. For example, analyst earnings forecast (s) = firm's underlying earnings (v) + noise (e). Assuming that noise is unrelated to a firm's fundamental value ($\text{cov}(v, e) = 0$), then the variance of the signal measures information uncertainty: $\text{var}(s) = \text{var}(v) + \text{var}(e)$, where $\text{var}(v)$ is a firm's underlying fundamental volatility and $\text{var}(e)$ reflects the quality of information. I do not distinguish a firm's underlying fundamental volatility from information quality because both effects contribute to the uncertainty of a firm's value and because it is difficult to empirically disentangle one from the other as observed empirical constructs capture both effects. This definition parallels the argument in Hirshleifer 2001 that uncertainty reflects both the uncertainty about a firm's fundamentals and a lack of accurate feedback.

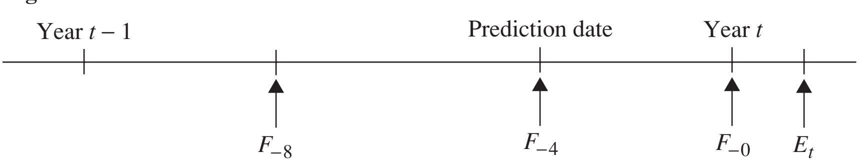
To test the role of information uncertainty in analyst forecast behavior, I first need an empirical proxy. One natural variable is firm size (*SIZE*), measured as the market capitalization at the prior fiscal year-end. It seems plausible that small firms have less information available for the market than large firms. Small firms may also have fewer customers, suppliers, and shareholders, and may not be able to bear high disclosure-preparation costs. Analysts and investors might have fixed costs of information acquisition, which makes small firms' stocks unattractive. Unfortunately, even if firm size is, in fact, a useful measure of uncertainty, it is likely to capture other things as well, potentially confounding my inferences. Although it is certainly interesting to see how analyst forecast behavior varies with firm size, this probably does not by itself constitute a clean test of my central hypothesis.

As an alternative, I consider dispersion in analyst forecasts (*DISP*) as a proxy for information uncertainty, which is measured as the standard deviation of analyst forecasts made four months prior to fiscal year-end, scaled by the prior year-end stock price. I require at least four earnings forecasts in calculating standard deviation for a given month. This measure is closely related to my definition of information uncertainty. In the prior literature, forecast dispersion is widely used to proxy for the uncertainty or the degree of consensus among analysts or market participants (e.g., Imhoff and Lobo 1992; Lang and Lundholm 1996; Barron, Kim, Lim, and Stevens 1998; Diether et al. 2002; and Zhang 2006). A larger dispersion in analyst forecasts corresponds to greater information uncertainty.

Research design

As the objective of this paper is to provide complementary evidence on the post-analyst-revision drift (e.g., Stickel 1991), I focus on a short window and test whether analysts underreact to new information that motivates their initial revisions.[2] I define the time-line in Figure 1.

Figure 1 Time-line



The prediction date is four months prior to a firm's fiscal year-end. I use the past forecast revision ($REV_{-8,-4} = F_{-4} - F_{-8}$) to summarize the nature of news, where the past forecast revision is the forecast made four months prior to fiscal year-end (F_{-4}) minus the forecast made four months earlier (F_{-8}).[3] Roughly, F_{-8} is the first forecast made after the release of the previous year's annual report. A negative forecast revision implies bad news, while a positive one implies good news. At the prediction date, I make predictions on the sign and magnitude of current forecast errors ($FE_{-4} = E_t - F_{-4}$) and subsequent forecast revisions for the next four months ($REV_{-4,-0} = F_{-0} - F_{-4}$). By construction, F_{-0} is the forecast made in the last month of a firm's fiscal year. For firms with a December fiscal year-end, the prediction date is August 31. On the basis of forecast revisions from April to August and forecast dispersion in August, I make predictions on the sign and relative magnitude of forecast errors in August and forecast revisions from August to December. The choice of August 31 as the prediction date is arbitrary. It is simply convenient to have the past four months' information available to make predictions for the next four months in a period after the previous year's annual report is released but before earnings are realized. Other choices of the prediction date do not change the tenor of the paper. To support the analyst underreaction hypothesis, I should observe positive FE_{-4} and $REV_{-4,-0}$ following upward revisions ($REV_{-8,-4}$) and negative ones following downward revisions. To support my main hypothesis that information uncertainty exacerbates analyst underreaction, I should observe more positive forecast errors and subsequent revisions following good news but more negative ones following bad news for firms with greater information uncertainty.

One concern with the empirical tests is the skewness in the distribution of earnings, forecast dispersion, and other variables. In the presence of skewness, any truncation or winsorization would shift the mean of the distribution (Kothari, Sabino, and Zach 2005). A high skewness in the dependent and independent variables could also violate the normality assumption in ordinary least squares (OLS) regressions. Additionally, it is not entirely clear what analysts' objective function is when they make earnings forecasts. Although most studies follow the traditional mean-variance-efficiency framework, some recent papers (e.g., Gu and Wu 2003; Basu and Markov 2004) argue that analysts are minimizing the median instead of mean forecast error due to earnings skewness. Another concern is the potential nonlinearity between analyst forecast behavior and information uncertainty. It seems plausible that the marginal effect of information uncertainty decreases as the level of uncertainty increases. To address these concerns, I first use a portfolio approach and report both the mean and median for each portfolio as my inferences in drawing conclusions. Then, I run regressions using percentile rankings to test my hypothesis. To deal with the cross-sectional correlation problem, I focus on the time-series means of the coefficients from annual cross-sectional regressions and use the time-series standard errors as in Fama and MacBeth 1973 for my inferences to avoid overstating the significance of my results.

3. Sample data and descriptive statistics

The sample data come from three sources. Analyst forecast and actual earnings data are from I/B/E/S. Book value and other financial data are from COMPUSTAT, and return data are from the Center for Research in Security Prices (CRSP). The sample period is from 1983 to 2001. To be included in the sample, each firm must have no missing data for analyst forecast, actual earnings, and prior year-end stock price.

There are at least two problems with the standard-issue I/B/E/S summary data set. First, I/B/E/S uses all existing analyst forecasts to calculate summary statistics, and some of these forecasts are stale. The stale forecasts can have a large effect on analyst forecast revision and forecast dispersion. Second, there is a rounding-error problem due to stock splits because I/B/E/S adjusts all data with stock splits and only rounds the estimate to the nearest cent (Baber and Kang 2002). Rounding error typically reduces forecast dispersion and the magnitude of forecast revisions and forecast errors, while stale forecasts increase forecast dispersion but reduce the magnitude of forecast revisions, which might lead to some mechanical relations among forecast dispersion, forecast revisions, and forecast errors.[4] To avoid these issues, I closely follow Diether et al. 2002 and compute summary variables from the raw individual forecast data, unadjusted for stock splits. The only exception is that I scale actual earnings and analyst forecasts by the cumulative adjustment factor from the I/B/E/S Adjustments File to make adjustments for stock splits and stock dividends.[5]

I measure analyst forecast revisions ($REV_{-8,\,-4}$ and $REV_{-4,\,-0}$) as the average of individual revisions by analysts who covered the firm in both months, from which the revision is calculated.[6] For example, $REV_{-8,\,-4}$ is the average of individual revisions by analysts covering the firm in both horizons -8 and -4. In this way, any initiation or drop of analyst coverage does not lead to a revision.

