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September 24, 2012

BC Utility Customers – AMPC/BCPSO/CEC
c/o Bull, Housser & Tupper LLP
3000 Royal Centre, P.O. Box 11130
1055 W. Georgia Street,
Vancouver, BC V6E 3R3

Attention: Mr. Brian Wallace

Dear Mr. Wallace:

Re: Generic Cost of Capital Proceeding

FortisBC Utilities (the "FBCU")[1]

Response to the British Columbia Utility Customers[2] (the "BC Utility Customers") Information Request ("IR") No. 1 on the Evidence of Dr. James H. Vander Weide, PhD

On August 3, 2012, the FortisBC Utilities filed its Written Evidence in the Generic Cost of Capital proceeding as referenced above. In accordance with the British Columbia Utilities Commission Order No. G-84-12 setting out the Amended Preliminary Regulatory Timetable, the FBCU respectfully submit the attached response to the BC Utility Customers IR No. 1 on the Evidence of Dr. James H Vander Weide, PhD.

If there are any questions regarding the attached, please contact the undersigned.

Yours very truly,

on behalf of the FORTISBC UTILITIES

Original signed:

Diane Roy

Attachment

cc (e-mail only): Commission Secretary
Registered Parties

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[1] comprised of FortisBC Inc., FortisBC Energy Inc., FortisBC Energy (Vancouver Island) Inc., and FortisBC Energy (Whistler) Inc.

[2] including the Association of Major Power Consumers of BC ("AMPC"), British Columbia Public Interest Advocacy Centre on behalf of the British Columbia Pensioners' and Seniors' Organization et al ("BCPSO") and the Commercial Energy Consumers Association of British Columbia ("CEC").

1. Topic: Fair return standard, page7

1.1 Given the closeness in the definition of fair return and cost of capital, in Dr. Vander Weide's judgement does comparable earnings testimony satisfy the fair return standard?

Response:

Dr. Vander Weide's statement, "The economic definition of the cost of capital is similar to the definition of a fair return", [page 6 of his written evidence] implies that regulators can satisfy the fair return standard by equating the regulated company's allowed return on total capital (debt plus equity) to an estimate of the company's economic weighted average cost of capital. As Dr. Vander Weide notes on page 9 of his written evidence, the economic definition of the weighted average cost of capital is based on the market costs of debt and equity and the market value percentages of debt and equity in a company's capital structure, whereas regulators have traditionally measured the weighted average cost of capital using the embedded cost of debt and the book values of debt and equity in a company's capital structure. Given that regulators do not typically equate the fair return on total capital to the economic weighted average cost of capital, depending on the value of the comparable earnings result, comparable earnings may or may not satisfy the fair return standard in practice.

1.2 Has Dr. Vander Weide ever presented comparable earnings testimony as developed by Ms. McShane?

Response:

No.

1.3 Can Dr. Vander Weide agree that the cost of capital is only an expected return "in equilibrium"? Otherwise when you expect more than you want you buy and vice versa?

Response:

Dr. Vander Weide agrees that the cost of capital is the expected return on capital that equates the supply and demand for capital subject to a specific degree of risk.

2. Topic: Comparable Risk Utilities, page 13

2.1 Please provide extracts from any rating agency reports that indicate that the regulatory risk of Dr. Vander Weide's US sample of firms is the same as that for the Canadian firms.

Response:

Dr. Vander Weide's testimony concerns the business and financial risks experienced by equity investors in public utilities such as FEI. In contrast, rating agency reports assess the business and financial risks of investing in a company's bonds. Because rating agency reports do not assess risks from the equity investors' point of view, Dr. Vander Weide did not study what rating agency reports may indicate about the regulatory risk of my sample of utilities compared to the regulatory risk of Canadian utilities.

2.2 Please provide extracts from any regulatory decisions in Canada that indicate that US data can be used in Canada without any qualifications or adjustments, that is not being used as a check or a "weighting" or where differences can be accounted for. Failing that please indicate where in Dr. Wander Weide's testimony he has "accounted for" or weighted or used his US "comparables" as a check.

Response:

Dr. Vander Weide agrees that regulatory decisions in Canada generally recognize that cost of equity data for U.S. utilities can be helpful in estimating the cost of equity for Canadian utilities if potential differences in the risks of U.S. and Canadian utilities are taken into account. Dr. Vander Weide discusses the potential differences in risks of U.S. and Canadian utilities in Section IV of his written evidence. He concludes that: "the business risk of natural gas and electric utilities is approximately the same in the U.S. as it is in Canada" [Vander Weide evidence at 20]; and (2) "Canadian utilities generally have greater financial risk than U.S. utilities because…they rely more heavily on debt financing than U.S. utilities." [Vander Weide evidence at 21]

2.3 Would Dr. Vander Weide agree that a proxy is not necessarily the same as the firm under examination or imply that its allowed ROE or risk can be used without qualification?

<u>Response:</u>

Dr. Vander Weide does not suggest that the allowed ROEs or risk of U.S. utilities can be used to estimate the cost of equity for Canadian utilities without examining potential differences in risk between U.S. and Canadian utilities. In fact, Dr. Vander Weide examines potential differences in business and financial risks of U.S. and Canadian utilities and concludes that the business risks of U.S. utilities are generally the same as those of Canadian utilities, while the financial risk of U.S. utilities is less than the financial risk of Canadian utilities.

3. Topic: Comparable utilities, pages 13-25

3.1 Please indicate where in Dr. Vander Weide's testimony he has compared capital market conditions in the US versus Canada?

<u>Response:</u>

Dr. Vander Weide does not compare capital market conditions in his direct written evidence because capital market conditions are reflected in the economic data he uses to estimate the cost of equity. In addition, Dr. Vander Weide is aware that capital market conditions in Canada and the U.S. are generally similar. Specifically, Dr. Vander Weide recognizes that interest rates in the two countries are generally similar, inflation expectations are similar, and equity investors in both countries are concerned with stock market volatility, volatility in commodity prices including oil and gas, and economic events that affect both Canada and the U.S., including the Euro debt crisis, and growing weakness in the Chinese, European, and other world economies. Dr. Vander Weide is also aware that the Canadian and U.S. economies are interdependent in the sense that Canada receives approximately fifty percent of its imports from the United States, and approximately seventy-five percent of Canadian exports are sold to the United States. Thus, many macroeconomic factors that affect the U.S. economy also affect the Canadian economy.

3.2 Please explain what Dr. Vander Weide understands by the term structure of interest rates or yield curves?

<u>Response:</u>

The term structure of interest rates or yield curve reflects the relationship between interest rates on securities with different maturities.

3.3 Does Dr. Vander Weide believe that the yield curves in the US and Canada are identical at the current point in time? If so please report the following interest rates for both the US and Canada: 3 month T. bills, 1 year treasury notes, 5 year treasury notes, over ten year bonds and 30 year bonds.

Response:

Dr. Vander Weide believes that the U.S. and Canadian yield curves are generally similar, but not identical. In August 2012, the average yields on 3-month Treasury bills, 1-year Treasury notes, 5-year Treasury notes, 10-year Treasury bonds, and 30-year Treasury bonds for the United States and Canada are shown in the table below. These data indicate that interest rates on Canadian securities are higher than interest rates on U.S. securities for maturities ranging from 3-months to ten years, and the interest rate on 30-year government securities is slightly higher for U.S. securities than for Canadian securities. (Data are from the U.S. Federal Reserve and the Bank of Canada.)

TABLE 1
COMPARISON OF YIELDS ON CANADIAN AND U.S. TREASURY SECURITIES
AUGUST 2012 AVERAGES

	3-month Treasury Bills	1-year Treasury Note	5-year Treasury Note	10-year Bonds	30-year Bonds
United States	0.10%	0.18%	0.71%	1.68%	2.77%
Canada	1.00%	1.12%	1.40%	1.83%	2.38%

3.4 Please provide the annual deficits of the Federal Governments of both the US and Canada as a proportion of GDP since the introduction of the ROE formula in 1994 and comment on whether the trajectories are the same.

Response:

Dr. Vander Weide agrees that the annual deficit of the U.S. Government as a proportion of GDP has been increasing and that the annual deficit for the Canadian Government has been decreasing. However, he did not gather or use the information requested in this interrogatory in preparing his written evidence in this proceeding because he believes such information is irrelevant to his conclusion that U.S. and Canadian utilities have similar risks, and, hence, similar costs of equity. Dr. Vander Weide believes that such information is irrelevant because there is no evidence that investors consider U.S. Government debt to be significantly more risky than Canadian Government debt. Foreign investors consider the United States to be a "safe haven," and large amounts of foreign capital have been flowing into U.S. Government securities in response to economic difficulties in other parts of the world. Dr. Vander Weide also notes that changes in U.S. economic activity have a considerable effect on Canadian economic activity because approximately fifty percent of Canadian imports come from the United States, and approximately seventy-five percent of Canadian exports are sold to the United States. Thus, economic events that affect the risk of investing in U.S. securities also affect the risk of investing in Canadian securities.

3.5 Please provide the annual average foreign exchange rate of US dollars per Canadian since 1994 and would Dr. Vander Weide agree that the Canadian $ has appreciated in value since the early 2000's?

Response:

Dr. Vander Weide agrees that the Canadian dollar has appreciated in value relative to the U.S. dollar since the early 2000s. Dr. Vander Weide did not gather data on average foreign exchange rates since 1994 in the preparation of his written evidence in this proceeding because he believes that such information has no bearing on his conclusion that information on the cost of capital for U.S. utilities is useful for evaluating the cost of capital for Canadian utilities. In this regard, Dr. Vander Weide notes that The Economist Intelligence Unit forecasts that the Canadian exchange rate will remain relatively constant through 2016. These data indicate that the Canadian dollar was/is valued at 1.02 U.S. dollars in 2011 and 2012, and that the Canadian dollar is expected to depreciate slightly to 0.97 U.S. dollars in 2015 and 2016.

TABLE 2
FORECASTED EXCHANGE RATE
CANADIAN $ TO U.S.$
ECONOMIST INTELLIGENCE UNIT, AUGUST 2012

	2011	**2012**	**2013**	**2014**	**2015**	**2016**
Exchange rate C$ to US$	1.02	1.02	0.99	0.98	0.97	0.97

3.6 Would Dr. Vander Weide agree that investors take currency appreciation and depreciation into account when make foreign investment decisions?

Response:

Dr. Vander Weide agrees that investors generally take expected currency appreciation and depreciation into account when making foreign investment decisions. Because the exchange rate of Canadian dollars to U.S. dollars is expected to be relatively constant over the next several years, Dr. Vander Weide does not agree that expected currency appreciation and/or depreciation affects the results of his written evidence in this proceeding.

3.7 Please explain what the concept of interest rate parity means and whether this affects the ability to compare US with Canadian interest rates.

Response:

Interest rate parity means that interest rates in two countries adjust to reflect expected appreciation or depreciation in the relative values of the countries' currencies. Dr. Vander Weide does not believe that the concept of interest rate parity currently affects one's ability to compare Canadian and U.S. interest rates and costs of equity because the value of the Canadian dollar is not expected to materially appreciate or depreciate relative to the value of the U.S. dollar over the next several years.

4. Topic: Quarterly DCF Model, page 25

4.1 Please provide abstracts of any regulatory decisions in Canada that have explicitly accepted the quarterly DCF model.

Response:

Dr. Vander Weide did not examine abstracts of regulatory decisions in Canada regarding the quarterly DCF model in preparing his written evidence.

4.2 Please provide the quarterly dividend per share data for each Canadian and US utilities used in Dr. Vander Weide's analysis and a discussion of whether in his judgement dividends are increased annually or quarterly.

Response:

Dr. Vander Weide agrees that utilities in Canada and the United States generally pay dividends quarterly and increase dividends annually. Dr. Vander Weide's decision to use the quarterly DCF model takes into account that utility stock prices reflect the present discounted value of future dividend payments and that the present value of future dividend payments depends on the specific timing of the dividend payments. Because dividends are paid quarterly, only the quarterly DCF model can equate the present value of expected future dividends to the current stock price.

4.3 Please confirm that if the dividend is paid quarterly then the investor can reinvest the dividend to buy more shares and thus earn a higher rate of return, whereas Dr. Vander Weide is assuming that the utility reinvests the money to earn a higher rate of return and is therefore double counting.

Response:

Cannot confirm. Dr. Vander Weide does not agree that there is a "double counting" of dividends when the analyst employs a quarterly DCF model. As discussed in response to BC Util Cust-Vander Weide IR 1.4.2, in employing the quarterly DCF model, Dr. Vander Weide is simply being consistent with the DCF model assumption that a company's stock price is equal to the discounted present value of all future dividend payments.

4.4 Please provide a numerical example of a utility with $100 rate base that is allowed a 10% ROE and pays out all earnings as a quarterly dividend of $2.50 under two situations: a) the investor uses the $2.50 dividend to reinvest by buying 2.5% more shares at the constant more price of $100 and b) the utility decides to only pay an annual dividend and thus invests the $2.50 on behalf of the investor. In each case what is the annual rate of return to the investor by the utility being allowed a 10% ROE.

Response:

Dr. Vander Weide cannot respond to this interrogatory because it asks him to make inconsistent assumptions: the first part of the question states that the company "pays out all earnings as a *quarterly dividend of $2.50* [emphasis added] under two situations"; and situation (b) is a situation when the company pays an *annual dividend*.

4.5 Please provide the DCF fair return estimates without the quarterly compounding of dividends.

Response:

As shown in the following tables, the difference in the average DCF result for the comparable utilities in Exhibit 6 using the annual DCF model versus the quarterly DCF model is five basis points (with no difference in the result rounded to one decimal point), and, for the comparable utilities in Exhibit 7, eight basis points.

TABLE 3
COMPARISON OF QUARTERLY AND ANNUAL MODEL RESULTS
EXHIBIT 6

LINE NO.	COMPANY	QUARTERLY MODEL RESULT	ANNUAL MODEL RESULT
1	AGL Resources	8.6%	8.5%
2	Alliant Energy	10.8%	10.7%
3	Amer. Elec. Power	8.8%	8.6%
4	Atmos Energy	9.0%	8.9%
5	CenterPoint Energy	8.5%	8.5%
6	CMS Energy Corp.	10.4%	10.5%
7	Consol. Edison	7.5%	7.4%
8	Dominion Resources	9.7%	9.7%
9	DTE Energy	8.9%	8.7%
10	Duke Energy	8.5%	8.4%
11	FirstEnergy Corp.	8.2%	8.1%
12	G't Plains Energy	14.6%	14.4%
13	Hawaiian Elec.	13.5%	13.2%
14	NextEra Energy	9.3%	9.4%
15	NiSource Inc.	14.0%	13.8%
16	Northeast Utilities	9.4%	9.5%
17	Northwest Nat. Gas	7.4%	7.3%
18	Pepco Holdings	11.1%	10.9%
19	Piedmont Natural Gas	8.7%	8.6%
20	Pinnacle West Capital	11.1%	10.9%
21	PNM Resources	12.5%	12.7%
22	Portland General	8.7%	8.5%
23	Public Serv. Enterprise	8.4%	8.4%
24	SCANA Corp.	9.3%	9.2%
25	Sempra Energy	10.7%	11.2%

LINE NO.	COMPANY	QUARTERLY MODEL RESULT	ANNUAL MODEL RESULT
26	Southern Co.	10.2%	10.2%
27	TECO Energy	9.4%	9.3%
28	Vectren Corp.	10.2%	10.1%
29	Westar Energy	10.9%	10.8%
30	WGL Holdings Inc.	8.8%	8.8%
31	Wisconsin Energy	8.6%	8.9%
32	Xcel Energy Inc.	9.5%	9.3%
33	Average	9.85%	9.80%
34	Financial flexibility	0.50%	0.50%
35	Model Result	10.35%	10.30%

TABLE 4
COMPARISON OF QUARTERLY AND ANNUAL MODEL RESULTS
EXHIBIT 7

LINE NO.	COMPANY	QUARTERLY MODEL RESULT	ANNUAL MODEL RESULT
1	AGL Resources	8.6%	8.5%
2	Alliant Energy	10.8%	10.7%
3	Amer. Elec. Power	8.8%	8.6%
4	Atmos Energy	9.0%	8.9%
5	Consol. Edison	7.5%	7.4%
6	DTE Energy	8.9%	8.7%
7	G't Plains Energy	14.6%	14.4%
8	Northeast Utilities	9.4%	9.5%
9	Northwest Nat. Gas	7.4%	7.3%
10	Piedmont Natural Gas	8.7%	8.6%
11	Pinnacle West Capital	11.1%	10.9%
12	Portland General	8.7%	8.5%

LINE NO.	COMPANY	QUARTERLY MODEL RESULT	ANNUAL MODEL RESULT
13	Southern Co.	10.2%	10.2%
14	TECO Energy	9.4%	9.3%
15	Vectren Corp.	10.2%	10.1%
16	Westar Energy	10.9%	10.8%
17	WGL Holdings Inc.	8.8%	8.8%
18	Wisconsin Energy	8.6%	8.9%
19	Xcel Energy Inc.	9.5%	9.3%
20	Average	9.53%	9.45%
21	Financial flexibility	0.50%	0.50%
22	Model Result	10.03%	9.95%

5. Topic: US DCF Estimates, pages 25-31

5.1 Please indicate whether in Dr. Vander Weide's judgement utilities are dividend intensive stocks and affected by the relative taxation of dividends versus capital gains.

