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Suppressed Negative Information and Future Underperformance*

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Abstract. I present evidence of inefficient information processing in equity markets by documenting that negative information withheld by securities analysts is incorporated in stock prices with a significant delay. I estimate the extent of the withheld negative information based on the proportion of analysts who stop revising their annual earnings forecasts. This measure predicts negative earnings surprises and negative price reaction around earnings announcements. It could also be used to generate profitable trading strategies. I show that institutions tend to sell their stock holdings as my measure of unreported negative news increases, thus ameliorating the mispricing.

JEL Classification: G12, G14, G20

1. Introduction

Firms that are doing badly are often reluctant to share the news with investors (see, e.g. Hong, Lim and Stein (2000)). Frequently, the bad news is suppressed not only by firms but also by the securities analysts who cover them. Analysts can be pressured to withhold bad news both by the management of firms they cover and by their own employers trying to secure an investment banking relationship with the firm. When the disadvantages of reporting bad news outweigh the advantages, analysts prefer to stop issuing forecasts over voicing

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negative opinions (McNichols and O'Brien (1997)). Because analysts face no pressure to withhold good news, diminished coverage is likely to be associated with bad news, and, most importantly, the bad news that is yet to become public. Although instances of reduced analyst coverage contain negative information, they are not easily identified—identifying them requires access to the entire cross-section of analysts' forecasts in real time. Such access has historically been costly and likely unavailable to retail investors who might act as price-setters for relatively smaller stocks. I document, consistently, that stock prices do not immediately reflect the negative information embedded in reduced analyst coverage, which I show to predict future stock underperformance. This result is more pronounced for the smaller stocks in the sample.

I use the I/B/E/S dataset of analyst earnings forecasts to identify instances of reduced analyst coverage. I/B/E/S carefully ensures the currency of earnings forecasts collected from individual analysts. Their research staff contacts analysts 105 days after the initial forecast to check whether it is still accurate. Forecasts 180 days past the issue date are considered outdated and removed from the dataset. Typically, on the Thursday before the third Friday of each month, the statistics describing the outstanding forecasts for a given firm are recorded in the I/B/E/S Summary file. The total number of outstanding forecasts is among other summary variables provided in the file. I compute changes in analyst coverage relative to the number of outstanding earnings forecasts for the same fiscal year 3 months earlier. Setting the reference point to 3 months ago is intended to underweight temporary declines in coverage, which might be due to data errors, relative to permanent declines in coverage, which will be manifested as such for 3 months running. Using this convention, I estimate that roughly 10–30% of the sample firms appear to experience a decline in analyst coverage in any given month.

To check whether declines in analyst coverage contain negative information for future returns, I construct portfolios based on whether or not analyst coverage has declined. I show that among stocks in the lowest and next lowest size quintiles of the sample of analyst covered firms, those for which analyst coverage has declined, underperform other stocks in their size quintile by 0.57 and 0.46% per month, respectively, on a risk-adjusted basis. Although the underperforming stocks belong to the lowest two quintiles of size distribution in the sample, they are by no means small stocks, the reason being that (1) analysts typically do not cover small firms, and (2) I exclude from the sample stocks priced below \$5 a share in order to minimize the noise caused by bid-ask bounce (following Jegadeesh and Titman (2001)). The average market capitalization decile assignment of the firms in the smallest size quintile is 5.50 in the beginning, and 3.84 at the end of the sample period, decile 10 containing the largest stocks (Table I).

I show the performance of firms with decreased analyst coverage to be strongly related to, albeit not fully explained by, momentum portfolio returns (Jegadeesh and Titman (1993)). This finding supports the view that the price momentum phenomenon is caused by underreaction to new information. Barberis, Shleifer and Vishny (1998) hypothesize that investors underreact to new information due to conservatism bias, and Hong et al. (2000) suggest that prices respond gradually and predictably to a gradual and predictable flow of information. The evidence presented in the paper consistently implies that bounded rationality or limited data processing capacity prevents the marginal investor from properly assessing the full extent of bad news embedded in analysts' silences.

I confirm that the future stock underperformance can be predicted by measures of withheld negative information. I devise an alternative measure of suppressed negative opinions, the positive skew in the distribution of outstanding analysts' forecasts. A positive skew implies the absence of highly pessimistic forecasts from the distribution of reported forecasts (this distribution should be symmetric if all forecasts are reported). I show that stocks with positively skewed forecasts underperform otherwise similar stocks in the future. This finding, similarly, suggests that the suppressed negative information is not immediately reflected in stock prices.

I subsequently attempt to estimate the magnitude of missing negative information embedded in reduced analyst coverage. I measure the suppressed negative information as the optimistic bias introduced into the mean outstanding forecast by supposedly pessimistic analysts who drop coverage. I assume that the missing analysts would have issued a forecast 1 cent below the currently lowest outstanding forecast. This parameterization is verified to be valid. When the ex-post earnings surprise is regressed on the estimated bias, controlling for other possible predictors, the estimated bias is shown to be a reliably significant negative predictor of the earnings surprise. I use this parameterized measure to show, again, that the suppressed negative information is not being immediately incorporated into stock prices. Information about annual earnings is revealed when quarterly earnings are announced. If stock prices already reflect the negative information withheld by analysts, my measure would not predict the stock price reactions around the earnings announcement days. However, I show it to be a significant negative predictor of announcement day returns, which implies that the marginal investor learns the full extent of bad news at the time of earnings announcements.