There are 49,923 firm-year observations from 1983 to 2001. I focus on this sample period because I/B/E/S has individual forecast data from 1983 and the sample is incomplete in 2002 when the data set (unadjusted for stock splits) was requested from I/B/E/S. To facilitate comparison across firms, I scale forecast errors and forecast revisions by the prior year-end stock price.[7] I delete those observations with an absolute value of measured forecast errors exceeding 100 percent, because these observations seem to be problematic and probably result from a data input error.[8]

Table 1, panel A presents descriptive statistics for variables of interest. Four months prior to fiscal year-end, the mean forecast error (FE_{-4}) is -0.93 percent while the median is -0.13 percent. The mean is more negative than the median, suggesting a left skewness in the distribution. The negative forecast error is consistent with the prior literature and suggests optimism in the overall sample. Analyst forecast dispersion is right-skewed, with a mean and median of 0.63 percent and 0.30 percent, respectively. The minimum analyst following (*COV*) is 1 and the maximum is 67, and firm size (*SIZE*) ranges from \$6.56 million to \$94,640.90 million. Panel B shows the correlation matrix. $REV_{-8,\,-4}$ is positively correlated with $REV_{-4,\,-0}$ (Pearson = 0.41, Spearman = 0.45) and FE_{-4} (Pearson = 0.28, Spearman

TABLE 1
Descriptive statistics

Panel A: Descriptive statistics

	Mean	s.d.	Minimum	Q1	Median	Q3	Maximum
SIZE	1,999.11	6,672.79	6.56	96.23	301.39	1,120.62	94,640.90
BM	0.65	0.46	−0.29	0.32	0.55	0.86	4.13
LEV	22.12%	18.90%	0.00%	5.61%	19.17%	34.08%	90.79%
RET_6	7.50%	35.40%	−83.64%	−12.61%	4.97%	22.90%	221.43%
VOL	1,051.40	3,933.90	1.25	33.75	131.47	578.43	66,076.60
COV	10.01	9.59	1	3	7	14	67
DISP	0.63%	0.93%	0.00%	0.13%	0.30%	0.71%	8.27%
FE_{-4}	−0.93%	6.94%	−60.42%	−1.41%	−0.13%	0.36%	62.16%
$REV_{-8,-4}$	−0.65%	2.72%	−23.82%	−0.99%	−0.10%	0.28%	12.20%
$REV_{-4,-0}$	−0.68%	2.37%	−22.44%	−0.94%	−0.15%	0.19%	8.73%

(The table is continued on the next page.)

TABLE 1 (Continued)

Panel B: Correlation matrix

	SIZE	*BM*	*LEV*	*RET_6*	*VOL*	*COV*	*DISP*	P_{t-1}	FE_{-4}	$REV_{-8,-4}$	$REV_{-4,-0}$
SIZE	1	−0.12*	0.03*	−0.02*	0.68*	0.40*	−0.12*	0.25*	0.03*	0.05*	0.06*
BM	−0.21*	1	0.11*	0.06*	−0.16*	−0.02*	0.37*	−0.14*	−0.10*	−0.13*	−0.13*
LEV	0.09*	0.19*	1	0.02*	−0.01	0.05*	0.16*	0.03*	−0.08*	−0.03*	−0.07*
RET_6	0.02*	0.08*	0.03*	1	0.03*	0.01*	0.02*	−0.15*	0.13*	0.30*	0.20*
VOL	0.82*	−0.31*	0.01	0.10*	1	0.37*	−0.12*	0.29*	0.02*	0.05*	0.05*
COV	0.71*	−0.04*	0.11*	0.05*	0.68*	1	0.01	0.17*	0.06*	0.05*	0.06*
DISP	−0.29*	0.47*	0.18*	0.00	−0.32*	0.02*	1	−0.12*	−0.18*	−0.33*	−0.30*
P_{t-1}	0.55*	−0.18*	0.04*	−0.15*	0.47*	0.31*	−0.29*	1	0.02*	0.02*	0.02*
FE_{-4}	0.11*	−0.04*	−0.07*	0.25*	0.10*	0.06*	−0.14*	0.02*	1	0.28*	0.49*
$REV_{-8,-4}$	0.11*	−0.08*	−0.03*	0.42*	0.15*	0.03*	−0.19*	0.02*	0.36*	1	0.41*
$REV_{-4,-0}$	0.12*	−0.08*	−0.06*	0.29*	0.13*	0.04*	−0.20*	0.02*	0.68*	0.45*	1

(The table is continued on the next page.)

TABLE 1 (Continued)

Notes:

The sample data come from three sources. Analyst forecast data are from I/B/E/S. Financial data are from COMPUSTAT. Return data are from CRSP. *SIZE* is the market value (data #25*data #199) at the prior year-end. *BM* is the book-to-market ratio [data #60/(data #25*data #199)] at the prior year-end. *LEV* is the leverage ratio [(data #34 + data #9)/data #6] at the prior year-end. *RET_6* is the accumulated six-month returns up to the prediction date, which is four months prior to a firm's fiscal year-end. *VOL* is the accumulated six-month dollar trading volume up to the prediction date (in millions). *COV* is analyst coverage, measured as the number of analysts covering the firm in the previous year. *DISP* is the dispersion in analyst forecasts, measured as the standard deviation of analyst forecasts made four months prior to a firm's fiscal year-end, scaled by the prior year-end stock price. I require at least four forecasts for a given firm-month in calculating standard deviations of earnings forecasts. FE_{-4} is forecast error, measured as I/B/E/S actual earnings minus earnings forecast scaled by the prior year-end stock price, where the forecast is made four months prior to a firm's fiscal year-end. $REV_{-8,\,-4}$ is the average of analysts' individual forecast revisions from eight months prior to fiscal year-end to four months prior to fiscal year-end, while $REV_{-4,\,-0}$ is the average of analysts' individual forecast revisions from four months prior to fiscal year-end to a firm's fiscal year-end. P_{t-1} is the prior year-end stock price. There are 26,245 firm-year observations for the *DISP* variable, 45,196 observations for *RET_6* and *VOL* variables, and 49,923 observations for other variables from 1983 to 2001. The top and bottom 1 percent of all variables except for *COV* are winsorized to avoid the effect of outliers. In panel B, Pearson correlations are shown above the diagonal and Spearman correlations below.