Response:

Dr. Vander Weide agrees that utilities typically pay dividends and that their stock prices are affected by the expected relative taxation of dividends and capital gains.

5.2 Please indicate the source of the data on the % of regulated operations in Exhibit 3.

Response:

The source of the data on the percent of regulated operations for the electric utilities in the proxy group is the Edison Electric Institute, which reports that they obtain the information from company Form 10-K filings. The source of the data on the percent of regulated operations for the natural gas utilities in the proxy group is the companies' Form 10-K filings.

5.3 For each firm in Exhibit 6 please provide the past five year growth experience and compare it to the forecast 5 year growth forecast.

Response:

Dr. Vander Weide did not examine historical dividend growth data for his proxy companies because the DCF model requires estimates of investors' future growth expectations, and Dr. Vander Weide's studies indicate that analysts' EPS growth forecasts are the best proxy for investors' future growth expectations.

5.4 Please provide the annual dividend and earnings per share for each firm in Exhibit 6 from 1990 or the latest period available.

Response:

Dr. Vander Weide did not examine annual dividend and earnings per share data for his proxy companies since 1990 because the DCF model requires estimates of investors' future growth expectations, and Dr. Vander Weide's studies indicate that analysts' EPS growth forecasts are the best proxy for investors' future growth expectations.

5.5 Please indicate any academic research that indicates that analyst forecasts are biased low estimates of future growth rates?

Response:

Attachment 5.5 contains an article by Abarbanell and Levy reviews academic literature on the potential bias in analysts' growth forecasts. The authors demonstrate that there is no evidence of bias in analysts' growth forecasts if the studies are adjusted to take into account that analysts provide forecasts of normalized earnings, that is, earnings prior to extraordinary losses, whereas actual earnings include extraordinary losses. Because extraordinary losses reflect one-time accounting adjustments, analysts properly consider normalized earnings to be a better indicator of future earnings growth. However, the comparison of normalized earnings to actual earnings that include extraordinary losses causes an incorrect perception that analysts' forecasts are optimistic.

5.6 Please indicate that what is of interest for the DCF model is the future dividend growth rate and not the earnings growth rate, and provide any support for the assumption that dividend growth rates over short horizon periods equal dividend growth rates.

Response:

Because the DCF model assumes that earnings and dividends grow at the same rate indefinitely, expected earnings and dividend growth rates are both of interest for the DCF model. Dr. Vander Weide uses analysts' earnings growth estimates to estimate expected future earnings and dividends growth because: (1) security analysts focus on forecasting earnings growth rather than dividend growth; (2) stock prices are highly responsive to unexpected changes in earnings growth; (3) analysts' earnings growth forecasts are more widely available than analysts' dividend growth forecasts; and (4) consensus analysts' growth forecasts are available from sources such as I/B/E/S, Reuters, Zacks, and Yahoo, whereas consensus dividend growth forecasts are not.

6. Topic: Canadian Risk premium estimates, pages 32-35.

6.1 Please recalculate the data in table 2 using total bond returns rather than yields.

Response:

Dr. Vander Weide did not make this calculation in the preparation of his written evidence because his studies pertain to the risk premium on a particular stock portfolio compared to risk-free government securities. Dr. Vander Weide uses the yield on government securities because only the yield on these securities is risk free.

6.2 Please provide references to any published academic studies that calculate risk premia based on yields rather than returns. Please confirm that the use of yields biases risk premia estimates up (down) when interest rates are falling (rising) since it ignores the capital gain to holding bonds.

Response:

(a) The Ibbotson® SBBI® Annual Classic and Valuation Yearbooks are the most widely cited sources of risk premium data. The Ibbotson data on annual rates of return were originally compiled at the Center for Research in Security Prices, University of Chicago Graduate School of Business. Roger Ibbotson, now Professor at Yale, was instrumental in developing this database. With regard to the use of bond yields or bond returns to estimate the cost of capital, Ibbotson SBBI® states that the income return, that is, the return arising from the bond coupon payment, but not the capital gain or loss, is most appropriate for use in calculating the equity risk premium:

> *"Another point to keep in mind when calculating the equity risk premium is that the income return on the appropriate-horizon Treasury security, rather than the total return, is used in the calculation. The total return is comprised of three return components: the income return, the capital appreciation return, and the reinvestment return. The income return is defined as the portion of the total return that results from a periodic cash flow or, in this case, the bond coupon payment. The capital appreciation return results from the price change of a bond over a specific period. Bond prices generally change in reaction to unexpected fluctuations in yields. Reinvestment return is the return on a*

given month's investment income when reinvested into the same asset class in the subsequent months of the year. The income return is thus used in the estimation of the equity risk premium because it represents the truly riskless portion of the return." [2012 Ibbotson® SBBI® Valuation Yearbook, Chapter 5, "The Equity Risk Premium," p. 55]

(b) Cannot confirm for the reasons stated in response to BC Util Cust-Vander Weide IR 1.6.2 (a).

6.3 Please provide copies of any testimony filed by Dr. Vander Weide that used yields in the period prior to 1991 when interest rates were often rising.

Response:

Dr. Vander Weide's current written evidence uses yields in the period prior to 1991.

6.4 Please indicate whether Dr. Vander Weide has ever filed testimony using risk premia based on bond returns rather than yields.

Response:

When comparing the return on stocks to the return on risk-free government securities, Dr. Vander Weide has always used the yield or income return on government securities because only the yield or income return is risk free.

6.5 Please confirm that BCE has been a part of the utilities index, and when it was, it included its ownership of Nortel.

Response:

BCE has been part of the S&P/TSX Utilities Index. It has not been part of the BMO Capital Markets Utility Group.

7. Topic: US forward looking Risk premia, pages 35-38

7.1 Please provide the estimates without the quarterly compounding of dividends.

Response:

Please refer to the response to BC Util Cust-Vander Weide IR 1.4.5. As shown in the comparison provided in response to BC Util Cust IR-Vander Weide 1.4.5, the quarterly compounding of dividends does not have a significant impact on the DCF results compared to the use of the annual model. Dr. Vander Weide uses the quarterly DCF model because it is theoretically correct.

7.2 Please confirm that these estimates rely on the contemporaneous rather than forecast long Treasury bond yield.

Response:

Cannot confirm. To develop the ex ante risk premium cost of equity, Dr. Vander Weide uses the Canadian forecast interest rate on long-term Canada bonds at the time of his studies, 2.95 percent (see Vander Weide written evidence at 37).

7.3 Please confirm that the last estimate is simply the DCF estimate and indicate what it would be for both gas and electric companies without the quarterly dividend compounding and using a one year forecast long treasury Yield.

Response:

Cannot confirm. The last line of Exhibit 10 or the last line of Exhibit 11 shows the DCF-based risk premium using data for May 2012. The ex ante risk premium model develops an estimate of the forward looking risk premium by regressing the risk premium results in the last columns of Exhibit 10 and Exhibit 11 against the bond yields shown in the third columns of these exhibits. The forecast risk premium is then obtained from the regression equation using the forecast bond yield. In addition, as discussed in response to 4.5, quarterly dividend compounding does not have a significant impact on the DCF result. With respect to the request to re-do the ex ante studies using a one-year forecast long Treasury bond yield in every period, Dr. Vander Weide does not have the data required to perform such a study.

8. Topic: CAPM Estimates

8.1 Please confirm that the Value Line beta estimates are adjusted toward 1.0 using the Blume adjustment.

Response:

Confirmed.

8.2 Please indicate whether Dr. Vander Weide is aware of any published academic research that indicates that utility betas "regress" toward their grand mean rather than 1.0 as assumed by the Blume adjustment.

Response:

Dr. Vander Weide is aware that utility betas have not regressed to 1.0. However, whether utility betas regress toward 1.0 or toward a "grand mean" is irrelevant to Dr. Vander Weide's conclusion that the CAPM underestimates the cost of equity for companies with betas less than 1.0. Dr. Vander Weide bases his conclusion primarily on his study of the referenced articles, which report results of studies that do not adjust betas for their tendency to move toward 1.0.

8.3 Please provide a graph of the utility betas in Dr. Vander Weide's sample of US firms since 1990 and indicate whether they have regressed or moved toward 1.0.

Response:

Please refer to the response to BC Util Cust-Vander Weide IR 1.8.2. Such a graph would be irrelevant to Dr. Vander Weide's conclusion that the CAPM underestimates the cost of equity for companies with betas less than 1.0. Dr. Vander Weide bases his conclusion primarily on his study of the referenced articles, which report results of studies that do not adjust betas for their tendency to move toward 1.0.

8.4 Please indicate why Dr. Vander Weide has used a US market risk premium estimate rather than a Canadian one since the fair return estimate is for a Canadian company.

Response:

Dr. Vander Weide uses the U.S. market risk premium data because the U.S. market risk premium data are based on a more broadly diversified stock market index than is available for use in Canadian risk premium data. The CAPM model requires estimates of the risk premium on a broadly diversified market because the CAPM assumes that the market index includes all risky securities in the economy.

8.5 Please provide a copy of the 2011 Year book.

Response:

Dr. Vander Weide purchases the SBBI® Yearbook for a fee from Morningstar. The book may be purchased at http://corporate.morningstar.com/US/asp/home2.aspx?xmlfile=7083.xml. In addition, Dr. Vander Weide notes that he obtained the Ibbotson market risk premium data in his evidence from the 2012 SBBI® Yearbook.

8.6 Please confirm that the CAPM studies referenced by Dr. Vander Weide to justify the graph on page 41 used short term Treasury Bill yield as the risk free rate and did not adjust beats the way that value Line does.

Response:

Confirmed.

8.7 Please provide the CAPM estimates similar to those on page 42 using Treasury bill yields and actual betas.

<u>Response:</u>

The requested study would not provide useful information regarding FEI's cost of equity. In his CAPM studies, Dr. Vander Weide uses adjusted betas equal to approximately 0.7. The unadjusted beta for a company with an adjusted beta of 0.7 would be approximately 0.55. The studies in the articles referenced by Dr. Vander Weide demonstrate that, for companies with unadjusted betas less than 1.0: (1) the CAPM underestimates the cost of equity; and (2) the difference between the required market return and the CAPM-estimated return is greater, the further the unadjusted beta estimate is from 1.0. These studies strongly support the conclusion that the CAPM-estimated cost of equity for a company with an unadjusted beta equal to 0.55 would significantly underestimate the company's cost of equity. Thus, the requested CAPM calculations would also significantly underestimate FEI's cost of equity. To illustrate the irrelevance of the requested study, consider the CAPM-estimated cost of equity using a Treasury bill yield of approximately 0.1 percent, a beta of 0.55, and a market risk premium of 6.6 percent. The CAPM-estimated cost of equity would be 3.7 percent. Given that the average allowed ROE for natural gas and electric utilities is approximately 10 percent, a 3.7 percent cost of equity estimate is not credible.

9. Topic: Allowed ROE and Common Equity Ratios, page 43-51

9.1 Please provide the book equity Canadian utilities in Table 4.

Response:

The deemed equity ratios in Table 4 are the deemed book equity ratios for these Canadian utilities. It is Dr. Vander Weide's understanding that Canadian utilities generally attempt to keep their actual book equity ratios close to their allowed or deemed book equity ratios so that they can earn their allowed returns on equity. In addition, please note that there is a typographical error in the ratio shown for Gazifère, which should be 40 percent rather than 38.5 percent.

9.2 Does Dr. Vander Weide judge it to be meaningful to compare FEI with PNG, Heritage Gas, and Alta Gas?

Response:

Dr. Vander Weide does not compare FEI's deemed equity only to the deemed equity ratios of PNG, Heritage Gas, and Alta Gas in Table 4. Rather, Table 4 shows a comparison of FEI's deemed equity ratio to the deemed equity ratios of all the companies listed in the table. Dr. Vander Weide believes it is meaningful to compare FEI's deemed equity ratio to the average deemed equity ratio for all the companies shown in Table 4.

9.3 Please indicate whether US regulatory commission regulate common equity ratios in the same way as do Canadian commission.

Response:

Canadian utility commissions generally set deemed equity ratios for all the utilities they regulate in one proceeding, and then apply the deemed equity ratios determined in the generic proceeding until a time when the commission considers that risk has materially changed. U.S. regulatory commissions generally do not set a deemed equity ratio in a generic proceeding.

Rather, U.S. regulatory commissions typically allow each utility to present evidence in support of its recommended capital structure in specific regulatory proceedings. The commission then examines the company's evidence and makes a determination on the reasonableness of requested capital structure.

Attachment 5.5

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Biased forecasts or biased earnings? The role of reported earnings in explaining apparent bias and over/underreaction in analysts' earnings forecasts ☆

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Abstract

The extensive literature that investigates whether analysts' earnings forecasts are biased and/or inefficient has produced conflicting evidence and no definitive answers to either question. This paper shows how two relatively small but statistically influential asymmetries in the tail and the middle of distributions of analysts' forecast errors can exaggerate or obscure evidence consistent with analyst bias and inefficiency, leading to inconsistent inferences. We identify an empirical link between firms' recognition of unexpected accruals and the presence of the two asymmetries in distributions of forecast errors that suggests that firm reporting choices play an important role in determining analysts' forecast errors.

JEL classification: G10; G14; M41

Keywords: Analysts' forecasts; Earnings management; Bias; Inefficiency

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1. Introduction

Four decades of research have produced an array of empirical evidence and a set of behavioral and incentive-based theories that address two fundamental questions: Are analysts' forecasts biased? And Do analysts underreact or overreact to information in prior realizations of economic variables? This empirical literature has long offered conflicting conclusions and is not converging to a definitive answer to either question. On the one hand, theories that predict optimism in forecasts are consistent with the persistent statistical finding in the literature of cross-sectional negative (i.e., bad news) mean forecast errors as well as negative intercepts from regressions of forecasts on reported earnings. On the other hand, such theories are inconsistent both with the finding that median forecast errors are most often zero and with the fact that the percentage of apparently pessimistic errors is greater than the percentage of apparently optimistic errors in the cross-section. A similar inconsistency is found in the literature on analyst over/underreaction to prior realizations of economic variables, including prior stock returns, prior earnings changes, and prior analyst forecast errors. Here, again, empirical evidence supports conflicting conclusions that analysts overreact to prior news, underreact to prior news, and both underreact and overreact as a function of the sign of prior economic news. Further reflecting the lack of consensus in the literature, a handful of studies fail to reject unbiasedness and efficiency in analyst forecasts after "correcting" methodological flaws or assuming nonstandard analyst loss functions.[1]

The accumulation of often inconsistent results concerning analyst rationality and incentives makes it difficult for researchers, practitioners, and policy makers to understand what this literature tells us. This motivates us to reexamine the body of evidence with the goal of identifying the extent to which particular theories for apparent errors in analysts' forecasts are supported by the data. Such an exercise is both appropriate and necessary at this juncture as it can, among other things, lead to modified theories that will be tested using the new and unique hypotheses they generate.

We extend our analysis beyond a synthesis and summary of the findings in the literature by identifying the role of two relatively small asymmetries in the cross-sectional distributions of analysts' forecast errors in generating conflicting statistical evidence. We note that the majority of conclusions concerning analyst-forecast rationality in the literature are directly or indirectly drawn from analyses of these distributions. The first asymmetry is a larger number and a greater magnitude of observations that fall in the extreme negative relative to the extreme positive tail of the forecast error distributions (hereafter, the *tail asymmetry*). The second asymmetry is a higher incidence of small positive relative to small negative forecast errors in cross-sectional distributions (hereafter, *the middle asymmetry*). The individual and combined impact of these asymmetries on statistical tests leads to three important observations. First, differences in the manner in which researchers

[1] A representative selection of evidence and theory relevant to both the bias and over/underreaction literatures is discussed in the body of the paper.

implicitly or explicitly weight observations that fall into these asymmetries contribute to inconsistent conclusions concerning analyst bias and inefficiency. Second, a variety of econometric techniques and data adjustments fail to eliminate inconsistencies in inferences across different statistical indicators and conditioning variables. Such techniques include using indicator variables or data partitions in parametric tests, applying nonparametric methods, and performing data truncations and transformations. Third, econometric approaches that choose loss functions that yield consistent inferences—essentially by attenuating the statistical impact of observations that comprise the asymmetries—will not provide definitive answers to the question of whether analysts' forecasts are biased and inefficient. This is because at this stage in the literature too little is known about analysts' actual loss functions, and such methods thus leave unresolved the question of why the asymmetries in forecast error distributions are present.