* Significant at the 0.01 level.

= 0.36), which underlines the importance of controlling for $REV_{-8,\,-4}$ in testing the role of information uncertainty on analyst forecast errors and subsequent forecast revisions. Firm size is highly correlated with analyst coverage and trading volume (*VOL*), but not with forecast dispersion.

4. Empirical evidence

Do analysts underreact in revising their forecasts?

In my first set of analyses, I attempt to replicate the analyst underreaction evidence for my sample. If analysts underreact to new information when revising their forecasts, their adjustments in earnings forecasts would not be sufficient. Accordingly, I expect to observe positive forecast errors and subsequent forecast revisions following good news and negative ones following bad news.

Table 2 presents the results based on the nature of news. Four months prior to firms' fiscal year-end, the mean and median forecast errors (FE_{-4}) are −1.51 percent ($t = -7.57$) and −0.44 percent ($z = -9.65$) following bad news and 0.69 percent

($t = 2.05$) and 0.12 percent ($z = 5.70$) following good news, respectively, which is consistent with prior findings that analysts display a tendency to underreact to new information in revising their forecasts (see Elliott, Philbrick, and Wiedman 1995). Forecast revisions for the next four months ($REV_{-4,\,-0}$) have a mean of −1.11 percent ($t = 16.85$) and median of −0.44 percent ($z = -13.02$) following bad news. Following good news, the mean forecast revision is close to zero, but the median is significantly positive ($REV_{-4,\,-0} = 0.08$ percent, $z = 7.25$). Such evidence indicates that analysts react in the right direction in the first four months when they revise their forecast, but their revision is not sufficient regardless of whether analysts have a linear or a quadratic loss function. As a result, current forecast errors and subsequent forecast revisions are generally negative following bad news and positive following good news. To get a sense of economic significance, I use the median earnings per share of 94 cents and median stock price of $18.12 in the sample as my benchmark. The median FE_{-4} of 0.12 percent for good-news firms corresponds to 2.17 cents. On the other hand, the number becomes −8.00 cents for bad-news firms.

If analysts underreact to new information in revising their earnings forecasts, they will walk down their estimates for bad-news firms and walk up their estimates for good-news firms as the forecast horizon decreases and more information comes out. Figure 2 shows the average FE for the bad-news and good-news subsamples over different forecast horizons, where bad or good news is based on the sign of the four-month forecast revision from horizon −8 to horizon −4. For bad-news

TABLE 2
The predictability of forecast errors and subsequent forecast revisions based on the nature of news

	Bad news ($REV_{-8,\,-4} < 0$)		Good news ($REV_{-8,\,-4} > 0$)	
	Mean	Median	Mean	Median
FE_{-4}	−1.51%	−0.44%	0.69%	0.12%
	(−7.57)	(−9.65)	(2.05)	(5.70)
$REV_{-4,\,-0}$	−1.11%	−0.44%	0.00%	0.08%
	(−16.85)	(−13.02)	(0.16)	(7.25)

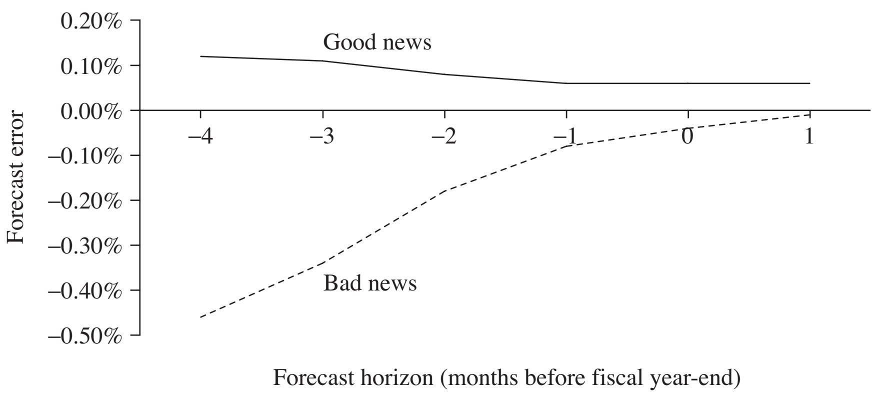
Notes:

The prediction date is four months prior to a firm's fiscal year-end. After observing $REV_{-8,\,-4}$, I make predictions on the sign and relative magnitude of forecast errors at the prediction date (FE_{-4}) and subsequent forecast revisions for the next four months ($REV_{-4,\,-0}$). Variables are as defined in Table 1. The sample data are from I/B/E/S from 1983 to 2001. There are 20,824 firm-year observations for the bad-news group ($REV_{-8,-4} < 0$) group and 11,574 observations for the good-news group ($REV_{-8,-4} > 0$). The t- and z-statistics are shown in parentheses, where the t-statistics for means are calculated from the Fama-MacBeth approach and the z-statistics for medians are from a nonparametric test.

firms, *FE* tends to be very negative at the prediction date (horizon −4) and increases as the forecast horizon decreases. For the good-news firms, *FE* tends to be more positive at the prediction date and decreases when it approaches the earnings announcement date. A negative (positive) *FE* in the bad-news (good-news) subsample supports the analyst underreaction hypothesis. Furthermore, the decrease of *FE* in absolute value over forecast horizons suggests that analysts underreact more in early months and that underreaction is reduced as more information becomes available.

The asymmetry in the speed of walking up versus walking down in Figure 2 and the magnitude of forecast errors and subsequent revisions in Table 2 merit further discussion. Analysts revise their estimates upward following good news, but they revise their estimates downward to a larger degree following bad news.[9] This makes intuitive sense for most firms, given that the magnitude of forecast revision is a good way to measure the information flow coming out of a firm. If a firm is sitting on good news, managers have every incentive to push this news out as fast as possible. When there is bad news, managers probably want to withhold it for some time. Bad news may be uncovered by financial analysts and other market participants when managers are unwilling to disclose voluntarily.[10] Therefore, information

Figure 2 The time-series pattern of forecast error following bad or good news



Notes:

Forecast error (*FE*) is the actual earnings minus analyst forecast scaled by the prior year-end stock price. This figure reports the time-series average of annual median forecast errors from 1983 to 2001. (Results for the time-series average of annual means are similar.) The forecast horizon measures the number of months prior to firms' fiscal year-end. For example, horizon −4 refers to four months prior to firms' fiscal year-end; horizon −3 refers to three months prior to fiscal year-end, and so on. The sample here is a subset of the sample used in the main analysis, because it requires no missing forecast error from forecast horizons −8 to 1 for each firm. There are an average of 1,097 and 833 annual observations per forecast horizon for the bad-news subsamples ($REV_{-8,-4} < 0$) and good-news subsamples ($REV_{-8,-4} > 0$), respectively.

uncertainty is likely to be greater when companies are sitting on bad news, because managers tend to be less forthcoming (Hong, Lim, and Stein 2000; Lim 2001). Consistent with this argument, Hong et al. (2000) find that bad news diffuses more slowly to the investing public than good news. Lang and Lundholm (1993) find that analyst ratings of corporate disclosures are lower for poor-performing companies than for well-performing companies. The larger magnitude of subsequent revisions for bad-news firms is also consistent with the evidence in Hutton, Miller, and Skinner 2003 that managers' disclosures of bad news are more credible than their disclosures of good news.