We present statistical evidence that demonstrates how the two asymmetries in forecast error distributions can indicate analyst optimism, pessimism, or unbiasedness. We also show how observations that comprise the asymmetries can contribute to, as well as obscure, a finding of apparent analyst inefficiency with respect to prior news variables, including prior returns, prior earnings changes, and prior forecast errors. For example, our empirical evidence explains why prior research that relies on parametric statistics always finds evidence of optimistic bias as well as apparent analyst underreaction to prior bad news for all alternative variables chosen to represent prior news. It also explains why evidence of apparent misreaction to good news is *not* robust across parametric statistics or across prior news variables, and why the degree of misreaction to prior bad news is always greater than the degree of misreaction to prior good news, regardless of the statistical approach adopted or the prior information variable examined.

Finally, while our analysis does not lead to an immediately obvious solution to problems of inferences in the literature, it does reveal a link between the reported earnings typically employed to benchmark forecasts and the presence of the two asymmetries in distributions of forecast errors. Specifically, we find that extreme negative unexpected accruals included in reported earnings go hand in hand with observations in the cross-section that generate the tail asymmetry. We also find that the middle asymmetry in distributions of forecast error is eliminated when the reported earnings component of the earnings surprise is stripped of unexpected accruals. This evidence suggests benefits to refining extant cognitive- and incentive-based theories of analyst forecast bias and inefficiency so that they can account for an endogenous relation between forecast errors and manipulation of earnings reports by firms. The evidence also highlights the importance of future research into the question of whether reported earnings are, in fact, the correct benchmark for assessing analyst bias and inefficiency. This is because common motivations for manipulating earnings can give rise to the appearance of analyst forecast errors of exactly the type that comprise the two asymmetries if unbiased and efficient forecasts are benchmarked against manipulated earnings. Thus, it is possible that some evidence previously deemed to reflect the impact of analysts' incentives and cognitive tendencies on forecasts is, after all, attributable to the fact that analysts do not have the motivation or ability to completely anticipate earnings management by firms in their forecasts.

This paper's emphasis is on fleshing out salient characteristics of forecast error distributions with an eye toward ultimately explaining how they arise. The analysis highlights the importance of new research that explains the actual properties of forecast error data and cautions against the application of econometric fixes that either fit the data to specific empirical models or fit specific empirical models to the data without strong a priori grounds for doing so. Our findings also represent a step toward understanding what analysts really aim for when they forecast, which is useful for developing more appropriate null hypotheses in tests of analysts' forecast rationality, and sounder statistical test specifications, as well as the identification of first-order effects that may require control when testing hypotheses that predict analyst forecast errors.

In the next section we describe our data and present evidence of the sensitivity of statistical inferences concerning analyst optimism and pessimism to relatively small numbers of observations that comprise the tail and middle asymmetries. Section 3 extends the analysis to demonstrate the impact of the two forecast error asymmetries on inferences concerning analyst over/underreaction conditional on prior realizations of stock returns and earnings changes, as well as on serial correlation in consecutive-quarter forecast errors. Section 4 presents evidence of a link between biases in reported earnings and the two asymmetries and discusses possible explanations for this link as well as the implications for interpreting evidence from the literature and for the conduct of future research. A summary and conclusions are provided in Section 5.

2. Properties of typical distributions of analysts' forecast errors and inferences concerning analysts' optimism, pessimism, and unbiasedness

2.1. Data

The empirical evidence in this paper is drawn from a large database of consensus quarterly earnings forecasts provided by Zacks Investment Research. The Zacks earnings forecast database contains approximately 180,000 consensus quarterly forecasts for the period 1985–1998. For each firm quarter we calculate forecast errors as the actual earnings per share (as reported in Zacks) minus the consensus earnings forecast outstanding prior to announcement of quarterly earnings, scaled by the stock price at the beginning of the quarter and multiplied by 100. Our results are insensitive to alternative definitions of forecasts such as the last available forecast or average of the last three forecasts issued prior to quarter-end. Inspection of the data revealed a handful of observations that upon further review indicated data errors. These observations had no impact on the basic features of cross-sectional distributions of errors that we describe, but they were nevertheless removed before carrying out the statistical tests reported in this paper. Empirical results obtained after removing these observations were virtually identical to those obtained when the distributions of quarterly forecast errors were winsorized at the 1st and 99th percentiles, a common practice for mitigating the possible effects of data errors followed in the literature. (To enhance comparability with the majority of studies cited below, all test results reported in the paper are based on the winsorized data.)

Lack of available price data reduced the sample size to 123,822 quarterly forecast errors. The data requirements for estimating quarterly accruals further reduced the sample on which our tabled results are based to 33,548 observations.[2] For the sake of brevity we present only results for this reduced sample. We stress, however, that the middle and tail symmetries we document below are present in the full sample of forecast errors and that the proportion of observations that comprise these asymmetries is roughly the same as that for the reduced sample. Moreover, the descriptive evidence and statistical findings relevant to apparent bias and inefficiency in analyst forecasts presented in this section and the next are qualitatively similar when we do not impose the requirement that data be available to calculate unexpected accruals.[3]

2.2. *The impact of asymmetries in the distribution of forecast errors on inferences concerning bias*

One of the most widely held beliefs among accounting and finance academics is that incentives and/or cognitive biases induce analysts to produce generally optimistic forecasts (see, e.g., reviews by Brown (1993) and Kothari, 2001). This view is repeatedly reinforced when studies that employ analysts' forecasts as a measure of expected earnings present descriptive statistics and refer casually to negative mean forecast errors as evidence of the purportedly "well-documented" phenomenon of optimism in analyst forecasts.[4] The belief is even more common among regulators (see, e.g., Becker, 2001) and the business press (see, e.g., Taylor, 2002). In spite of the prevalent view of analyst forecast optimism, summary statistics associated with forecast error distributions reported in Panel A of Table 1 raise doubts about this conclusion.

[2] As described in Section 4, we use a quarterly version of the modified Jones model to estimate accruals. For the purposes of sensitivity tests, we also examine a measure of unexpected accruals that excludes nonrecurring and special items (see, Hribar and Collins, 2002), and use this adjusted measure in conjunction with *Zacks*' consensus forecast estimates and actual reported earnings, which also exclude such items. All the results involving unexpected accruals reported in the paper are qualitatively unaltered using this alternative measure.

[3] The results are also qualitatively similar when data from alternative forecast providers (I/B/E/S and First Call) are employed, indicating that the findings we revisit in this study are not idiosyncratic to a particular data source (see, Abarbanell and Lehavy, 2002).

[4] The perception is also strengthened in a number of studies that place analyst forecasts and reported earnings numbers (i.e., the two elements that comprise the forecast error) on opposite sides of a regression equation. These studies uniformly find significant intercepts and either casually refer to them as consistent with analyst optimism or emphasize them in supporting their prediction of analyst bias. Evidence presented below, however, indicates a nonlinear relation between forecasts and earnings, which contributes to nonzero intercepts in OLS regressions.

Table 1
Descriptive statistics on quarterly distributions of forecast errors (Panel A), the tail asymmetry (Panel B), and the middle asymmetry (Panel C), 1985–1998

Panel A: Statistics on forecast error distributions	
Number of observations	33,548
Mean	−0.126
Median	0.000
% Positive	48%
% Negative	40%
% Zero	12%
Panel B: Statistics on the "tail asymmetry" in forecast error distributions	
P5	−1.333
P10	−0.653
P25	−0.149
P75	0.137
P90	0.393
P95	0.684

Panel C: Statistics on the "middle asymmetry" in forecast error distributions

Range of forecast errors (1)	Ratio of positive to negative forecast errors (2)	% of total number of observations (3)
Overall	1.19	100
Forecast errors = 0		12
[−0.1, 0) & (0, 0.1]	1.63*	29
[−0.2, −0.1) & (0.1, 0.2]	1.54*	18
[−0.3, −0.2) & (0.2, 0.3]	1.31*	10
[−0.4, −0.3) & (0.3, 0.4]	1.22*	7
[−0.5, −0.4) & (0.4, 0.5]	1.00	5
[−1, −0.5) & (0.5, 1]	0.83*	11
[Min, −1) & (1, Max]	0.40*	9

This table provides descriptive statistics on quarterly distributions of forecast errors for the period of 1985–1998. Analyst earnings forecasts and actual realized earnings are provided by *Zacks Investment Research*. Panel A provides the mean, median, and frequencies of quarterly forecast errors. Panel B provides percentile values of forecast error distributions. Panel C reports the ratio of positive to negative forecast errors for observations that fall into increasingly larger and nonoverlapping symmetric intervals moving out from zero forecast errors. For example, the forecast error range of [−0.1, 0) & (0, 0.1] includes all observations that are greater than or equal to −0.1 and (strictly) less than zero and observations that are greater than zero and less than or equal to 0.1. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price.

* A test of the difference in the frequency of positive to negative forecast errors is statistically significant at or below a 1% level.

As can be seen in Panel A, the only statistical indication that supports the argument for analyst optimism is a fairly large negative mean forecast error of −0.126. In contrast, the median error is zero, suggesting unbiased forecasts, while the percentage of positive errors is significantly greater than the percentage of negative errors (48% vs. 40%), suggesting apparent analyst pessimism.

To better understand the causes of this inconsistency in the evidence of analyst biases among the summary statistics, we take a closer look at the distribution of forecast errors. Panel A of Fig. 1 presents a plot of the 1st through the 100th percentiles of the pooled quarterly distributions of forecast errors over the sample period. Moving from left to right, forecast errors range from the most negative to the most positive.

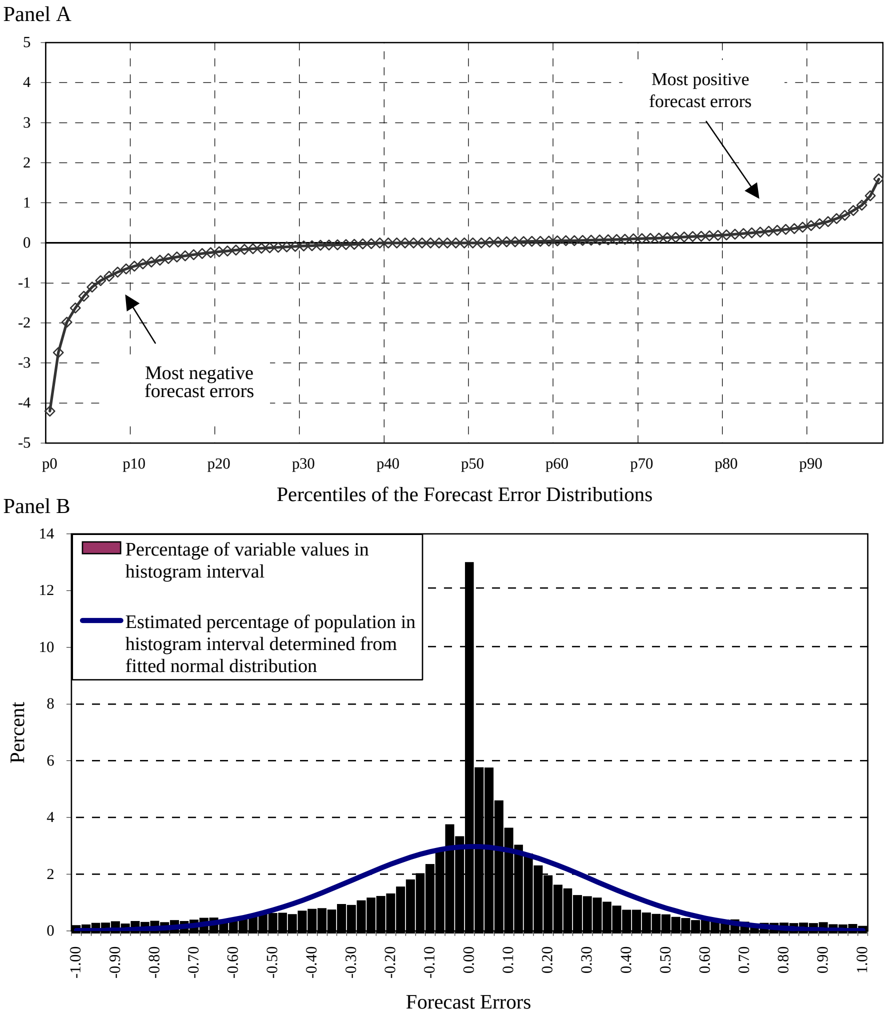


Fig. 1. Percentile values of quarterly distributions of analyst forecast errors (Panel A) and histogram of forecast errors for observations within forecast errors of -1 to $+1$ (Panel B). Panel A depicts percentile values of quarterly distributions of analyst forecast errors. Panel B presents percentage of forecast error values in histogram intervals for observations within a forecast error of -1% to $+1\%$ of the beginning-of-period stock price. Forecast error equals reported earnings minus the consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price ($N = 33,548$).

One distinctive feature of the distribution is that the left tail (ex-post bad news) is longer and fatter than the right tail, i.e., far more extreme forecast errors of greater absolute magnitude are observed in the ex-post "optimistic" tail of the distribution than in the "pessimistic" tail. We refer to this characteristic of the distribution as the *tail asymmetry*. Although Fig. 1 summarizes the distribution of observations over the entire sample period, unreported results indicate that a tail asymmetry is present in each quarter represented in the sample. To get a sense of the magnitude of the asymmetry, we return to Panel B of Table 1, where the 5th percentile (extreme negative forecast errors) is nearly twice the size observed for the 95th percentile (-1.333 vs. 0.684). Alternatively, we find that 13% of the observations fall below a negative forecast error of -0.5, while only 7% fall above a positive error of an equal magnitude (not reported in the table).

Closer visual inspection of the data reveals a second feature of the distribution depicted in Panel B of Fig. 1—a higher frequency of small positive forecast errors versus small negative errors. Specifically, the figure presents the frequencies of forecast errors that fall in fixed subintervals of 0.025 within the range of -1 to $+1$. Clearly, the *incidence* of small positive relative to small negative errors increases as forecast errors become smaller in absolute magnitude. We refer to this property of the distribution as the *middle asymmetry*.[5] Statistics on the magnitude of the middle asymmetry are reported in Panel C of Table 1. This panel presents the ratio of positive (i.e., apparently pessimistic) errors to negative errors for observations that fall into increasingly larger and nonoverlapping symmetric intervals moving out from zero forecast errors. Consistent with the visual evidence in Panel B of Fig. 1, this ratio increases for smaller, symmetric intervals of forecast errors, reaching 1.63 in the smallest interval examined (significantly different from 1, as well as significantly different from the ratios calculated for the larger intervals).[6] Another distinguishing feature of the distribution seen in Panel C of Table 1 and evident in both Panels A and B of Fig. 1 is the large number of exactly zero observations (12%). Depending on one's previous exposure to the data or instincts about the task of forecasting, the magnitude of the clustering at exactly zero may not seem

[5] The visual evidence in Panel B of Fig. 1 is consistent with specific circumstances in which analysts have incentives to produce forecasts that fall slightly short of reported earnings (see, e.g., Degeorge et al., 1999; Matsumoto, 2002; Brown, 2001; Burgstahler and Eames, 2002; Bartov et al., 2000; Dechow et al., 2003; Abarbanell and Lehavy, 2003a, b). However, prior studies have not considered the impact of observations that comprise the middle asymmetry on inferences concerning the *general* tendency of analysts to produce biased and/or inefficient forecasts.

[6] An analysis of unscaled forecast errors confirms that rounding down a greater number of negative than positive forecast errors to a value of zero when errors are scaled by price does not systematically induce the middle asymmetry (see, Degeorge et al., 1999). Similarly, there is no obvious link between the presence of the middle asymmetry and round-off errors induced by the application of stock-split factors to consensus forecast errors discussed in Baber and Kang (2002) and Payne and Thomas (2002). Abarbanell and Lehavy (2002) present evidence confirming the presence of the middle asymmetry in samples confined to firms with stock-split factors of less than 1.

surprising. Nevertheless, the large number of forecasts of exactly zero has important impacts on statistical inferences.[7]

The statistics presented above indicate that the tail asymmetry pulls the mean forecast error toward a negative value, supporting the case for analyst optimism. But, as shown in Panel C of Table 1, the excess of *small* positive over *small* negative errors associated with the middle asymmetry is largely responsible for a significantly higher overall incidence of positive to negative forecast errors in the distribution, thus supporting the case for analyst pessimism. Finally, a zero median forecast error, which supports an inference of analyst unbiasedness, reflects the countervailing effects of the middle asymmetry and tail asymmetries. A rough calculation pertaining to the nonzero forecast errors in the interval between [−0.1, 0) and (0, 0.1] gives a sense of these effects. There are 9662 observations in this region. If nonzero forecast errors were random, we would expect 4831 forecasts to be positive, when in fact 5928 are positive, indicating that small errors in the distribution of absolute magnitude less than or equal to 0.1 contribute 1097 more observations to the right of zero than would be expected if the distribution was symmetric. This region of the forecast error distribution contains 29% of all observations but contributes more than 42% of the total number of pessimistic errors in excess of optimistic errors and represents roughly 3.3% of the entire distribution. Their impact offsets, all else being equal, the contribution of approximately 2.5% of negative observations in excess of what would be expected if the distribution of errors were symmetric, arising from the tail asymmetry (relative to the extreme decile cutoffs of a fitted normal distribution). Because 12% of the forecast error sample has a value of exactly zero, the relative sizes of the tail and middle asymmetries are each sufficiently small (and offsetting) to ensure that the median error remains at zero.

The evidence in Table 1 and Fig. 1 yields two important implications for drawing inferences about the nature and extent of analyst bias. First, depending on which summary statistic the researcher chooses to emphasize, support can found for analyst optimism, pessimism, and even unbiasedness. Second, if a researcher relies on a given summary statistic to draw an inference about analyst bias, a relatively small percentage of observations in the distribution of forecast errors will be responsible for his or her conclusion. This is troublesome because extant hypotheses that predict analyst optimism or pessimism typically do not indicate how often the phenomenon will occur in the cross-section and often convey the impression that

[7] Because many factors can affect the process that generates the typical distribution of forecast errors, there is no reason to expect them to be normally or even symmetrically distributed. Supplemental analyses unreported in the tables reject normality on the basis of skewness and kurtosis. It is interesting to note, however, that kurtosis in the forecast error distribution does not align with the typical descriptions of leptokurtosis (high peak and fat tails) or platykurtosis (flat center and/or shoulders). Relative to decile cutoffs of the fitted normal distribution, we find that the most extreme negative decile of the actual distribution contains only 5% of the observations and the most extreme positive decile contains only 2.5% of the observations. Thus, even though the extreme negative tail is roughly twice the size of the extreme pessimistic tail, extreme observations are actually *underrepresented* in the distribution relative to a normal, especially in the positive tail. The thinner tails and shoulders of the distribution highlight the role of peakedness as a source of deviation from normality, a fact that is relevant to assessing the appropriateness of statistics used by researchers to draw inferences about analyst forecast bias.

bias will be pervasive in the distribution (see, studies suggesting that analysts are hard-wired or motivated to produce optimistic forecasts, e.g., Affleck-Graves et al. (1990), Francis and Philbrick (1993), and Kim and Lustgarten (1998), or that selection biases lead to hubris in analysts' earnings forecasts, e.g., McNichols and O'Brien, 1997).[8]

Some studies have explicitly recognized the disproportional impact of extreme negative forecast errors on conclusions drawn in the literature, but for the most part they have had little influence on general perceptions. For example, Degeorge et al. (1999) predict a tendency for pessimistic errors to occur but recognize the common perception that analyst forecasts are optimistic; they note in passing that extreme negative forecast errors are responsible for an optimistic mean forecast in their sample. Some studies also tend to deal with this feature of the data in an ad hoc manner. Keane and Runkle (1998), for example, recognize the impact of extreme negative forecast errors on statistical inferences concerning analyst forecast rationality and thus eliminate observations from their sample based on whether reported earnings contain large negative special items. However, Abarbanell and Lehavy (2002) show that there is a very high correlation between observations found in the extreme negative tail of forecast error distributions and firms that report large negative special items, even when special items are excluded from the reported earnings benchmark used to calculate the forecast error. Thus, by imposing rules that eliminate observations from their sample based on the size of negative special items, Keane and Runkle (1998) effectively truncate the extreme negative tail of forecast error distributions, and in so doing nearly eliminate evidence of mean optimism in their sample.

Some researchers are less explicit in justifying the removal of observations from the distribution of forecast errors when testing for forecast rationality, or are unaware that they have done so in a manner that results in sample distributions that deviate substantially from the population distribution. For example, many studies implicitly limit observations in their samples to those that are less extreme by choosing ostensibly symmetric rules for eliminating them, such as winsorization or truncations of values greater than a given absolute magnitude.[9] It should be evident from Panel A of Fig. 1 that such rules inherently mitigate the statistical impact of the

[8] A notable exception is the attribution of optimism in analysts' earnings forecasts to incentives to attract and maintain investment banking relationships (see, e.g., Lin and McNichols, 1998; Dugar and Nathan, 1995). Evidence consistent with this argument is based on fairly small samples of firms issuing equity. We emphasize that all the qualitative results in this paper are unaltered after eliminating observations for which an IPO or a seasoned equity offering took place within 1 year of the date of a forecast. Furthermore, the number of observations removed from the sample for this reason represents a very small percentage of those in each of the quarters in our sample period.

[9] For example, Kothari (2001) reports that Lim (2001) excludes absolute forecast errors of \$10 per share or more, Degeorge et al. (1999) delete absolute forecast errors greater than 25 cents per share, Richardson et al. (1999) delete price-deflated forecast errors that exceed 10% in absolute value, and Brown (2001) winsorizes absolute forecast errors greater than 25 cents per share (which implies a much larger tail winsorization than typically undertaken to remove possible data errors). While none of these procedures, when applied to our data, completely eliminates the tail asymmetry, all of them substantially attenuate to varying degrees its statistical impact on our tests.

tail asymmetry and arbitrarily transform the distribution, frequently without a theoretical or institutional reason for doing so.[10]

One might justify truncating data on the grounds that the disproportional impact of the extreme tail makes it difficult detect general tendencies, or that such "errors" may not accurately reflect factors relevant to analysts' objective functions (see, e.g., Abarbanell and Lehavy, 2003b; Gu and Wu, 2003; Keane and Runkle, 1998). However, it is possible for researchers to "throw the baby out with the bathwater" if they assume that these observations do not reflect the effects of incentives or cognitive biases, albeit in a more noisy fashion than other observations in the distribution. Another concern that arises from transforming the distribution of errors without justification is that it may suppress one feature of the data (e.g., the tail asymmetry), leaving another unusual but more subtle feature of the distribution (e.g., the middle asymmetry) to dominate an inference that forecasts are generally biased or to offset the other and yield an inference that forecasts are generally unbiased. This is an important issue because there has been a tendency in the literature on forecast rationality for new hypotheses to crop up motivated solely by the goal of explaining "new" empirical results. For example, after truncating large absolute values of forecast errors, Brown (2001) finds that the mean and median forecasts in recent years indicate a shift away from analyst optimism and toward analyst pessimism. Increasing pessimism as a function of market sentiment as reflected in changes in price level or changes in analyst incentives has also been a subject of growing interest in the behavioral finance literature. Clearly, when data inclusion rules that systematically reduce the tail asymmetry are applied, empirical evidence in support of increasing or time-varying analyst pessimism will be affected by the size and magnitude of the remaining middle asymmetry.

Perhaps the most unsatisfying aspect of the evidence presented in Table 1 is the fact that general incentive and behavioral theories of analyst forecast errors are not sufficiently developed at this stage to predict that when forecast errors are extreme they are more likely to be *optimistic* and when forecast errors are small they are more likely to be *pessimistic*. That is, individual behavioral and incentive theories for analyst forecast errors do not account for the simultaneous presence of the two asymmetries that play such an important role in generating evidence consistent with analyst bias and, as we show in the next section, analyst forecast inefficiency with respect to prior information (see Abarbanell and Lehavy, 2003a, for an exception).

3. The effect of the two asymmetries on evidence of apparent analyst misreaction to prior stock returns, prior earnings changes, and prior forecast errors

In this section, we demonstrate how observations that comprise the tail and middle asymmetries in forecast error distributions *conditional on prior realizations of*

[10] For example, in our data an arbitrary symmetric truncation of the distribution at the 10th and the 90th percentiles reduces the measure of skewness in the remainder of the distribution to a level that does not reject normality and results in a mean forecast error near zero among the remaining observations. A similar effect occurs with an arbitrary one-sided truncation of the negative tail at a value as low as the 3rd percentile.

economic variables contribute to inconsistent inferences concerning the efficiency of analysts' forecasts. One important message of the ensuing analysis is that the likelihood that a forecast error observation falls into one or the other asymmetry varies by the sign and magnitude of the prior news. This feature of the data links the empirical literature on analyst inefficiency to the heretofore separate literature on analyst bias. This is because observations that comprise the two asymmetries and lead—depending on the statistic relied on—to inconsistent inferences concerning analyst bias also contribute to conflicting inferences concerning whether analysts underreact, overreact, or react efficiently to prior news.

We consider realizations of three economic variables: prior period stock returns, prior period earnings changes, and prior period analyst forecast errors. These three variables are those most often identified in previous studies of analyst forecast efficiency.[11] Consistent with the previous literature, we define prior abnormal returns (*PrAR*) as equal to the return between 10 days after the last quarterly earnings announcement to 10 days prior to the current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period.[12] Prior earnings changes (*PrEC*) are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the price at the beginning of the period, and prior forecast errors (*PrFE*) are the prior quarter's forecast error.

The remainder of this section proceeds as follows: we first present evidence on the existence of the tail and middle asymmetries in distributions of forecast errors conditional on the sign of prior news variables. We then analyze the role of the asymmetries in producing indications of analyst inefficiency in both summary statistics and regression coefficients and discuss the robustness of these findings. Next, we show the disproportionate impact of observations that comprise the asymmetries in generating evidence of serial correlation in analyst forecast errors. Finally, we discuss the shortcomings of econometric "fixes" that intentionally or unintentionally ameliorate the impact of one or both asymmetries on inferences concerning analyst forecast rationality.

3.1. *The tail and middle asymmetries in forecast error distributions conditional on prior news variables*

Tests of analyst forecast efficiency typically partition distributions of forecast errors based on the sign of the prior news to capture potential differences in analyst reactions to prior good versus prior bad news. Accordingly, before we review the

[11] Studies that examine the issue of current period forecast efficiency with respect to prior period realization of returns or earnings (e.g., Abarbanell, 1991; Easterwood and Nutt, 1999) commonly frame the question in terms of whether analysts over- or underreact to prior news. In contrast, studies that examine the issue of current period forecast efficiency with respect to analysts' own past forecast errors are generally limited to the question of whether there is significant serial correlation in lagged forecast errors, without regard to how the sign and magnitude of prior forecast errors affect that correlation.

[12] All reported results are qualitatively similar when prior abnormal returns are measured between 10 days after the last quarterly earnings announcement to either 30 days prior or 1 day prior to the current quarter earnings announcement.

statistical evidence, we first examine the features of forecast error distributions conditional on the sign of prior news variables. Panels A–C of Fig. 2, which depict the percentiles of the distributions of forecast errors conditional on the sign of each of the three prior news variables, show that prior bad news partitions are characterized by larger tail asymmetries than prior good news partitions for all prior news variables.

Panels A–C of Fig. 3—which depict the frequencies of forecast errors that fall in fixed subintervals of 0.025 within the range of -0.5 to $+0.5$ for *PrAR*, *PrEC*, and *PrFE*, respectively—show that prior good news partitions are characterized by larger middle asymmetries than prior bad news partitions for all three prior news variables.[13]

Together, Figs. 2 and 3 suggest that distributions of forecast errors conditional on the sign of prior news retain the characteristic asymmetries found in the unconditional distributions in Section 2. However, the likelihood of a subsequent forecast error falling into the middle asymmetry is greater following prior good news, while the likelihood of a forecast error falling into the tail asymmetry is greater following prior bad news.[14] Below we investigate the impact of the variation in the size of the asymmetries in distributions of forecast errors conditional on the sign of news on inferences about analyst inefficiency that are drawn from summary statistics (Section 3.1.1) and regression coefficients (Section 3.1.2).

3.1.1. Inferences about analyst efficiency from summary statistics

Panel A of Table 2 shows how the two asymmetries impact summary statistics, including means, medians, and the percentages of negative to positive forecast errors in distributions of forecast errors conditional on the sign of prior news. We begin with the case of prior bad news. Prior bad news partitions for all three variables produce significantly negative mean forecast errors (-0.195 for *PrAR*, -0.291 for *PrEC*, and -0.305 for *PrFE*), supporting an inference of analyst underreaction (i.e., the mean forecast is too high following bad news). The higher percentages of negative than positive forecast errors in the bad news partitions of each variable (e.g., 50% vs. 40% for negative *PrEC*) are also consistent with a tendency for analysts to underreact to prior bad news. The charts in Figs. 2 and 3 foreshadow these results. The relatively larger tail asymmetry in prior bad news partitions drives parametric means to large negative values. Similarly, the larger negative relative to

[13] The concentration of small (extreme) errors among positive (negative) prior returns news is not induced by scaling by prices that are systematically higher (lower) following a period of abnormal positive (negative) returns, since the middle and tail asymmetries are still present in distributions of unscaled forecast errors and errors deflated by forecasts.

[14] Abarbanell and Lehavy (2003a) report the same patterns in forecast error distributions conditional on classification of ranked values of stock recommendations, P/E ratio, and market-to-book ratios into high and low categories. It is certainly possible that some form of irrationality or incentive effect leads to different forecast error regimes on either side of a demarcation point of zero, and therefore coincidentally sorts the two asymmetries that are located on either side of a zero. However, the continued presence of relatively small but statistically influential asymmetries in the conditional distributions may overwhelm the researcher's ability to detect these incentive or behavioral factors, or may give the false impression that such a factor is pervasive in the distribution when it is not.

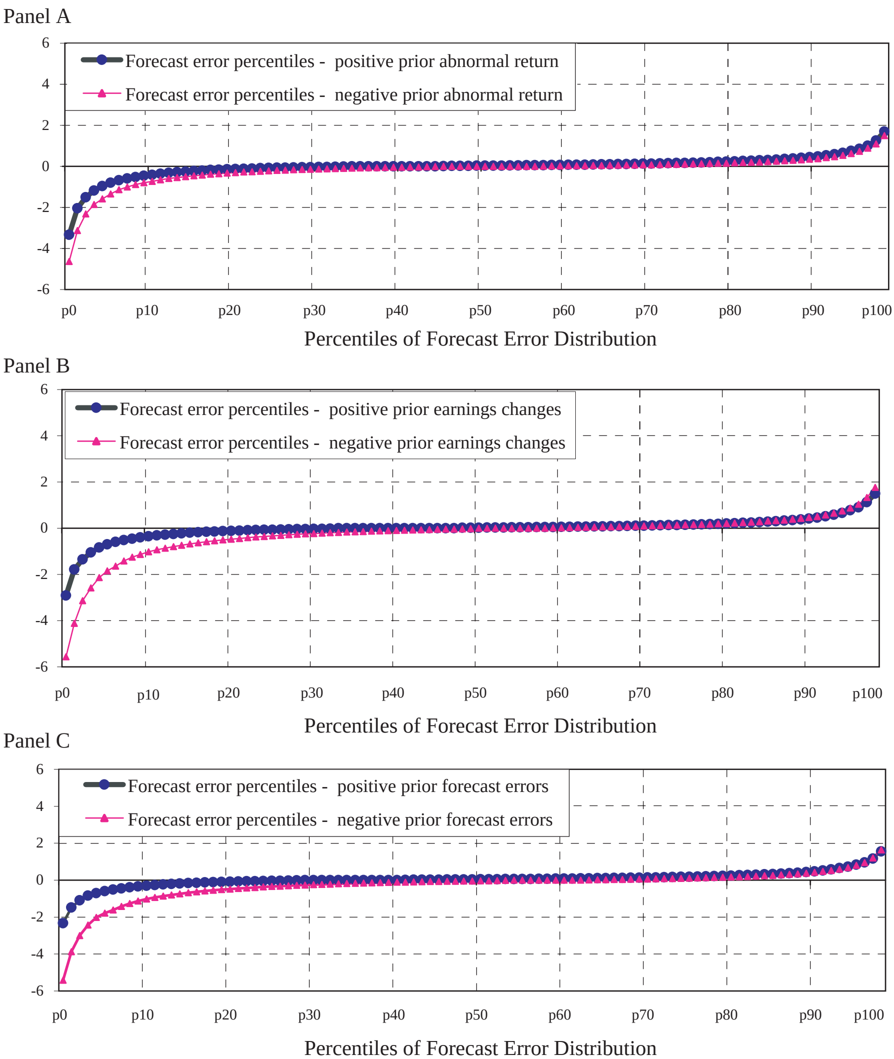
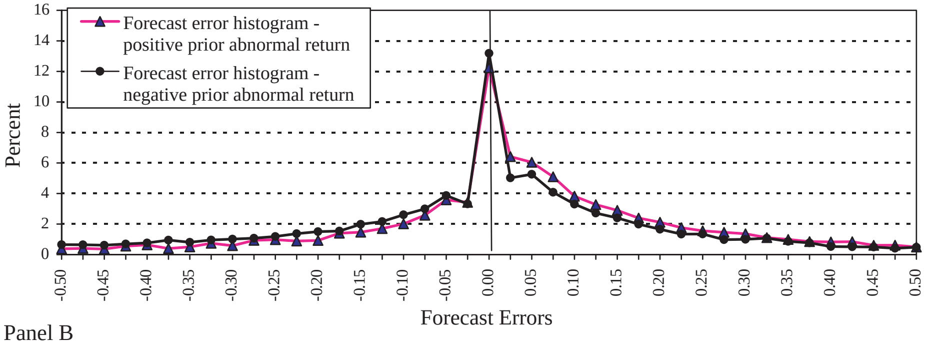


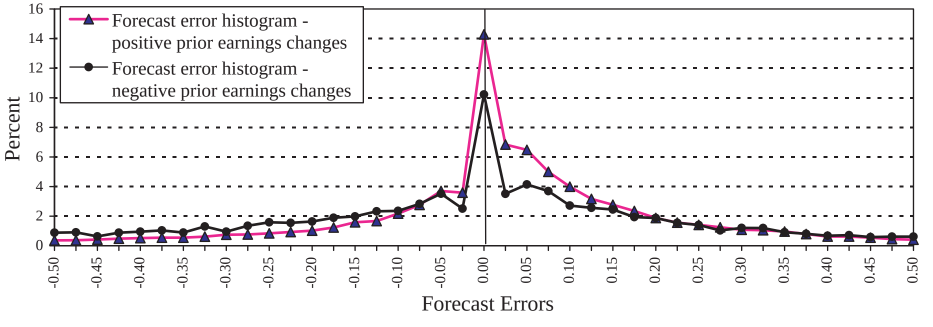
Fig. 2. Forecast error equals reported earnings minus consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price. Prior market-adjusted return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the beginning-of-period price.

positive tails account for greater overall frequencies of negative than positive errors, consistent with underreaction to bad news for all three variables. This is so even though prior bad news distributions of forecast errors for *PrAR* and *PrEC* are characterized by middle asymmetries, which, all else equal, tend to push the ratio of positive to negative errors toward values greater than 1.