Portfolio analysis on the role of information uncertainty

My main hypothesis states that greater information uncertainty produces more positive forecast errors and subsequent forecast revisions because analysts underreact more to new information in cases of greater uncertainty. Therefore, I predict that forecast errors and subsequent forecast revisions are more positive (negative) following good (bad) news for high-*DISP* firms than for low-*DISP* firms.

Table 3 shows forecast errors and subsequent forecast revisions across different uncertainty portfolios after the magnitude of news ($REV_{-8,-4}$) has been controlled for. To control for the magnitude of $REV_{-8,-4}$, I adopt a two-way conditional sorting technique. Specifically, I first sort firms into five quintiles based on $REV_{-8,-4}$ for the bad-news/good-news subsample, and then within each $REV_{-8,-4}$ quintile I further sort the observations into three groups based on *DISP* (groups 1 to 3). Finally, I pool all five group 1 firms together into one portfolio, all group 2 firms together into another portfolio, and so on. In this way, I sort the bad-news/good-news subsample into three equal-size portfolios, which have substantial variation of *DISP* but nearly the same level of $REV_{-8,-4}$. To the extent that $REV_{-8,-4}$ partially captures information uncertainty, my estimated effects are downward biased. Therefore, even if I do not find a significant relation between my information uncertainty proxy and analyst forecast behavior, I cannot conclude that information uncertainty does not play a role in analyst forecast behavior, because part of information uncertainty may be captured by $REV_{-8,-4}$. Similarly, if I do find a significant relation between my information uncertainty proxy and forecast errors and subsequent revisions, my estimates in all likelihood understate the effect.

A clear pattern emerges from Table 3. High-uncertainty portfolios exhibit more negative forecast errors and subsequent forecast revisions following bad news but more positive ones following good news. For example, the mean (median) FE_{-4} of high-*DISP* firms is −2.11 percent (−0.69 percent) following bad news, and 0.85 percent (0.19 percent) following good news. On the other hand, low-*DISP* portfolios have a significantly smaller FE_{-4} in magnitude, with a mean (median) of −0.02 percent (−0.20 percent) following bad news and 0.81 percent (0.10 percent) following good news. The mean and median differences of FE_{-4} between high- and low-dispersion portfolios are significantly negative for the bad-news subsample, while they are positive for the good-news subsample. The analysis on $REV_{-4,-0}$ yields similar patterns. Dispersion is positively (negatively) related to subsequent forecast revisions following good (bad) news, indicating a

TABLE 3
The predictability of forecast errors and subsequent forecast revisions based on the nature of news and the level of uncertainty

		$REV_{-8,-4}$		FE_{-4}		$REV_{-4,-0}$	
	DISP	Mean	Median	Mean	Median	Mean	Median
Bad news	Low	−1.23%	−0.65%	−0.02%	−0.20%	−0.54%	−0.23%
($REV_{-8,-4} < 0$)	Medium	−1.36%	−0.71%	−0.47%	−0.37%	−0.84%	−0.42%
	High	−1.99%	−0.73%	−2.11%	−0.69%	−1.41%	−0.65%
	High−low			−2.09%	−0.49%	−0.87%	−0.42%
				(−6.94)	(−8.92)	(−10.99)	(−13.33)
Good news	Low	0.67%	0.38%	0.81%	0.10%	0.08%	0.07%
($REV_{-8,-4} > 0$)	Medium	0.79%	0.40%	1.13%	0.15%	0.12%	0.10%
	High	1.11%	0.40%	0.85%	0.19%	−0.01%	0.07%
	High−low			0.04%	0.09%	−0.08%	0.00%
				(0.22)	(1.97)	(−1.37)	(0.15)

Notes:

The prediction date is four months prior to a firm's fiscal year-end. After I observe $REV_{-8,-4}$ and *DISP*, I make predictions on the sign and relative magnitude of forecast errors at the prediction date (FE_{-4}) and subsequent analyst forecast revisions for the next four months ($REV_{-4,-0}$). Variables are as defined in Table 1. To control for the magnitude of $REV_{-8,-4}$, I adopt a two-way conditional sorting technique. Specifically, I first sort firms into five quintiles based on $REV_{-8,-4}$ for the bad-news/good-news subsample, and then within each $REV_{-8,-4}$ quintile, I further sort the observations into three groups based on *DISP* (groups 1 to 3). Finally, I pool all five group 1 firms together into one portfolio, all group 2 firms together into another portfolio, and so on. The sample data are from I/B/E/S from 1983 to 2001. There are 14,893 firm-year observations for the bad news ($REV_{-8,-4} < 0$) subsample and 11,093 observations for the good news ($REV_{-8,-4} > 0$) subsample. The *t*- and *z*-statistics are shown in parentheses, where the *t*-statistics for means are calculated from the Fama-MacBeth approach and the *z*-statistics for medians are from a nonparametric test.

consistent relation between forecast dispersion and the degree of analyst underreaction. The impact of information uncertainty on analyst forecast behavior is much stronger following bad news than following good news. The difference between high- and low-*DISP* portfolios is highly significant in all four measures following bad news. In contrast, the difference is significant in only one measure following good news.

To gauge the economic significance of the numbers, assume that both low- and high-*DISP* firms have a stock price of \$18.12 and annual earnings per share of \$0.94. A low-*DISP* firm has a median forecast error of −3.62 cents following bad news and 1.81 cents following good news. These numbers become −12.50 cents and 3.44 cents for a high-*DISP* firm. The evidence that information uncertainty decreases (increases) forecast errors and subsequent revisions following bad (good) news supports my main hypothesis. It suggests that analysts incorporate new information in their forecast revisions almost completely in cases of low uncertainty, but their response to new information is far from complete when there is greater information uncertainty.