Panel A



Panel B



Panel C

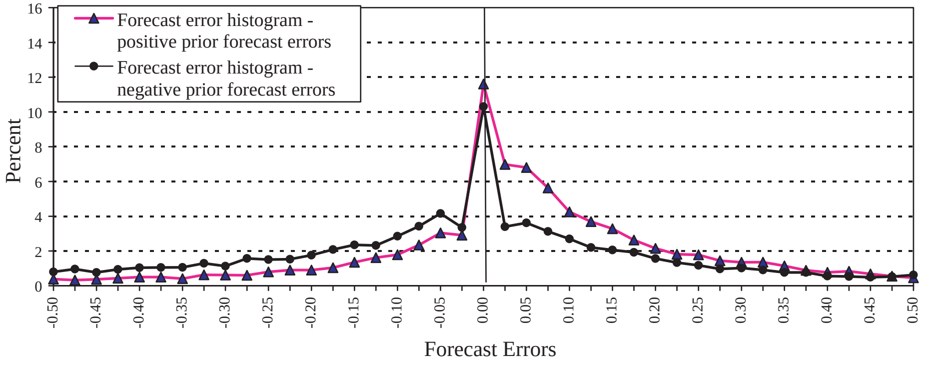


Fig. 3. Histogram of forecast errors by sign of prior abnormal returns (Panel A), prior earnings changes (Panel B), and prior forecast errors (Panel C). This figure presents the percentage of forecast error values in histogram intervals for observations within forecast error of -0.5 to $+0.5$ by sign of prior abnormal return (Panel A), prior earnings changes (Panel B), and prior forecast errors (Panel C). Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price. Prior abnormal return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the beginning-of-period price.

Table 2
Mean, median, and frequency of forecast errors (Panel A), and ratio of positive to negative forecast errors in symmetric regions for bad (Panel B) and good (Panel C) prior news variables

Panel A: Mean, median, and frequency of forecast errors by sign of prior news variables

Statistic	Sign of prior abnormal return		Sign of prior earnings changes		Sign of prior forecast errors	
	Negative (1)	Positive (2)	Negative (3)	Positive (4)	Negative (5)	Positive (6)
Mean	−0.195*	−0.041*,#	−0.291*	−0.036*,#	−0.305*	0.017*,#
Median	0.000	0.028	−0.015	0.020	−0.043	0.042
% Zero forecast errors	13%	12%	10%	14%	10%	11%
% Positive forecast errors	42%	54%	40%	52%	36%	59%
% Negative forecast errors	45%	34%	50%	34%	54%	30%
N	16,940	13,833	11,526	21,062	12,999	15,415

Panel B: Ratio of positive to negative forecast errors for negative *realizations of prior news*

Range of forecast errors	Negative prior abnormal return		Negative prior earnings changes		Negative prior forecast errors	
	Ratio of positive to negative FE (1)	% of total (2)	Ratio of positive to negative FE (3)	% of total (4)	Ratio of positive to negative FE (5)	% of total (6)
Overall	0.94	100	0.81	100	0.66	100
Forecast errors = 0		13		10		10
[−0.1, 0) & (0, 0.1]	1.39	27	1.26	21	0.94	23
[−0.2, −0.1) & (0.1, 0.2]	1.27	17	1.15	17	0.94	17
[−0.3, −0.2) & (0.2, 0.3]	0.99	10	0.93	11	0.75	10
[−0.4, −0.3) & (0.3, 0.4]	0.96	7	0.93	8	0.72	7
[−0.5, −0.4) & (0.4, 0.5]	0.73	5	0.74	6	0.59	5
[−1, −0.5) & (0.5, 1]	0.60	11	0.56	14	0.52	14
[Min, −1) & (1, Max]	0.29	10	0.28	14	0.24	14

Panel C: Ratio of positive to negative forecast errors for positive *realizations of prior news*

Range of forecast errors	Positive prior abnormal return		Positive prior earnings changes		Positive prior forecast errors	
	Ratio of positive to negative FE (1)	% of total (2)	Ratio of positive to negative FE (3)	% of total (4)	Ratio of positive to negative FE (5)	% of total (6)
Overall	1.58	100	1.53	100	1.99	100
Forecast errors = 0		12		14		11
[−0.1, 0) & (0, 0.1]	1.86	31	1.82	33	2.33	33
[−0.2, −0.1) & (0.1, 0.2]	1.89	18	1.85	18	2.42	19
[−0.3, −0.2) & (0.2, 0.3]	1.85	10	1.66	9	2.22	10
[−0.4, −0.3) & (0.3, 0.4]	1.70	6	1.49	6	2.03	7
[−0.5, −0.4) & (0.4, 0.5]	1.52	5	1.28	4	1.70	4
[−1, −0.5) & (0.5, 1]	1.25	10	1.17	9	1.44	10
[Min, −1) & (1, Max]	0.62	8	0.58	7	0.83	6

Panel A provides statistics on forecast errors (FE) by sign of prior abnormal return, prior earnings changes, and prior forecast errors. Panel B (Panel C) reports the ratio of positive to negative forecast errors for observations that fall into increasingly larger and nonoverlapping symmetric intervals moving out from zero forecast errors for negative (positive) prior abnormal returns, prior earnings changes, and prior forecast errors. Prior abnormal return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by beginning-of-period price. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

*Significantly different than zero at a 1% level or better.

#Mean forecast error for positive prior news variables is significantly different than mean forecast error for negative prior news variables at a 1% level or better.

The impact of the tail asymmetry on the inference of underreaction to prior bad news can be seen in Panel B of Table 2, which presents the number of observations in increasingly larger nonoverlapping symmetric intervals starting from zero for the three prior bad news partitions. Even though large errors in the intervals [min, −1) and (1, max] make up a relatively small percentage of the observations in the bad news distributions of *PrAR*, *PrEC*, and *PrFE* (10%, 14%, and 14%, respectively), errors of these absolute magnitudes comprise 3.45 (=1/0.29) 3.57 (=1/0.28), and 4.17 (=1/0.24) bad news observations for every good news observation, respectively.

Apparent consistency across summary statistical indicators of analyst underreaction to prior bad news does not carry over to the case of prior good news. The mean error for the good news partitions of *PrAR* and *PrEC* reported in columns 2 and 4 of Panel A of Table 2 are negative, consistent with analyst *overreaction* (i.e., the mean forecast is too high following good news), but is positive in the case of good news *PrFE*, suggesting *underreaction*. These mixed parametric results are attributable to the fact that tail asymmetries, although relatively small compared to their bad news counterparts, are still sufficiently large to produce negative mean errors for both prior good news partitions of *PrAR* and *PrEC* (see Fig. 2). However, they are not large enough to generate a negative median for these variables because, as seen in Panel C of Table 2, there is an even greater *frequency* of small positive errors associated with middle asymmetries in the good news partitions than for unconditional distributions (e.g., the ratio of positive errors to negative errors is 1.86 in the interval [−0.1, 0), (0, 0.1] of the *PrAR* partition but only 1.63 in that same interval of the unconditional distribution). The middle asymmetries are thus sufficiently large to offset relatively small tail asymmetries in these good news partitions, leading to indications of underreaction to good news in nonparametric statistics.[15]

3.1.2. *Inferences about analyst efficiency from regression analysis*

While means, medians, and ratios of positive to negative forecast errors are viable statistics from which to draw inferences of analyst inefficiency, most studies rely on slopes of regressions of forecast errors on prior news variables. The most persistent findings from such regressions are significant positive slope coefficients that are consistent with overall analyst *underreaction* to prior news realizations. To examine

[15] In this study, as in any study that partitions prior news variables by sign, we treat all prior variables as if they were interchangeable for the purposes of drawing inferences concerning a general tendency toward analyst inefficiency. Clearly, partitioning on the sign of news is likely to lead to misclassification in the case of prior earnings news, since the average firm is *not* likely to have an expected change of zero. Moreover, both prior earnings changes and prior forecast errors entail the use of an earnings benchmark, which, as discussed in the next section, introduces another potential problem of classification associated with potential time-series correlations induced by earnings management. These are interesting issues worthy of further consideration. However, they do not preclude an analysis of how the tail and middle asymmetries in forecast error distributions have combined to generate inconsistent indications of analyst inefficiency in the existing literature. If anything, these issues further strengthen the case for adopting the approach of identifying salient features of distributions of forecast errors in an effort to develop more precise hypotheses and design more appropriate empirical tests.

Table 3
Slope coefficients from OLS and rank regressions of forecast errors on prior news variables

	Explanatory variable					
	Prior abnormal return		Prior earnings changes		Prior forecast errors	
	OLS	Ranked	OLS	Ranked	OLS	Ranked
Overall	0.744	0.162	0.819	0.160	0.238	0.253
	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Prior bad news	1.602	0.213	2.306	0.130	0.231	0.265
	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Prior good news	0.089	0.199	−0.835	0.157	0.045	0.170
	0.28	<0.01	0.01	<0.01	0.11	<0.01

This table reports slope coefficient estimates from OLS and rank regressions of forecast errors on prior abnormal return, prior earnings changes, and prior forecast errors with the White-corrected p-values. Prior abnormal return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by beginning-of-period price. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

the effect of the two asymmetries on this inference, we first estimate the slope coefficients for separate OLS and rank regressions of forecast errors on *PrAR*, *PrEC*, and *PrFE*. After applying White corrections suggested by the regression diagnostics, the estimates, as shown in the first row of Table 3, confirm that the typical finding reported in the prior literature of overall underreaction holds for all three prior news variables in our sample, inasmuch as all three coefficients are positive and reliably different from zero. Similarly, rank regressions produce significant positive slope coefficients in the case of all three prior news variables.

Next, we compare the inferences from regression slope coefficients estimated by the sign of prior news to assess their consistency with the parametric and nonparametric evidence presented in Panel A of Table 2 and the preceding regression results for the overall samples. These results are presented in Table 3. Consistent with regression results for the overall sample, prior bad news partitions of all three variables produce OLS and rank slope coefficients that are significantly positive, indicating once again analyst underreaction to prior bad news. These results are consistent with indications of underreaction in both the parametric and nonparametric summary statistics associated with all three bad news partitions reported in Panel A of Table 2. In sharp contrast, however, regression results for the prior good news partitions generate inconsistent indications across both OLS and rank regression slope coefficients and across prior news variables. The OLS slope coefficient is positive but insignificant in the case of good news *PrAR* and *PrFE*, resulting in a failure to reject efficiency in these cases, but it is reliably negative for the good news *PrEC* variable, consistent with analyst *overreaction* to prior good earnings news. That is, OLS performed on the prior good news partitions of forecast errors produces *no* evidence of apparent analyst underreaction observed both in the overall samples and in the prior bad news partitions. In contrast, and adding to the ambiguity, rank regressions do produce reliably positive slope coefficients consistent with underreaction for all three prior good news variables. This finding is also consistent with the rank regression results for both the overall samples and the prior bad news partitions for all three prior news variables that suggest analyst underreaction.

It is evident from the foregoing collection of parametric and nonparametric results that it is difficult to draw a clear inference regarding the existence and nature of analyst inefficiency with respect to prior news. These results are a microcosm of similar inconsistencies found in the literature on analyst efficiency with respect to prior news, examples of which are discussed below. In keeping with our goal of assessing the extent, to which theories that predict systematic errors in analysts forecasts are supported by the evidence, we next delve further into the robustness of specific findings concerning analyst-forecast efficiency. As in the case of inferences on bias in analysts' forecasts, we find inconsistencies and a lack of robustness of evidence, which are linked to the relative size of the two asymmetries present in forecast error distributions.

3.2. How robust is evidence of analyst underreaction to bad news?

To further isolate the disproportional influence of the asymmetries on statistics, we examine the relation between forecast errors and prior news variables in finer partitions of the prior news variables. Our goal is to demonstrate that while the statistical indications of analyst underreaction to prior bad news are largely consistent in Tables 2 and 3, the phenomenon is not robust in the distribution of forecast errors. Fig. 4 depicts the percentiles of the distributions of forecast errors for the lowest, highest, and the combined distribution of the 2nd through the 9th decile of each prior news variable. One pattern evident in all of the panels is that the most extreme prior bad news decile is always associated with the most extreme negative forecast errors.

The effect of this association is evident in Fig. 5, which summarizes the mean and median forecast errors by decile of prior news for all three variables: The largest negative mean error by far is produced in the 1st decile of all prior news variables. This finding helps explain why overall bad news partitions of prior news yield parametric means that are always consistent with analyst underreaction.[16]

To gauge the effect of observations in the lowest prior news decile (which, as seen in Fig. 4, are associated with extreme negative forecast errors), we reestimate the

[16] Furthermore, in unreported results we find that OLS regressions by individual deciles produce significant positive coefficients in *only* the 1st decile among all deciles associated with prior bad news for all three prior variables. The combination of greater (lower) variation in the independent variable and a strong linear (nonlinear) relation between prior news and forecast errors in the first decile (other deciles) contribute to these results, as we discuss later.

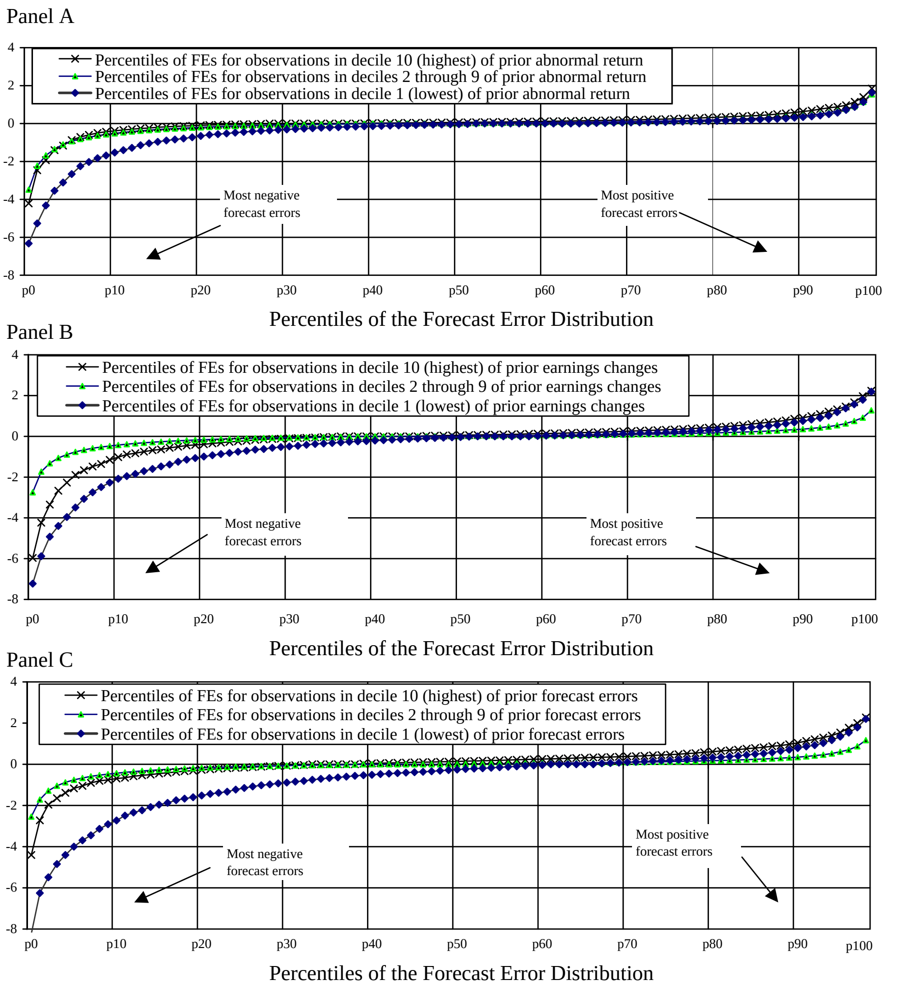


Fig. 4. The tail asymmetry in forecast errors within selected deciles of prior news variables. This figure depicts percentiles of quarterly distributions of analysts' forecast errors that fall in selected deciles (lowest, highest, and the combined distribution of the 2nd through the 9th decile) of prior abnormal returns (Panel A) prior earnings changes (Panel B) and prior forecast errors (Panel C). Forecast error equals reported earnings minus consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price. Prior market-adjusted return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the beginning-of-period price.

OLS regressions for the overall sample after excluding observations in this decile (unreported in the tables). We find that removing the 1st decile of prior news results in declines in the overall coefficients from values of 0.744, 0.819, and 0.238, to values

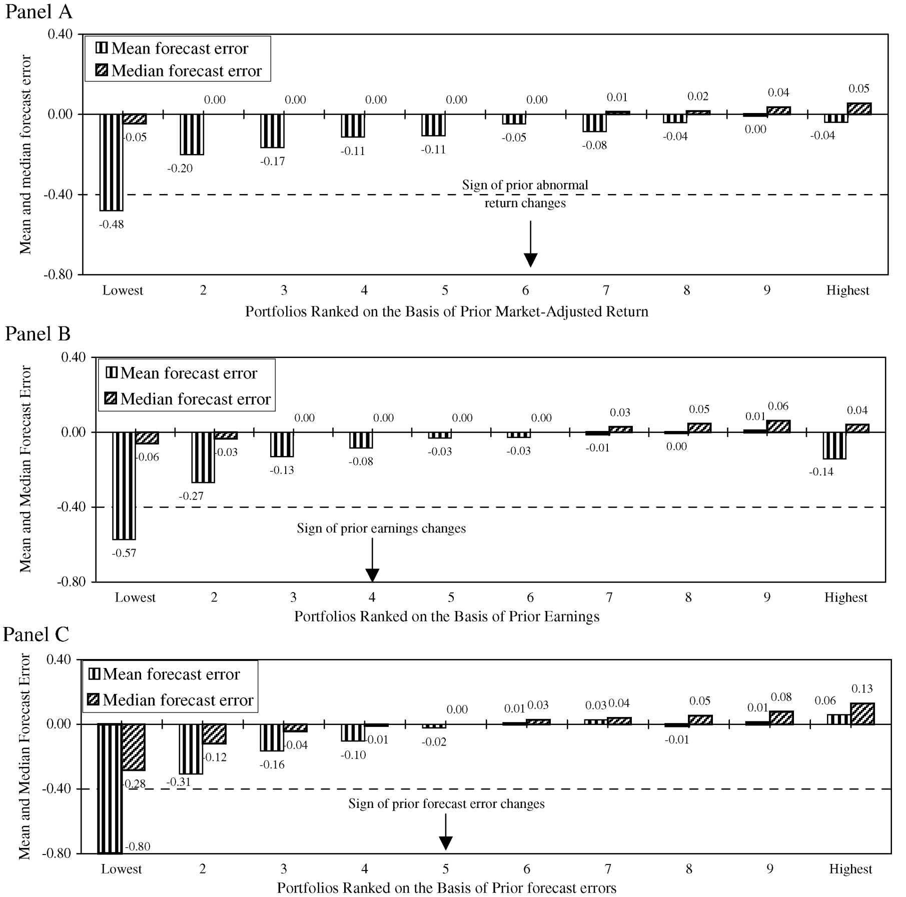


Fig. 5. Mean and median forecast errors by decile ranking of prior abnormal return (Panel A), prior earnings changes (Panel B), and prior forecast errors (Panel C). This figure depicts mean and median forecast errors for portfolios ranked on the basis of prior abnormal return (Panel A), prior earnings changes (Panel B), and prior forecast errors (Panel C). Prior abnormal return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the beginning-of-period price. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

of 0.380, -0.559, and 0.194, for *PrAR*, *PrEC*, and *PrFE*, respectively, and *t*-statistics are significantly reduced in each case. Removal of individual deciles 2–9 before reestimating the regressions leads to virtually no change in the coefficients for all three prior news variables, whereas removal of the 10th decile actually leads to increases in the coefficients for all three variables. Notably, the disproportionate influence of extreme forecast error observations associated with extreme prior news is an effect that is not specifically predicted by extant behavioral or incentive-based theories of analyst inefficiency.[17]

The middle asymmetry also contributes, albeit more subtly than the tail asymmetry, to producing OLS regression coefficients that are consistent with underreaction to bad news. As seen in the first row of Panels A–C of Table 4 ("Overall"), which presents the ratio of positive to negative forecast errors by deciles of all three prior news variables, the percentage of positive errors increases as prior news improves. Consider, for example, in Panel A, the evidence for the first 5 deciles of *PrAR*, which only pertain to prior bad news realizations. The steadily increasing rate of small positive errors as *PrAR* improves will contribute to a positive slope coefficient in OLS regressions of forecast errors on prior bad news, reinforcing an inference of underreaction from this statistic. The concern raised by evidence in the remaining rows of Panel A of Table 4 is that less extreme prior bad news generates increasingly higher incidences of small positive versus small negative forecast errors—that is, observations that represent exactly the opposite of analyst underreaction.

Finally, recall that nonparametric statistics, including percentages of negative errors, rank regression slopes, and medians, also provide consistent indications of analyst underreaction to bad news. The nonparametric evidence in Panel A of Table 4 suggests however that this finding is also not as robust as it first appears. In the case of *PrAR*, for example, only the two most extreme negative deciles are associated with a reliably higher frequency of negative errors, which would not be expected if analyst underreaction to bad news was a pervasive phenomenon. In fact, there is a monotonic increase in the rate of positive to negative errors in the deciles that contain bad news realizations, with the 3rd decile containing a statistically equal number of each, and deciles 4–6 containing a reliably *greater* number of positive than negative errors.[18] Thus, observations that form the tail asymmetry, which is most pronounced in extreme bad news *PrAR*, even have a disproportional impact on some nonparametric evidence of underreaction to bad news, including indications from medians, percentages of negative errors, and rank regressions.[19]

[17] It is not well recognized that the inference of underreaction to prior bad news generated by the parametric tests favored in the literature is common to all prior news variables and is always driven by the concentration of extreme negative errors associated with extreme prior bad news. This conclusion can be drawn from studies investigating over/underreaction to prior returns (see, e.g., Brown et al., 1985; Klein, 1990; Lys and Sohn, 1990; Abarbanell, 1991; Elgers and Murray, 1992; Abarbanell and Bernard, 1992; Chan et al., 1996) and studies investigating over/underreaction to prior earnings changes (see, e.g., De Bondt and Thaler, 1990; Abarbanell and Bernard, 1992; Easterwood and Nutt, 1999).

[18] The 6th decile of *PrAR* includes small negative, small positive, and a limited number of zero observations. The demarcation point of zero occurs in the 4th decile of *PrEC*, reflecting a greater likelihood of positive earnings changes than negative earnings changes. The demarcation occurs in the 5th decile of *PrFE*, reflecting both a high percentage of zero prior forecast errors as well as the higher incidence overall of positive versus negative errors associated with the middle asymmetry. As suggested in footnote 15, simply partitioning prior news at the value of zero (as is done in the literature) may not lead to appropriate comparisons with respect to analyst efficiency across prior news variables in all situations.

[19] Recall that rank regressions of forecast errors and prior news produce large positive and significant slope coefficients, consistent with underreaction to bad news prior returns even though the incidence of positive errors is equal to or greater than the incidence of negative forecast errors in all but the most

Table 4
Ratio of small positive to small negative forecast errors in symmetric regions by decile ranking of prior abnormal return (Panel A), prior earnings changes (Panel B), and prior forecast error (Panel C)

Range of forecast errors	Lowest	2	3	4	5	6	7	8	9	Highest
Panel A: Ratio of small positive to small negative forecast errors and percentage of total decile observations within deciles of prior abnormal return										
Overall	0.66	0.78	0.97	1.08	1.17	1.27	1.33	1.39	1.76	2.12
[−0.1, 0) & (0, 0.1]	1.39	1.12	1.35	1.51	1.53	1.61	1.66	1.75	1.84	2.43
	24%	30%	32%	34%	35%	36%	38%	36%	34%	31%
[−0.2, −0.1) & (0.1, 0.2]	1.11	1.16	1.26	1.24	1.49	1.53	1.46	1.54	2.41	2.60
	18%	19%	21%	19%	20%	21%	20%	20%	21%	21%
[−0.3, −0.2) & (0.2, 0.3]	0.75	0.83	0.99	1.15	1.14	1.31	1.72	1.56	2.02	2.64
	10%	11%	11%	11%	12%	12%	11%	12%	12%	11%
Panel B: Ratio of small positive to small negative forecast errors and percentage of total decile observations within deciles of prior earnings changes										
Overall	0.75	0.77	0.86	0.91	1.16	1.53	1.83	1.87	1.83	1.45
[−0.1, 0) & (0, 0.1]	1.52	1.30	1.18	1.14	1.38	2.10	2.36	2.07	2.00	1.98
	16%	21%	28%	41%	56%	54%	45%	33%	25%	18%
[−0.2, −0.1) & (0.1, 0.2]	1.25	1.15	1.11	1.08	1.29	1.57	2.24	2.54	2.20	1.91
	13%	19%	21%	23%	19%	20%	24%	25%	22%	15%
[−0.3, −0.2) & (0.2, 0.3]	0.97	0.98	0.91	0.79	0.93	1.19	2.03	2.17	1.98	2.19
	9%	12%	13%	12%	7%	9%	11%	13%	13%	11%
Panel C: Ratio of small positive to small negative forecast errors and percentage of total decile observations within deciles of prior forecast errors										
Overall	0.53	0.58	0.70	0.74	1.32	2.25	2.06	1.91	1.95	1.82
[−0.1, 0) & (0, 0.1]	1.10	0.90	0.91	0.87	1.50	3.02	2.22	2.05	2.09	1.65
	8%	15%	24%	37%	65%	58%	46%	33%	24%	13%
[−0.2, −0.1) & (0.1, 0.2]	1.27	0.94	0.88	0.90	1.16	2.17	2.68	2.59	2.75	1.99
	10%	17%	23%	25%	18%	21%	24%	25%	23%	16%
[−0.3, −0.2) & (0.2, 0.3]	0.90	0.71	0.69	0.64	1.28	1.69	2.16	2.66	2.20	2.32
	9%	12%	14%	11%	7%	8%	10%	14%	15%	13%

This table reports the ratio of small positive to small negative forecast errors for observations that fall into increasingly larger and nonoverlapping symmetric intervals moving out from zero forecast errors and the percentage of observations that fall in these intervals of the total nonzero forecast errors in that decile. Prior abnormal return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the beginning-of-period price. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

(*footnote continued*)
extreme deciles of bad news *PrAR*. This occurs because the most negative ranks of *PrAR* are paired with the most negative forecast errors, which when combined with the increasing incidence of pessimistic errors as bad news becomes less extreme (in principle, overreaction), accounts for an overall positive association in the rank slope coefficient that is consistent with apparent underreaction.

3.3. How robust is the evidence of misreaction to prior good news?

As seen in Tables 2 and 3, evidence can be found for either analyst underreaction or overreaction to prior good news, depending on the statistical approach and/or prior variable on which the researcher focuses. Our goal in this section is to examine the robustness of parametric evidence of analyst overreaction and nonparametric evidence of analyst underreaction to good news.

In Panel A of Fig. 4, the most extreme prior good news decile in the case of *PrAR* does not display a tail asymmetry substantially different from the combined deciles 2–9. In contrast, in the case of *PrEC* (in Panel B) the most extreme positive decile actually exhibits the second largest degree of tail asymmetry inasmuch the combined inner decile distribution (deciles 2–9) has a considerably smaller tail asymmetry. In the case of *PrFE*, depicted in Panel C, the most extreme positive decile displays a slightly greater degree of tail asymmetry than the combined deciles 2–9. Thus, although the tail asymmetry is always present in extreme prior good news deciles, there is considerable variation in the degree of tail asymmetry across extreme good news realizations of prior news variables—a phenomenon that once again is not contemplated by general incentive and behavioral theories.

The statistical impact of variation in the degree of tail asymmetries in extreme good news deciles across prior variables is reflected in the mean forecast errors by decile presented in Fig. 5. Notably, as seen in Panel B, the relatively large tail asymmetry associated with extreme good news *PrEC* leads to a negative mean error in the 10th decile (i.e., overreaction), which aligns with the large tail asymmetry observed in Panel B of Fig. 4. In contrast, mean forecast errors for the good news *PrEC* deciles 5–9 are small and in many cases significantly positive (i.e., consistent with underreaction) because the tail asymmetry associated with these observations is small. The disproportional influence of the 10th decile of *PrEC* is also evident in regression results. In addition to being responsible for the only overall prior good news partition that produces a significant OLS slope coefficient, it is the only individual decile comprising good news for any variable that produces a significant slope coefficient (unreported in the tables). We note that removal of the 10th decile from the overall regression of forecast errors on *PrEC* leads to an increase in the slope coefficient from a value of 0.819 to 3.17, with a corresponding increase in the t-statistic. That is, the strong negative association between forecast errors and prior good news in this decile, which contributes disproportionately to the finding of overreaction to good news, also introduces severe nonlinearity in the overall regression.[20]

[20] The increasing rate of small positive errors as good news becomes more extreme contributes to positive slope coefficients in OLS regressions of forecast errors on prior good news. This is analogous to the impact of increasing rates of positive errors as bad news becomes less extreme, an effect more evident when the most extreme decile of good news is removed. The concern here, however, is that more extreme prior news leads to higher incidences of less extreme positive forecast errors—a phenomenon that is not only counterintuitive but is not predicted by extant incentive and behavioral theories of analyst inefficiency.

The most extreme good news *PrEC* decile is, therefore, largely responsible for the negative slope coefficient and the negative mean observed for good news *PrEC* partitions, suggesting the dominant influence of a small number of observations from the left tail of the distribution of forecast errors in producing parametric evidence of overreaction to good news prior earnings changes. Easterwood and Nutt (1999) refer to regression results that indicate a combination of underreaction to bad news and overreaction to good news as *generalized optimism*. From the evidence presented thus far it is clear that a small number of extreme negative forecast error observations associated with both extreme bad and extreme good news *PrEC* realizations are largely responsible for this finding. The question of the robustness of the finding of generalized optimism is magnified in the case of statistical indications of overreaction to good news because, as was reported in Table 2, good news *PrAR* and *PrFE* do not generate consistent parametric evidence of generalized optimism, even in the extreme deciles. This lends a "razor's edge" quality to the result that hinges on whether there is a sufficiently large number of extreme bad and good news realizations associated with extremely negative forecasts.[21] Furthermore, ambiguity in interpreting the evidence is introduced because there is no extant behavioral or incentive theory of analyst inefficiency that predicts that, when overreaction occurs, it will be concentrated among extreme prior news and come in the form of extreme analyst overreaction.

Finally, just as in the case of prior bad news, the presence of asymmetries also raises questions about the robustness of nonparametric evidence of analyst misreaction to prior good news. Recall from Section 3.1.1 that, in contrast to parametric statistics, nonparametric statistics suggested analyst *underreaction* to prior good news for all three prior news variables. The evidence in Tables 2 and 4 indicates that large middle asymmetries reinforce nonparametric indications of underreaction—in particular, the increasing relation between the magnitude of good news and the likelihood of small positive forecast errors, a relation that is monotonic in the case of *PrAR* and *PrFE*. Thus, the middle asymmetry, and its variation with the magnitude of prior good news, has a disproportionate impact on the inference of underreaction to good news from nonparametric statistics, including indications from medians, percentages of negative errors, and rank regressions. Notably, the percentage of positive forecast errors is substantially larger than the percentage of negative errors even in the most extreme *PrEC* decile. That is, the decile largely responsible for producing the only statistical evidence that analysts overreact to good news displays a strong tendency for errors that are consistent with underreaction.

3.4. The tail and middle asymmetries and serial correlation in analysts' forecasts

The preceding results indicate that regression evidence of underreaction is disproportionately influenced by apparent extreme underreaction to extreme bad

[21] Easterwood and Nutt (1999) eliminate the middle third of the prior earnings news distribution before estimating OLS slope coefficients, which provide the statistical support for their conclusion that analysts underreact to bad news and overreact to good news. Clearly, this test design gives even greater weight to observations that comprise the tail asymmetry.

prior news and is also impacted by the increase in the middle asymmetry as prior news improves. The asymmetries have important impacts on alternative (to regression) tests of analyst inefficiency in the literature. For example, as mentioned earlier, the analysis of the relation between current and prior forecast errors is typically not couched in terms of over- or underreaction to signed prior news, but rather in terms of overall serial correlation in lagged analyst forecast errors (see, e.g., Brown and Rozeff, 1979; Mendenhall, 1991; Abarbanell and Bernard, 1992; Ali et al., 1992; Shane and Brous, 2001; Alford and Berger, 1999). These studies focus almost exclusively on parametric measures of serial correlation and primarily on the first lag, or consecutive period errors.