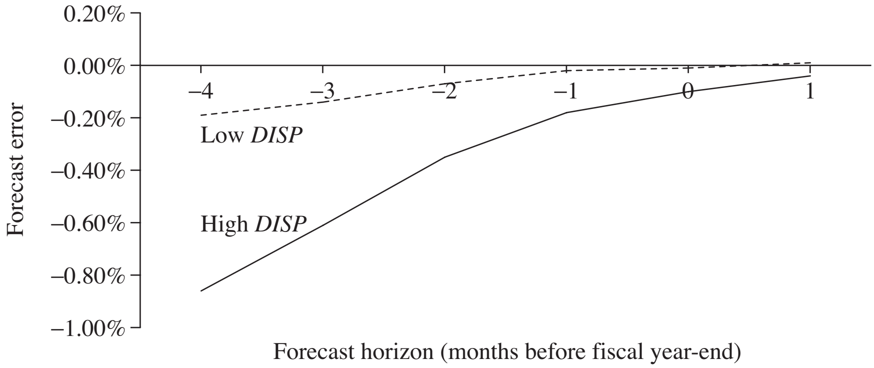
To further examine the relationships among forecast errors, forecast revisions, and the level of uncertainty, I examine forecast errors over different forecast horizons for the bottom and top dispersion quartiles of the bad- and good-news subsamples, respectively. Again, I adopt a two-way conditional sorting technique to control for the magnitude of news. Specifically, I first sort firms into five quintiles based on $REV_{-8,\,-4}$ for the bad-news/good-news subsample, and then within each $REV_{-8,\,-4}$ quintile, I further sort the observations into four groups based on *DISP* (groups 1 to 4). Finally, I pool all five group 1 firms together into one portfolio, all group 2 firms together into another portfolio, and so on. In this way, I sort the bad-news/good-news subsample into four *DISP* quartiles conditional on $REV_{-8,\,-4}$. Unreported results show that the magnitude of $REV_{-8,\,-4}$ is roughly the same for high- and low-*DISP* quartiles in the bad- or good-news subsample, suggesting that I have successfully controlled for the magnitude of news when measuring the effect of information uncertainty. At the prediction date (horizon = −4), I observe $REV_{-8,\,-4}$ and *DISP*, and make predictions on the sign and relative magnitude of subsequent forecast revisions and forecast errors. A few regularities are evident from Figure 3. First, high-dispersion firms have larger forecast errors in absolute value regardless of the forecast horizon. Second, for both dispersion quartiles, forecast errors decrease in magnitude as the forecast horizon decreases and more information comes out. These results provide robust evidence in support of my main hypothesis.

Regression analysis on the role of information uncertainty

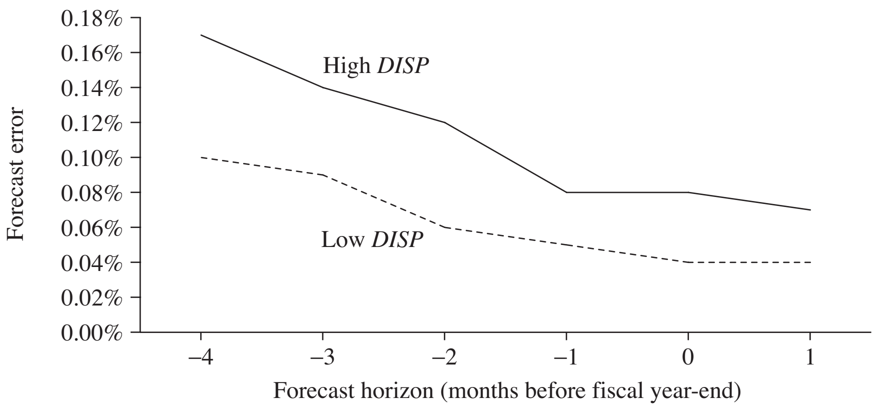
In order to mitigate the concern that my results are driven by variables omitted from the portfolio analyses but correlated with analyst forecast dispersion, I use the regression approach to provide further evidence on the role of information uncertainty on analyst forecast behavior. I consider the following control variables in the regressions: firm size, the book-to-market ratio, analyst coverage, the leverage ratio, six-month accumulated return, and dollar trading volume up to the prediction date.

Figure 3 The time-series pattern of forecast error for the bottom and top dispersion quartiles conditional on the size of news

Panel A: Bad news



Panel B: Good news



Notes:

Forecast error (*FE*) is the actual earnings minus analyst forecast scaled by the prior year-end stock price and calculated as the time-series average of annual medians from 1983 to 2001. *DISP* is forecast dispersion as defined in Table 1. The forecast horizon measures the number of months prior to firms' fiscal year-end. For example, horizon −4 refers to four months prior to firms' fiscal year-end; horizon −3 refers to three months prior to fiscal year-end, and so on. To control for the size of news, I adopt a two-way conditional sorting technique. Specifically, I first sort firms into five quintiles based on $REV_{-8,-4}$ for the bad-news/good-news subsample, and then within each $REV_{-8,-4}$ quintile, I further sort the observations into four groups based on *DISP* (groups 1 to 4). Finally, I pool all five group 1 firms together into one portfolio, all group 2 firms together into another portfolio, and so on. The sample here is a subset of the sample used in the main analysis, as it requires no missing forecast error from forecast horizons 8 to −1 for each firm. On average, there are 173 and 142 observations per forecast horizon for each dispersion quartile following bad news ($REV_{-8,-4} < 0$) and good news ($REV_{-8,-4} > 0$) each year, respectively.

Firm size (*SIZE*) has often been used as a proxy for the amount of information that is publicly available about a firm, but it is a catch-all variable and might capture something else. Book-to-market (*BM*) and leverage (*LEV*) may capture the degree of financial distress and the selection bias (e.g., McNichols and O'Brien 1997). Analyst coverage (*COV*) is related to the post-analyst-revision drift (Gleason and Lee 2003) and therefore might be related to analysts' subsequent forecast revisions as well. I include the past six-month accumulative returns (*RET_6*) to proxy for other information revealed to the market that might affect analysts' forecast behavior (e.g., Brown, Hagerman, Griffin, and Zmijewski 1987).[11] Finally, I include dollar trading volume (*VOL*) to capture analysts' incentive to generate commissions and investment banking business. Given that trading volume is measured differently in the National Association of Securities Dealers Automated Quotations (NASDAQ) because of the trades between market makers (Lee and Swaminathan 2000), I use the dummy variable D_{NAS} to indicate NASDAQ firms, where D_{NAS} equals 1 for NASDAQ firms and 0 otherwise. I employ the following regression models for bad- and good-news subsamples separately:

$$\begin{aligned} FE\_{-4}\ (REV\_{-4,\,-0}) = {} & \alpha_0 + \alpha_1 REV\_{-8,\,-4} + \alpha_2 REV\_{-8,\,-4}{*}DISP + \alpha_3 REV\_{-8,\,-4}{*}SIZE \\ & + \alpha_4 REV\_{-8,\,-4}{*}BM + \alpha_5 REV\_{-8,\,-4}{*}COV + \alpha_6 REV\_{-8,\,-4}{*}LEV \\ & + \alpha_7 REV\_{-8,\,-4}{*}RET\_6 + \alpha_7 REV\_{-8,\,-4}{*}VOL \\ & + \alpha_9 REV\_{-8,\,-4}{*}D_{NAS}VOL + \varepsilon \qquad (1), \end{aligned}$$

where the dependent variable is FE_{-4} or $REV\_{-4,\,-0}$. Actual values are converted into percentile rankings, with a scale of [0, 1]. I obtain percentile rankings by annually ranking observations and assigning them in equal numbers to 100 portfolios for each variable.