Table 5 presents the Pearson and Spearman correlation between consecutive quarterly forecast errors for the overall sample and within each of the deciles of current forecast errors. The mean correlations for the entire sample are statistically significant, with yearly averages of 0.15 and 0.22, respectively. Note that the first decile, which includes the observations in the extreme left tail that are associated with the tail asymmetry, produces the greatest Pearson and Spearman correlations of 0.17 and 0.19, respectively. In contrast, the correlations in all other deciles are much smaller and most often statistically insignificant in the case of the Pearson measure. It is interesting to note that if distributions of forecast errors were symmetric, then forming deciles on the basis of current forecast errors (a procedure only followed in Table 5) would be expected to attenuate, relative to the overall sample serial correlation, the estimated correlation in every decile. However, the facts that correlation is not attenuated in the most extreme negative forecast error decile (in fact, it is larger than the overall correlation) and that the Pearson correlation is insignificant in the most extreme positive forecast error decile are additional indications of the important role the tail asymmetry plays in the findings of serial correlation. We note that when the deciles are formed based on *prior* forecast errors (that is they are sorted on the independent variable, as is done in all other tests performed in the paper) we still find that Pearson correlations are highest in the most extreme negative forecast error decile.[22]

Finally, we note that the strongest Spearman correlations in the table, other than the most extreme negative decile of current forecast errors, are found in deciles 6 and 7, i.e., those with a high concentration of current and prior small pessimistic forecast errors. The evidence is also inconsistent with what would be expected based on forming deciles on current forecast errors, where correlation in the middle deciles would be driven to zero. The higher correlations in deciles 6 and 7 are found whether deciles are formed on current or prior forecast errors. The evidence suggests the need for further exploration into the role of observations in the middle asymmetry in producing estimated serial correlation consistent with apparent analyst underreaction to their own forecast errors.

[22] It is also interesting to note from columns 4 and 5 that the first decile is not only associated with the largest mean values for current forecast errors, but is also associated with the largest mean value among the prior (i.e., lagged) forecast error deciles.

Table 5
Serial correlation in consecutive-period forecast errors

Decile ranking of forecast errors (1)	Pearson correlation in consecutive forecast errors (2)	Spearman correlation in consecutive forecast errors (3)	Mean forecast errors (4)	Mean prior quarter forecast errors (5)
Lowest	0.17#	0.19#	−2.08	−0.79
2	0.04&	0.07#	−0.44	−0.26
3	0.03	0.06#	−0.17	−0.12
4	0.06#	0.05&	−0.06	−0.04
5	0.06#	0.03&	0.00	−0.07
6	−0.01	0.09#	0.03	0.04
7	0.01	0.08#	0.08	0.04
8	−0.02	0.04&	0.15	−0.01
9	0.00	0.04&	0.29	0.02
Highest	0.00	0.04&	0.90	−0.12
Overall	0.15#	0.22#	−0.13	−0.13

This table reports the Pearson and Spearman correlation coefficients and means of current and prior quarter forecast errors *within* deciles of the ranked (current) forecast error distribution. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by beginning-of-period price.

#(&) Represents a statistically significant correlation at a 1% (5%) level.

3.5. Summary and implications of the tail and middle asymmetries on inferences of analyst efficiency

An important conclusion from the analysis of conditional forecast error distributions is that the sign of prior news variables sorts observations from the tail and middle asymmetries in a manner that (1) reinforces the inference of underreaction found in parametric statistics for all prior *bad* news partitions, an inference that is largely the result of the dominant impact of the tail asymmetry; and (2) can create offsetting or reinforcing effects that contribute to producing conflicting signs of means and regression slope coefficients within and across different prior *good* news partitions of the variables. Thus, the presence of middle and tail asymmetries in conditional distributions of forecast errors helps explain why evidence of underreaction to bad news appears to be so robust in the literature while evidence of under- and overreaction to good news is not. Attenuation of means and slope coefficients due to the relatively greater impact of the middle asymmetry in good news distributions of forecast errors also helps explain why, in every study to date that employs parametric tests and concludes that analysts' forecasts are inefficient, the magnitude of misreaction to bad news is always found to be greater than the magnitude of misreaction to good news.

It is tempting to infer from the insignificance of slope coefficients pertaining to regressions of forecast errors on prior news generated for some good news partitions reported in Table 3 and in all inner deciles of distributions of all prior news variables that, apart from cases of extreme prior news, analysts produce efficient forecasts (see, footnote 16). However, the sensitivity of statistical findings in prior good news partitions documented above suggests that we exercise caution in reaching this conclusion. Results in Fig. 4 and Table 4, along with unreported results, verify that all decile partitions of *PrAR* and *PrEC* are characterized by both middle and tail asymmetries, and that every good (bad) news decile of *PrFE* is characterized by a middle (tail) asymmetry. While it is possible that failure to reject zero slope coefficients in the inner deciles is the result of a general tendency for analyst forecasts to be efficient when prior news is not extreme, we must concede the possibility that the lower variation in the independent variable and small numbers of observations associated with tail and middle asymmetries *within deciles* combine to produce nonlinearities and lower power in a manner that obscures evidence of analyst inefficiency. That is, slicing up the data into greater numbers of partitions does not appear to eliminate the potential impact of both asymmetries in influencing inferences concerning the existence and nature of analyst inefficiency in parametric tests.[23]

The evidence in this section reveals how asymmetries can produce and potentially obscure indications of analyst inefficiency, depending on the statistical approach adopted by the researcher. Next, we describe examples of procedures that (perhaps unintentionally) mitigate the impact of observations that comprise the asymmetries, but may not necessarily shed new light on the question of whether analysts' forecasts are efficient.

3.6. Data transformations, nonlinear statistical methods, and alternative loss functions

Apart from partitioning forecast errors in parametric tests and applying nonparametric tests, some studies implicitly or explicitly adjust the underlying data in order to attenuate the disproportional impacts and nonlinearities induced by the tail asymmetry. Two such approaches are truncating and winsorizing forecast errors. As in the case of inferences concerning bias discussed in Section 2, the effects of arbitrary truncations on inferences concerning analyst under- and overreaction can be significant. Keane and Runkle (1998), for example, argue that evidence of misreaction to prior earnings news is overstated as a result of uncontrolled cross-correlation in forecast errors. However, they explicitly state that their finding of efficiency—after applying GMM to control for bias in standard errors induced by cross-correlation—rests on having first imposed a

[23] Severe heteroscedasticity in the decile regression residuals are consistent with this argument. In addition, while we do not advocate arbitrary truncations of the data to mitigate the impact of the asymmetries we find that small symmetric truncations of tail observations within decile distributions similar to those described in the previous section for the unconditional distribution of forecast errors result in significant slope coefficients in many of the inner deciles of prior returns and prior earnings changes. Because small truncations of extreme observations reduce the number of observations in each decile and further reduce variation in the independent variable, it is possible that the statistical significance of the coefficients after truncation in these cases reflects the presence of analyst inefficiency and/or the elimination of the offsetting impact of the tail asymmetry in a manner that allows the middle asymmetry to dominate an inference of inefficiency.

sample selection criterion that results in the truncation of large forecast error observations in the extreme negative tail of the distribution. Their argument for doing so is that the Compustat reported earnings used to benchmark forecasts for such observations includes large negative transitory items that analysts do not forecast. Abarbanell and Lehavy (2002) show that tail asymmetries also characterize distributions of forecast errors based on the earnings reported by commercial forecast data sources such as I/B/E/S, Zacks, and First Call, which are, in principle, free of such special items. They also report a high correlation between the observations that fall into the extreme negative tail of the distribution of forecast errors calculated with Compustat-reported earnings and those that fall into the extreme negative tail of distributions calculated with earnings provided by forecast data services. Thus, it remains to be seen whether the finding of analyst forecast rationality continues to hold when GMM procedures are applied to untruncated distributions of forecast error based on "cleaned" reported earnings numbers rather than truncated distributions of forecast errors based on Compustat earnings.[24]

An alternative to arbitrarily truncating a subset of observations is to transform the entire distribution of forecasts, a common procedure used to eliminate nonlinearities, stabilize variances, or induce a normal distribution of forecast errors to avoid violating the assumptions of the standard linear model. For example, log and power transformations mitigate skewness and the disproportionate impact of extreme observations when the dependent variable is forecast errors. However, each type of transformation alters the structure of the data in a unique way, and it is possible for different transformations to yield different inferences concerning analyst inefficiency. That is, transformations of distributions of forecast error are not likely to lead to greater consensus in the literature unless strong a priori grounds for preferring one transformation to another can be agreed upon. Such grounds can only be found by gaining a better understanding of what factors are responsible for creating relevant features of the untransformed data—an understanding that in turn would require more exacting theories than have thus far been produced as well as more institutional research into the analysts' actual forecasting task.

Finally, instead of adapting the data to fit the model the researcher may choose to adapt the model to fit the data. Disproportionate variation in the degree of tail asymmetry as a function of the sign and magnitude of prior news suggests, at a minimum, that parametric tests of analyst inefficiency should be adapted to allow for the nonlinear relationship between forecast errors and prior news. For example, after Basu and Markov (2003) replaced the quadratic assumption in their standard OLS regression with a linear loss function assuming that analysts minimize absolute forecast errors, they found little evidence to support analyst inefficiency. Imposing this loss function has an effect similar to truncating extreme observations, since such

[24] We note that although arbitrarily truncating the dependent variable (e.g., Keane and Runkle, 1998) may seem to be a more egregious form of biasing a test, the evidence presented earlier suggests that arbitrarily truncating observations in the middle of the distribution of the prior earnings news (e.g., Easterwood and Nutt, 1999) can also create problems when researchers draw inferences about the tendency for analysts to misreact to prior news, inasmuch as this procedure can further accentuate the already disproportionate impact of the tail asymmetry.

observations are given less weight in the regression (as opposed to being removed outright from the distribution).[25]

Clearly there is something to be learned from examining how inferences change under different assumed loss functions. However, at this stage in the literature, the approach will have limited benefits for a number of reasons. First, while a logical case can be made for one loss function that leads to the failure to reject unbiasedness and efficiency, an equally strong case for a loss function that leads to a rejection of unbiasedness and efficiency can also be made, without either assumption being inconsistent with existing empirical evidence of how analysts are compensated. In such cases, the conclusion about whether analyst forecasts are rational will hinge on which assumption best describes analysts' true loss function—a subject about which we know surprisingly little.[26] Second, it is possible that some errors are actually partially explained by cognitive or incentive factors that are coincidental with or are exacerbated by other factors that give rise to the same errors the researcher underweights by assuming a given loss function. Finally, although assuming a given loss function—like the choice of alternative test statistics or data truncations—may lead to a statistical inference consistent with rationality, such an approach ignores the empirical fact that the two notable asymmetries are present in the distribution. Given their influence on inferences, providing compelling reasons for these asymmetries is a prerequisite for judging whether and in what circumstances incentives or cognitive biases induce analyst forecast errors.

In the next section we take a step toward understanding how the asymmetries in forecast error distributions arise by identifying a link between the presence of observations that comprise the two asymmetries and unexpected accruals included in the reported earnings used to benchmark forecasts. This link suggest the possibility that some "errors" in the distribution of forecast errors may arise only because the forecast was inappropriately benchmarked with *reported* earnings, when in fact the analyst had targeted a different earnings number.

4. Linking bias in reported earnings to apparent bias and inefficiency in analyst forecasts

4.1. Accounting conservatism and unexpected accruals

Abarbanell and Lehavy (2003a) argue that an important factor affecting the recognition of accounting accruals is the conservative bent of GAAP. Because

[25] Note that, as discussed earlier, there may be greater difficulty detecting irrationality (alternatively, a greater likelihood of failing to reject efficiency) using regression analysis once procedures that attenuate the impact of left tail observations are introduced because the middle asymmetry is still present.

[26] The fact that the evidence of misreaction to even extreme good news is mixed for different definitions of prior news and different parametric statistics presents a challenge to adapting behavioral theories to better fit the data. Unless we can identify a common cognitive factor that explains why differences in apparent misreaction depend on the extremeness of prior news, the empirical case for any form of generalized bias or inefficiency will hinge on a relatively small number of observations comprising the tail and middle asymmetries that are not predicted by the theory.

conservative accounting principles facilitate the immediate recognition of economic losses but restrict the recognition of economic gains, the maximum amount of possible income-decreasing accruals that a typical firm can recognize in a given accounting period will be larger than the maximum amount of income-increasing accruals (see, e.g., Watts, 2003). Table 6 provides evidence that supports this intuition.

The table presents selected summary statistics associated with cross-sectional distributions of firms' quarterly unexpected accruals over the sample period.[27] The mean unexpected accrual over the sample period is -0.217. While the distribution is negatively skewed, the median is 0.023 and the percentage of positive and negative unexpected accruals is nearly equal. It is evident from Table 6 that, while the unexpected accrual distribution is relatively symmetric in the middle, it is characterized by a longer negative than positive tail. For example, the magnitude of the average values at the 25th and 75th percentiles is nearly identical. However, symmetric counterpart percentiles outside these values begin to diverge by relatively large amounts, beginning with a comparison of the values at the 10th and 90th percentiles. The differences become progressively larger with comparisons of counterpart percentiles farther out in the tails. For example, the average 5th and 3rd percentile values are approximately 1.17 times larger than the average 95th and 97th percentiles, and the average value of the 1st percentile is 1.30 times larger than the average value of the 99th percentile. We stress that, although the percentile values of unexpected accruals vary from quarter to quarter, the basic shape of the distribution is similar in every quarter.

4.2. *Linking unexpected accruals to asymmetry in tails of forecast error distributions*

The measure of unexpected accruals we employ is based on historical relations known prior to the quarter for which earnings are forecast. Although the term "unexpected" is used, it is possible—in fact likely—that analysts will acquire new information about changes in the relations between sales and accruals that occurred during the quarter before they issue their last forecast for a quarter. Nevertheless, we can use the measure of unexpected accruals to identify, ex-post, cases in which significant changes in accrual relations did take place, and then assess whether the evidence is consistent with analysts' issuing a final forecast of earnings for the quarter either unaware of some of these changes or unmotivated to forecast them.

If analysts' forecasts do not account for the fact that some firms will recognize accruals placing them in the extreme negative tails of the distribution of unexpected accruals, then there will be a direct link between the negative tail of this distribution and the extreme negative tail of the forecast error distribution. The conjectured link

[27] Unexpected accruals reported in the tables are the measure produced by the modified Jones model applied to quarterly data (see Appendix A for calculations). To facilitate comparison with our forecast error measure, we express unexpected accruals on a per share basis scaled by price and multiplied by 100. As indicated earlier, the qualitative results are unaltered when we employ the unmodified Jones model and other estimation techniques found in the literature, including one that excludes nonrecurring and special items.

Table 6
Descriptive statistics on quarterly distributions of unexpected accrual, 1985–1998

Unexpected accrual	
Number of observations	33,548
Mean	−0.217
Median	0.023
Standard deviation	5.600
Skewness	−1.399
Kurtosis	16.454
% Positive	50.8
% Negative	49.2
% Zero	0.0
P1	−20.820
P3	−11.547
P5	−8.386
P10	−4.574
P25	−1.349
P75	1.350
P90	4.185
P95	7.148
P97	9.891
P99	15.945

This table reports descriptive statistics on quarterly distributions of unexpected accruals. Unexpected accruals are calculated using the modified Jones model as described in the appendix (expressed as unexpected accrual per share scaled by price and multiplied by 100).

is depicted in Fig. 6. The figure shows mean forecast errors in intervals of (+/−) 0.5% centered on the percentiles of unexpected accruals. For example, the mean forecast error corresponding to the Xth percentile of unexpected accruals is computed using observations that fall in the interval of $X-0.5$ to $X+0.5$ percentiles of the unexpected accruals distribution.

It is clear from Fig. 6 that extreme negative forecast errors are associated with extreme negative unexpected accruals. That is, the evidence suggests a direct connection between the tail asymmetry in the forecast error distribution (documented in earlier sections) and an asymmetry in tails of the unexpected accrual measure.[28] This link continues to be observed even when we employ consensus earnings estimates and reported earnings that are, in principle, stripped of

[28] Another example of this link relates to the evidence on serial correlation in forecast errors presented earlier. Recall from Table 5 that the most extreme prior forecast error decile is also associated with the most negative mean current forecast errors. In unreported results we find that this decile is also characterized by the largest negative lagged and current unexpected accruals observed for these deciles (whether forecast error deciles are formed on the current or prior forecast errors). Thus, consecutive quarters of large, negative unexpected accruals go hand-in-hand with consecutive quarters of extreme negative forecast error observations that, in turn, are associated with high levels of estimated serial correlation.

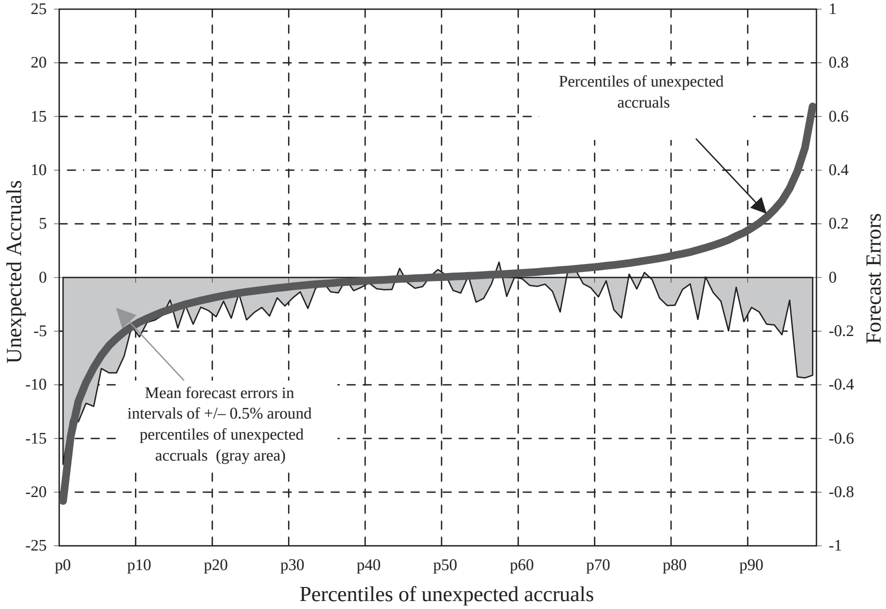


Fig. 6. Linking unexpected accruals and the asymmetry in tails of forecast error distributions. This figure depicts percentiles of unexpected accruals and mean forecast errors (gray area) in intervals of (+/−) 0.5% around unexpected accruals percentiles. For example, the mean forecast errors corresponding to the Xth percentile of unexpected accruals is computed using observations that fall in the interval of $X-0.5$ to $X+0.5$ percentiles of the unexpected accruals distribution. Forecast error equals reported earnings minus consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price. Unexpected accruals are the measure produced by the modified Jones model as described in the appendix (expressed as percentage of unexpected accrual per share scaled by price and multiplied by 100).

nonrecurring items and special charges (because Zacks indicates that analysts do not attempt to forecast these items), and a measure of unexpected accruals that also strips such items (see, Hribar and Collins, 2002). This suggests that an association exists between extreme negative accruals deemed "special or nonrecurring" and extreme negative accruals that do not fit this description. One possible reason for this association is that firms take an "unforecasted earnings bath," recognizing operating expenses larger than justified by the firm's actual performance for the period at the same time as they recognize large discretionary or nondiscretionary negative transitory operating and nonoperating items (see, Abarbanell and Lehavy, 2003b).

A second explanation for the association between large negative unexpected accruals and large negative forecast errors is that all the models of unexpected accruals examined in this study are prone to misclassifying nondiscretionary accruals as discretionary in periods when firms are recognizing large, negative transitory items. Combining the misclassification argument with a cognitive based argument that analysts react too slowly to extreme current performance would account for the observed link between unexpected accruals and forecast errors. While a more detailed analysis is beyond the scope of this paper, the evidence in Fig. 6 sheds additional light on the question of misclassification. It is seen in the figure that the largest percentiles of *positive* unexpected accruals are actually associated with fairly large negative mean forecast errors. The upside down U-shape that characterizes mean forecast errors over the range of unexpected accruals is inconsistent with a straightforward misclassification argument.[29] This is because if extreme positive unexpected accruals reflected misclassification in the case of firms that experience strong current performance, these would be the same cases in which analysts' forecasts would tend to underreact to extreme current good news and issue forecasts that fall short of reported earnings. The association between firm recognition of large negative transitory items and large negative operating items and the association between forecast errors and unexpected accruals are empirical phenomena that clearly deserve further exploration.

4.3. Linking unexpected accruals and the asymmetry in the middle of forecast error distributions

Table 7 provides evidence suggesting that unexpected accruals are also associated with the middle asymmetry in forecast error distributions. Column 2 presents a comparison of the ratio of positive to negative errors in narrow intervals centered on a zero forecast error (as reported in Panel B of Table 1) to the analogous ratio when forecast errors are based on reported earnings after "backing out" the realization of unexpected accruals for the quarter. In sharp contrast to the results reported in Table 1, the results in Table 7 indicate that after controlling for unexpected accruals, the number of small positive forecast errors *never* exceeds the number of small negative forecast errors in any interval. For example, the ratio of good to bad earnings surprises in the interval between [−0.1, 0) and (0, 0.1] is 1.63 (a value reliably different from 1) when errors are computed using earnings as reported by the firm, compared to 0.95 (statistically indistinguishable from 1) when errors are based on reported earnings adjusted for unexpected accruals. Thus, as in the case of the tail asymmetry, there is an empirical link between firms' recognition of unexpected accruals and the middle asymmetry. Given the impact of the tail and middle asymmetries on inferences concerning analyst bias and inefficiency described in Sections 2 and 3, researchers should take into account the role of unexpected accruals in the reported earnings typically used to benchmark forecast.

[29] The plot of *median* forecast errors around unexpected accrual percentiles also displays an upside down U-shape. However, as one might expect from the summary statistics describing the forecast error distributions in Table 1, the magnitude of these median errors is much smaller than mean errors, and large negative median forecast errors are only found in the most extreme positive and negative unexpected accrual percentiles.

Table 7
Linking unexpected accruals and the asymmetry in the middle of forecast error distributions

Range of forecast errors (1)	Ratio of positive to negative forecast errors based on *reported* earnings (2)	Ratio of positive to negative forecast errors based on earnings adjusted for unexpected accruals (3)
Overall	1.19*	0.96*
[−0.1, 0) & (0, 0.1]	1.63*	0.95
[−0.2, −0.1) & (0.1, 0.2]	1.54*	0.97
[−0.3, −0.2) & (0.2, 0.3]	1.31*	1.09
[−0.4, −0.3) & (0.3, 0.4]	1.22*	0.97
[−0.5, −0.4) & (0.4, 0.5]	1.00	0.99
[−1, −0.5) & (0.5, 1]	0.83*	0.95*
[Min, −1) & (1, Max]	0.40*	0.95*

This table provides the ratio of positive to negative forecast errors for observations that fall into increasingly larger and nonoverlapping symmetric intervals moving out from zero forecast errors. For example, the forecast error range of [−0.1, 0) & (0, 0.1] includes all observations that are greater than or equal to −0.1 and (strictly) less than zero and observations that are greater than zero and less than or equal to 0.1. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price. Earnings before unexpected accruals (used to compute the forecast error ratios in column 3) are calculated as the difference between reported earnings and the empirical measure of unexpected accruals.
*A test of the difference in the frequency of positive to negative forecast errors is statistically significant at or below a 1% level.

4.4. Explanations for a link between asymmetries in forecast error distributions and unexpected accruals

One general explanation for the link between unexpected accruals and the presence of asymmetries in forecast error distributions is that incentive or judgment factors that affect analysts' forecasts are exacerbated when estimates of unexpected accruals are likely to be unusual. For example, it is possible that cases of underreaction that appear to be concentrated among firms with the most extreme bad news reflect situations in which analysts have the weakest (strongest) incentives to lower (inflate) forecasts or suffer from cognitive obstacles that prevent them from revising their forecasts downward. At the same time, it has been argued in the accounting literature that unexpected accrual models produce biased downward estimates in exactly the same circumstances, i.e., when firms are experiencing extremely poor performance (see, e.g., Dechow et al., 1995).[30] This combination of

[30] The controversy over bias in unexpected accrual estimates relates to the issue of whether they truly reflect the exercise of discretion on the part of management. The conclusion that such measures are flawed is generally based on results from misclassification tests in which the maintained assumption is that historical data have not been affected by earnings management. This assumption can be challenged on logical grounds and, somewhat circularly, on the grounds that no evidence in the empirical literature supports this assumption.

potentially unrelated factors could account for the fact that extreme negative unexpected accruals accompany analysts' final forecasts for quarters characterized by prior bad news. Analogously, a higher incidence of small positive versus small negative errors as news improves is consistent with a greater likelihood of a *fixed* amount of judgment-related underreaction or incentive-based inflation of forecasts the better the prior news. The fact that unexpected accruals also appear to be related to the presence of the middle asymmetry may be coincidental to a slight tendency for unexpected accrual estimates to be positive in cases of firms experiencing high growth and positive returns (see, e.g., McNichols, 2000).[31]

Clearly there is a long list of possible combinations of unrelated factors that can simultaneously give rise to the two asymmetries in forecast error distributions and their apparent link to unusual unexpected accruals, which makes it difficult to pinpoint their source. Nevertheless, researchers still have good reason to consider these empirical facts when developing empirical test designs, choosing test statistics, and formulating and refining analytical models. One important reason is that if analysts' incentives or errors in judgment are responsible for systematic errors, it should be recognized that these factors appear to frequently produce very specific kinds of errors; i.e., small positive and extreme negative errors. To date, however, individual incentive and cognitive-based theories do not identify the economic conditions, such as extreme good and bad prior performance, that would be more likely to trigger or exacerbate incentive or judgment issues in a manner leading to exactly these types of errors. These explanations are also not easily reconciled with an apparent schizophrenia displayed by analysts who tend to slightly underreact to extreme good prior news with great regularity, but overreact extremely in a limited number of extreme good news cases. Finally, current behavioral and incentive-based theories do not account for actions undertaken by *firms* that produce reported earnings associated with forecast errors of the type found in the tail and middle asymmetries. Until such theories begin to address these issues it is not clear how observations that fall into the observed asymmetries should be treated in statistical tests of general forms of analyst irrationality. The identification of specific types of influential errors and their link to unexpected accruals documented in this paper provides a basis or expanding and refining behavioral and incentive theories of forecast errors.

A second reason for focusing on the empirical properties of forecast error distributions and their link to unexpected accruals is because it supports an alternative perspective on the cause of apparent forecast errors; i.e., the possibility that analysts either lack the ability or motivation to forecast discretionary biases in reported earnings. If so, then earnings manipulations undertaken to beat forecasts or to create reserves (e.g., earnings baths) that *are not* anticipated in analysts' forecasts

[31] McNichols (2000) argues that a positive association between unexpected accruals and growth reflects a bias in unexpected accrual models, but she does not perform tests to distinguish between this hypothesis and the alternative that high-growth firms are more likely to recognize a positive discretionary accrual to meet an earnings target, as argued in Abarbanell and Lehavy (2003a). We note that the presence of the middle asymmetry among firms with prior bad news returns and earnings changes is inconsistent with the misclassification argument.

may in part account for concentrations of small positive and large negative observations in distributions of forecast errors.[32] This suggests that evidence previously inferred to indicate systematic errors in analysts' forecasts might actually reflect the inappropriate benchmarking of forecasts.[33] An important implication of this possibility is that researchers may be formulating and testing new incentive and cognitive theories or turning to more advanced statistical methods and data transformations in order to explain forecast errors that are apparent, not real.

5. Summary and conclusions

In this paper we reexamine the evidence in the literature on analyst-forecast rationality and incentives and assess the extent to which extant theories for analysts' forecast errors are supported by the accumulated empirical evidence. We identify two relatively small asymmetries in cross-sectional distributions of forecast error observations and demonstrate the important role they play in generating statistical results that lack robustness or lead to conflicting conclusions concerning the existence and nature of analyst bias and inefficiency with respect to prior news. We describe how inferences in the literature have been affected, but these examples by no means enumerate all of the potential problems faced by the researcher using earnings surprise data. Our examples do demonstrate how some widely held beliefs about analysts' proclivity to commit systematic errors (e.g., the common belief that analysts generally produce optimistic forecasts) are not well supported by a broader analysis of the distribution of forecast errors. After four decades of research on the rationality of analysts' forecasts it is somewhat disconcerting that the most definitive statements observers and critics of earnings forecasters appear willing to agree on are ones for which there is only tenuous empirical support.

We stress that the evidence presented in this paper is not inconsistent with forecast errors due to analysts' errors in judgment and/or the effects of incentives. However, it does suggest that refinements to extant incentive and cognitive-based theories of systematic errors in analysts' forecasts may be necessary to account for the *joint* existence of both a tail asymmetry and a middle asymmetry in cross-sectional

[32] Abarbanell and Lehavy (2003b) offer theoretical, empirical, and anecdotal support for the assumption that analysts may not be motivated to account for or capable of anticipating earnings management in their forecasts. Based on this assumption they develop a framework in which analysts always forecast unmanaged earnings and firms undertake extreme income-decreasing actions or manipulations that leave reported earnings slightly above outstanding forecasts to inform investors of their private information. They describe a setting in which neither analysts nor managers behave opportunistically and investors are rational, where the two documented asymmetries in forecast error distributions arise and are foreshadowed by the sign and magnitude of stock returns before the announcement of earnings. In their setting, prior news predicts biases in the reported earnings benchmark, not biases in analysts' forecasts.

[33] Gu and Wu (2003) offer a variation on this argument suggesting that the analysts forecast the median earnings of the firm's ex-ante distribution, which also suggests that for some firms ultimate reported earnings (reports that differ from median earnings) are not the correct benchmark to use to assess whether analysts' forecasts are biased.

distributions of forecast errors. At the very least, researchers attempting to assess the descriptiveness of such theories should be mindful of the disproportionate impact of relatively small numbers of observations in the cross-section on statistical inferences.[34]

The evidence we present also highlights an empirical link between unexpected accruals embedded in the reported earnings benchmark to forecasts and the presence of the tail and middle asymmetries in forecast error distributions. Such biases in reported earnings benchmarks may point the way toward expanding and refining incentive and cognitive-based theories of analyst errors in the future. However, these results also raise questions about whether analysts are expected or motivated to forecast discretionary manipulations of reported earnings by firms. Thus, these results also highlight the fact that research to clarify the true target at which analyst forecasts are aimed is a prerequisite to making a compelling case for or against analyst rationality. Organizing our thinking around the salient properties of forecast error distributions and how they arise has the potential to improve the chaotic state of our current understanding of analyst forecasting and the errors analysts may or may not systematically commit.

Appendix A. The calculation of unexpected accruals

Our proxy for firms' earnings management, quarterly unexpected accruals, is calculated using the modified Jones (1991) model (Dechow et al., 1995); see Weiss (1999) and Han and Wang (1998) for recent applications of the Jones model to estimate quarterly unexpected accruals. All required data (as well as earnings realizations) are taken from the 1999 Compustat Industrial, Full Coverage, and Research files.

According to this model, unexpected accruals (scaled by lagged total assets) equal the difference between the predicted value of the scaled expected accruals ($NDAP$) and scaled total accruals (TA). Total accruals are defined as

$$TA_t = (\Delta CA_t - \Delta CL_t - \Delta Cash_t + \Delta STD_t - DEP_t)/A_{t-1},$$

where ΔCA_t is the change in current assets between current and prior quarter, ΔCL_t the change in current liabilities between current and prior quarter, $\Delta Cash_t$ the change in cash and cash equivalents between current and prior quarter, ΔSTD_t the change in debt included in current liabilities between current and prior quarter, DEP_t the current-quarter depreciation and amortization expense, and A_t the total assets.

[34] For example, given the recent attention in the literature to incentive factors that give rise to small, apparently pessimistic forecast errors (see footnote 5), it is important that researchers testing general behavioral theories understand that the middle asymmetry has the ability to produce evidence consistent with cognitive failures or, potentially, to obscure it. Similarly, the tail asymmetry has played a role in producing both parametric and nonparametric evidence that supports incentive-based theories of bias and inefficiency. However, such theories identify no role for extreme news or extreme forecast errors in generating predictions and do not acknowledge or recognize their crucial role in providing support for hypotheses.

The predicted value of expected accruals is calculated as

$$NDAP_t = \alpha_1(1/A_{t-1}) + \alpha_2(\Delta REV_t - \Delta REC_t) + \alpha_3 PPE_t,$$

where ΔREV_t is the change in revenues between current and prior quarter scaled by prior quarter total assets, ΔREC_t the change in net receivables between current and prior quarter scaled by prior quarter total assets, and PPE_t the gross property plant and equipment scaled by prior quarter total assets.

We estimate the firm-specific parameters, α_1, α_2, and α_3, from the following regression using firms that have at least ten quarters of data:

$$TA_{t-1} = a_1(1/A_{t-2}) + a_2\Delta REV_{t-1} + a_3 PPE_{t-1} + \varepsilon_{t-1}.$$

The modified Jones model resulted in 35,535 firm-quarter measures of quarterly unexpected accruals with available forecast errors on the Zacks database.

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