Because the sample is partitioned on the sign of news ($REV\_{-8,\,-4}$), I interact $REV\_{-8,\,-4}$ with other variables in order to control for the magnitude of news. The main variable of interest is $REV\_{-8,\,-4}{*}DISP$, which measures the effect of *DISP* on forecast errors and subsequent forecast revisions conditional on the size of news. Again, to the extent that $REV\_{-8,\,-4}$ partially captures information uncertainty, my estimated effects are understated. To support my hypothesis, I expect a negative coefficient of $REV\_{-8,\,-4}{*}DISP$ for bad-news firms but a positive one for good-news firms. Table 4, panel A reports the results when FE_{-4} is used as the dependent variable. $RE\_{-8,\,-4}{*}DISP$ is highly significant in univariate regressions (model A) for both bad- and good-news subsamples, with coefficients of −0.142 ($t = -7.39$) and 0.055 ($t = 2.35$), respectively. After I include control variables in the regression (model C), $REV\_{-8,\,-4}{*}DISP$ continues to display strong explanatory power in both subsamples, with a coefficient of −0.135 ($t = -7.60$) following bad news and 0.038 ($t = 2.06$) following good news. The negative coefficients of $REV\_{-8,\,-4}{*}DISP$ for the bad-news subsample mean that high-*DISP* firms tend to have more negative forecast errors than low-*DISP* firms following bad news, while the positive coefficients of $REV\_{-8,\,-4}{*}DISP$ for the good-news subsample mean that high-*DISP* firms tend to have more positive forecast errors than low-*DISP* firms following good news. In terms of magnitude, information uncertainty has a stronger effect in the bad-news subsample than in the good-news subsample. This evidence strongly supports my main hypothesis.

The signs of the coefficients on the control variables are largely as expected. The coefficients of $REV_{-8,\,-4}$ are strongly positive in all models, suggesting the importance of controlling for the size of news. Acting alone, *SIZE* also exhibits significant but opposite effects on forecast errors (model B), with coefficients of 0.045 (t = 2.90) and −0.055 (t = −2.14) for bad- and good-news subsamples, respectively. In multivariate regressions, the size effect is still significant for the bad-news sample but becomes insignificant for the good-news sample. The opposite effects of *SIZE* for bad- and good-news firms are consistent with the notion that firm size acts as another proxy for information uncertainty in the sense that smaller firm size corresponds to greater information uncertainty. It also calls into question the practice in the prior literature of using firm size as a control variable in pooled regressions (see, e.g., Das, Levine, and Sivaramakrishnan 1998). *RET_6* is highly positive for both bad- and good-news subsamples, supporting Abarbanell and Lehavy's 2003 finding that analysts underreact to the information in past stock returns.

Panel B presents the results when $REV_{-4,\,-0}$ is used as the dependent variable. I find that *DISP* has a negative (positive) and significant impact on subsequent forecast revisions following bad (good) news. The opposite impacts of *DISP* on forecast errors and subsequent forecast revisions following bad and good news support my hypothesis that analysts underreact more to new information when there is greater uncertainty. On the contrary, the evidence is inconsistent with analyst forecast rationality or optimism suggested in prior literature.

In summary, I find evidence consistent with the hypothesis that upward (downward) forecast revisions predict positive (negative) forecast errors and subsequent revisions and that forecast errors and subsequent revisions are more pronounced for firms with greater information uncertainty. These results provide empirical support for the notion that analysts underreact to new information when revising their earnings forecasts and that they underreact to a higher degree in cases of greater information uncertainty. Finally, the effect of information uncertainty is stronger following bad news than following good news.

5. Alternative explanations and robustness checks

The data alignment problem

Prior literature suggests that I/B/E/S actual earnings suffered from an alignment problem in the 1980s, but that has been largely solved since 1991. To test the robustness of the information uncertainty argument, I conduct all analyses on the 1983–91 and 1992–2001 subperiods separately. Unreported results show that my results hold in both subperiods. When compared with the whole sample period, the magnitude of the forecast errors decreases after 1991, but the t-statistics increase as a result of a smaller variation of forecast errors across years. For example, the median FE_{-4} are −0.34 percent and 0.10 percent for the bad- and good-news subsamples in the 1992–2001 subperiod, with z-statistics of −11.04 and 10.34, respectively. In

TABLE 4
Regressions of forecast error or forecast revision

Panel A: Regressions of forecast error (FE_{-4})

	Bad news ($REV_{-8,-4} < 0$)			Good news ($REV_{-8,-4} > 0$)		
	A	B	C	A	B	C
Intercept	−0.032	−0.044	−0.028	−0.037	−0.040	−0.029
	(−13.68)	(−21.32)	(−8.70)	(−9.13)	(−7.39)	(−6.47)
$REV_{-8,-4}$	0.670	0.612	0.560	0.583	0.647	0.599
	(83.57)	(68.62)	(29.23)	(34.58)	(40.48)	(5.88)
$REV_{-8,-4}*DISP$	−0.142		−0.135	0.055		0.038
	(−7.39)		(−7.60)	(2.35)		(2.06)
$REV_{-8,-4}*SIZE$		0.045	0.128		−0.055	−0.054
		(2.90)	(5.56)		(−2.14)	(−1.48)
$REV_{-8,-4}*BM$			−0.059			−0.020
			(−0.76)			(−0.33)
$REV_{-8,-4}*COV$			0.064			−0.133
			(0.97)			(−1.77)
$REV_{-8,-4}*LEV$			−0.024			−0.044
			(−2.12)			(−2.41)
$REV_{-8,-4}*RET\_6$			0.114			0.162
			(7.30)			(9.85)
$REV_{-8,-4}*VOL$			−0.080			0.089
			(−3.29)			(2.38)
$D_{NAS}*REV_{-8,-4}*VOL$			0.074			−0.045
	(3.57)	(−1.97)				
Adjusted R^2	0.647	0.641	0.660	0.484	0.486	0.522

(The table is continued on the next page.)

TABLE 4 (Continued)

Panel B: Regressions of subsequent forecast revision ($REV_{-4,-0}$)

	Bad news ($REV_{-8,-4} < 0$)			Good news ($REV_{-8,-4} > 0$)		
	A	B	C	A	B	C
Intercept	−0.042	−0.058	−0.038	−0.044	−0.052	−0.036
	(−14.01)	(−23.82)	(−4.71)	(−10.47)	(−9.83)	(−10.00)
$REV_{-8,-4}$	0.724	0.626	0.543	0.596	0.661	0.562
	(89.97)	(82.48)	(10.60)	(26.67)	(36.62)	(5.74)
$REV_{-8,-4}*DISP$	−0.201		−0.192	0.070		0.052
	(−9.63)		(−9.14)	(2.29)		(1.98)
$REV_{-8,-4}*SIZE$		0.090	0.114		−0.018	−0.043
		(11.28)	(3.16)		(−0.59)	(−1.13)
$REV_{-8,-4}*BM$			−0.223			0.030
			(−1.04)			(1.01)
$REV_{-8,-4}*COV$			0.274			−0.140
			(0.96)			(−1.62)
$REV_{-8,-4}*LEV$			−0.007			−0.048
			(−0.52)			(−2.41)
$REV_{-8,-4}*RET\_6$			0.144			0.184
			(8.41)			(8.37)
$REV_{-8,-4}*VOL$			−0.021			0.105
			(−0.96)			(2.93)
$D_{NAS}*REV_{-8,-4}*VOL$			0.018			−0.043
			(1.70)			(−1.59)
Adjusted R^2	0.690	0.679	0.703	0.500	0.501	0.539

(The table is continued on the next page.)

TABLE 4 (Continued)

Notes:

This table reports regressions of forecast error and subsequent forecast revision. Variables are as defined in Table 1. Actual values are substituted by percentile rankings, which are converted to a [0, 1] scale. Rankings are obtained by annually ranking observations and assigning them in equal numbers to 100 portfolios for each variable. The regressions are run for the bad-news and good-news subsamples separately. The regression coefficients are time-series means of annual cross-section regressions, and the *t*-statistics, shown in parentheses, are the average slopes divided by their time-series standard errors (Fama-MacBeth). On average, there are 748 firm-year observations in annual regressions for the bad-news subsample ($REV_{-8,\,-4} < 0$) and 600 observations for the good-news subsample ($REV_{-8,\,-4} > 0$), respectively. The data are from I/B/E/S from 1983 to 2001.

the regressions testing the effect of information uncertainty on FE_{-4} and $REV_{-4,\,-0}$, the coefficients of uncertainty proxies are significant and have expected signs in both subperiods. The robustness of my results in both subperiods excludes the data alignment problem or region shift as a potential explanation for my results.

Analyses on a subsample of firms with December fiscal year-end

Although my prediction is based on ex ante variables, the strategies in section 4 are not implementable in the sense that the overall cross-sectional distribution of *DISP* and other variables is unknown until every firm reaches the prediction date. To avoid the "look-ahead bias" and ensure that the information on portfolio formation and regressions is available on the prediction date, I repeat my analyses in a subsample of firms with December fiscal year-end, which account for about 65 percent of the whole sample. In untabulated results, I find a qualitatively similar pattern of analyst behavior — namely, analysts underreact to new information when revising earnings forecasts, and underreact more in cases of greater information uncertainty.

6. Conclusion

In this paper, I investigate analyst forecast inefficiency from an information perspective. I find that analysts appear to not adjust sufficiently away from their prior beliefs and underweight new information in revising their earnings forecasts regardless of whether analysts have a linear or a quadratic loss function. As a result, current forecast errors and subsequent forecast revisions are negative following bad news but positive following good news. More importantly, information uncertainty plays a critical role in analyst forecast behavior. Greater information uncertainty produces more negative forecast errors and subsequent forecast revisions following bad news yet more positive ones following good news. In other words, analysts' revisions are almost complete when there is low information uncertainty, but the revisions are far from complete in cases of greater uncertainty. The positive (negative) effect of information uncertainty on forecast errors and subsequent analyst revisions following good (bad) news supports the underreaction hypothesis. The evidence is inconsistent with analyst forecast rationality or optimism suggested in prior literature.

Endnotes

1. Analyst forecast rationality predicts zero forecast errors (ex ante) following good or bad news and provides no role for information uncertainty. Analyst optimism predicts negative forecast errors, on average, and more negative ones in cases of greater information uncertainty regardless of the nature of news (Das, Levine, and Sivaramakrishnan 1998).
2. The short window is in line with the evidence in the finance literature that investors underreact to new information in the short term (within one year). This research design is different from that in Easterwood and Nutt 1999, which uses the information in previous years and offers a different conclusion on analyst forecast behavior. On the other hand, the evidence presented in this paper closely matches the return evidence on the post-analyst-revision drift papers (e.g., Stickel 1991; Jiang et al. 2005; and Zhang 2006), which share similar research designs.
3. In an unreported analysis, I use past stock returns, which are the other proxy for the nature of news in Zhang 2006 and Jiang et al. 2005, as the alternative information event and observe similar, though weaker, results. Arguably, past stock returns are a noisier measure, compared with past analyst forecast revisions, because positive (negative) stock returns are not necessarily good (bad) news to analysts.
4. Specifically, stale forecasts may introduce a positive autocorrelation in analysts' forecast revisions, while the rounding error may introduce a positive relation between forecast errors and forecast revisions. Previous studies using I/B/E/S data usually do not control for such mechanical relations.
5. In the I/B/E/S Adjustments File, the effective date is always the publication date of the monthly analyst forecast data, which is the third Thursday of each month. However, individual analysts' forecasts are effective immediately after the true effective date. Therefore, using the I/B/E/S Adjustments File cannot properly adjust all individual forecasts, and doing so would lead to high forecast dispersion in stock-split months. The step is different from Diether et al. 2002.
6. This measure of forecast revision makes annual data more suitable for this study, because forecast revisions are often zero if I use quarterly data.
7. I obtain similar results when I use assets per share as the deflator.
8. The main results are stronger when I set the cutoff at 20 percent of the stock price, especially for good-news firms.
9. Large negative forecast revisions in the bad-news subsample cancel out small positive forecast revisions in the good-news subsample, resulting in a negative forecast revision overall. The overall negative revision is consistent with the evidence in Kang, O'Brien, and Sivaramakrishnan 1994 and Lim 2001 that analysts walk down their estimates as the forecast date approaches the earnings announcement date.
10. There is a large body of literature suggesting that managers are more likely to disclose good news than bad news. For example, Penman (1980) and Waymire (1984) find that the majority of management forecasts are favorable relative to market expectation.

Patell (1976) and Lev and Penman (1990) find that management's average forecast news is good news. Miller (2002) documents the evidence that firms increase discretionary disclosure during periods of increased earnings. However, counterexamples can be found — firms with substantial bad news and high litigation risks tend to issue warnings earlier (see Skinner 1994).

11. To the extent that the good/bad news motivating analyst initial revisions affects stock returns differently because of the different levels of information uncertainty, my research design is conservative as I include *RET_6* as a control variable in the regression.

References

Abarbanell, J. S. 1991. Do analysts' earnings forecasts incorporate information in prior stock price changes? *Journal of Accounting and Economics* 14 (2): 147–65.

Abarbanell, J. S., and V. Bernard, 1992. Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior. *The Journal of Finance* 47 (3): 1181–207.

Abarbanell, J. S., and R. Lehavy. 2003. Biased forecasts or biased earnings? The role of reported earnings in explaining apparent bias and over/underreaction in analysts' earnings forecasts. *Journal of Accounting and Economics* 36 (1–3): 105–46.

Ali, A., A. Klein, and J. Rosenfeld. 1992. Analysts' use of information about permanent and transitory earnings components in forecasting annual EPS. *The Accounting Review* 67 (1): 183–98.

Baber, W. R., and S. Kang. 2002. The impact of split adjusting and rounding on analysts' forecast error calculations. *Accounting Horizons* 16 (4): 277–89.

Barron, O., O. Kim, S. Lim, and D. Stevens. 1998. Using analysts' forecasts to measure properties of analysts' information environment. *The Accounting Review* 73 (4): 421–33.

Basu, S., and S. Markov. 2004. Loss function assumptions in rational expectations tests on financial analysts' earnings forecasts. *Journal of Accounting and Economics* 38 (1–3): 171–203.

Brown, L., R. Hagerman, P. Griffin, and M. Zmijewski. 1987. An evaluation of alternative proxies for the market's assessment of unexpected earnings. *Journal of Accounting and Economics* 9 (2): 159–93.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. Investor psychology and security market under- and over-reactions. *The Journal of Finance* 53 (6): 1839–86.

Das, S., C. B. Levine, and K. Sivaramakrishnan. 1998. Earnings predictability and bias in analysts' earnings forecasts. *The Accounting Review* 73 (2): 277–94.

Diether, K., C. Malloy, and A. Scherbina. 2002. Difference of opinion and the cross section of stock returns. *The Journal of Finance* 57 (5): 2113–41.

Easterwood, J., and S. Nutt. 1999. Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism? *The Journal of Finance* 54 (5): 1777–97.

Edwards, W. 1968. Conservatism in human information processing. In *Formal Representation of Human Judgment*, ed. B. Kleinmutz, 17–52. New York: Wiley.

Elliott, J., D. Philbrick, and C. Wiedman. 1995. Evidence from archival data on the relation between security analysts' forecast errors and prior forecast revisions. *Contemporary Accounting Research* 11 (2): 919–38.

Fama, E. F. 1970. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance* 25 (2): 384–417.

Fama, E. F., and J. D. MacBeth. 1973. Risk, return and equilibrium: Empirical tests. *Journal of Political Economy* 81 (3): 607–36.

Gleason, C., and C. Lee. 2003. Analyst forecast revisions and market price discovery. *The Accounting Review* 78 (1): 193–225.

Gu, Z., and J. S. Wu. 2003. Earnings skewness and analyst forecast bias. *Journal of Accounting and Economics* 35 (1): 5–29.

Hirshleifer, D. 2001. Investor psychology and asset pricing. *The Journal of Finance* 56 (4): 1533–96.

Hong, H., T. Lim, and J. Stein. 2000. Bad news travels slowly: Size, analyst coverage and the profitability of momentum strategies. *The Journal of Finance* 55 (1): 265–96.

Hutton, A., G. Miller, and D. Skinner. 2003. The role of supplementary statements with management earnings forecasts. *Journal of Accounting Research* 41 (5): 867–90.

Imhoff, E., and G. Lobo. 1992. The effect of ex ante earnings uncertainty on earnings response coefficients. *The Accounting Review* 67 (2): 427–39.

Jiang, G., C. Lee, and G. Zhang. 2005. Information uncertainty and expected returns. *Review of Accounting Studies* 10 (2–3): 185–221.

Kang, S., J. O'Brien, and K. Sivaramakrishnan. 1994. Analysts' interim earnings forecasts: Evidence on the forecasting process. *Journal of Accounting Research* 32 (1): 103–12.

Kothari, S. P. 2001. Capital markets research in accounting. *Journal of Accounting and Economics* 31 (1–3): 105–231.

Kothari, S. P., J. Sabino, and T. Zach. 2005. Implications of survival and data trimming for tests of market efficiency. *Journal of Accounting and Economics* 39 (1): 129–61.

Lang, M., and R. J. Lundholm. 1993. Cross-sectional determinants of analyst rating of corporate disclosures. *Journal of Accounting Research* 31 (2): 246–71.

Lang, M., and R. J. Lundholm. 1996. Corporate disclosure policy and analyst behavior. *The Accounting Review* 71 (4): 467–92.

Lee, C., and B. Swaminathan. 2000. Price momentum and trading volume. *The Journal of Finance* 55 (5): 2017–69.

Lev, B., and S. Penman. 1990. Voluntary forecast disclosure, nondisclosure and stock prices. *Journal of Accounting Research* 28 (1): 49–76.

Lim, T. 2001. Rationality and analysts' forecast bias. *The Journal of Finance* 56 (1): 369–85.

Lys, T., and S. Sohn. 1990. The association between revisions of financial analysts' earnings forecasts and security-price changes. *Journal of Accounting and Economics* 13 (4): 341–63.

McNichols, M., and P. O'Brien. 1997. Self-selection and analysts coverage. *Journal of Accounting Research* 35 (3): 167–99.

Mendenhall, R. 1991. Evidence of possible underweighting of earnings-related information. *Journal of Accounting Research* 29 (1): 170–80.

Miller, E. 1977. Risk, uncertainty, and divergence of opinion. *The Journal of Finance* 32 (4): 1151–68.

Miller, G. 2002. Earnings performance and discretionary disclosure. *Journal of Accounting Research* 40 (1): 173–204.

Patell, J. 1976. Corporate forecasts of earnings per share and stock price behavior: Empirical tests. *Journal of Accounting Research* 14 (2): 246–76.
Penman, S. 1980. An empirical investigation of the voluntary disclosure of corporate earnings forecasts. *Journal of Accounting Research* 18 (1): 132–60.
Skinner, D. 1994. Why firms voluntarily disclose bad news. *Journal of Accounting Research* 32 (1): 38–60.
Stickel, S. 1991. Common stock returns surrounding earnings forecast revisions: More puzzling evidence. *The Accounting Review* 66 (2): 402–16.
Waymire, G. 1984. Additional evidence on the information content of management earnings forecast. *Journal of Accounting Research* 22 (2): 703–18.
Zhang, X. F. 2006. Information uncertainty and stock returns. *The Journal of Finance* 61 (1): 105–37.