I have argued that prices fail to incorporate the information contained in reduced coverage due to information processing mistakes of the marginal investor. To confirm this claim, I check trading patterns of institutions, which are widely believed to be sophisticated investors. If my measure of missing negative information truly captures unreported bad news, institutions would sell their holdings as this measure increases. I show that institutions in the aggregate do, indeed, reduce their holdings of a stock when my measure of withheld negative information increases. Institutions thus trade against mispricing, thereby helping to ensure market efficiency. This finding not only confirms the validity of my measure of withheld negative information but also suggests that future underperformance of stocks that have experienced declines in analyst coverage is caused by their initial overpricing in the face of bad news rather than their lower riskiness.

The evidence presented in this paper contributes to the literature on bounded rationality. Retail investors, having limited capacity both to collect and analyze data are therefore prone to making information processing mistakes. Because firms and analysts prefer not to report bad news, the absence of new signals should, on average, be interpreted as bad news. But the marginal investor frequently fails to make this judgment with the result that stocks with indicators of withheld information predictably underperform in the future. Not surprisingly, this holds to a higher extent for smaller stocks, for which retail investors are more likely to be the price setters.[1] Due to the bounded rationality of the marginal investor, and possibly high arbitrage costs, agency problems that cause firms and analysts to withhold negative information end up reducing the informativeness of prices. Arbitrage might fail to correct the mispricing due either to high trading costs or short sale constraints.

The rest of the paper is organized as follows. Section 2 describes analysts' incentives. Section 3 presents empirical evidence that measures of currently withheld opinions predict future stock underperformance. Section 4 shows that institutions trade against the mispricing and thus help ameliorate the problem. Section 5 concludes. The data used in this paper are described in the appendix.

2. Analysts' Incentives and Self-selection in Coverage

Sell-side analysts are not paid directly by investors. Instead, they typically receive a percentage of trading commissions that their forecasts help generate for their brokerage houses. Given widespread unwillingness or inability to sell short, a "buy" recommendation would generate higher trading volume than a "sell" recommendation. More importantly, analysts who record a positive outlook improve their employers' odds of winning investment banking deals. Indeed, a number of recent papers have documented that the prospect of

[1] Odean (1998), Barber and Odean (1999), and Barber and Odean (2000) provide other examples of bounded rationality of retail investors.

securing investment banking deals induces analysts to express more optimistic views (see, e.g., Bradshaw, Richardson and Sloan (2003), Michaely and Womack (1999), Jegadeesh, Kim, Krische and Lee (2004), and Cowen, Groysberg and Healy (2003)).[2]

Historically, analysts have depended on firms' management for inside information, and managers could pressure analysts to issue optimistic reports by denying access to private information.[3] Studies show that analysts' earnings forecasts contain private information in addition to a statistical model based only on public information. Not surprisingly, access to private information is highly valued by investors. Institutional Investor, a firm that compiles annual analyst rankings, ranks access to management sixth out of thirteen valuable analyst attributes, ahead of accuracy of earnings estimates, written reports, stock selection, and financial modeling. The Regulation "Fair Disclosure," adopted in October 2000, forbids selective disclosure of information in order to make analysts more independent of the firm's management. But, as documented in the financial press, its implementation has encountered numerous difficulties (see, e.g., the Oct 2 2001 *New York Times* article, "In a Surprise Move, AOL Replaces Its Chief Financial Officer").

Analysts build influence and reputation by bing accurate. Reputational concerns prevent analysts from issuing overly optimistic forecasts. The pressure to be accurate, but at the same time not be pessimistic relative to other analysts, induces some analysts who have received a sufficiently low signal about a firm to drop coverage rather than issue a negative report. This phenomenon, first documented by McNichols and O'Brien (1997), has been termed "self-selection in analyst coverage." The *Wall Street Journal*'s Sep 6 2002 article, "Analysts Pressured on Reports," corroborates the empirical evidence: "One analyst was informed by an investment banker of the unwritten rule number one: 'If you can't say something positive, don't say anything at all.'"

3. Predicting Future Underperformance

3.1 THE SAMPLE

In this Section 1 explore whether stock prices reflect the negative information embedded in diminished analyst coverage. Reduced coverage is defined in terms of the number of analysts who stopped issuing or revising current fiscal

[2] For a description of agency problems in analysts' incentives in the popular press, see the June 2001 article in *Smart Money Magazine*, "Analyze This," and the Oct 8 1998 *Business Week* article, "Wall Street's Spin Game."

[3] See Lim (2001) for a model of the tradeoff analysts face between being accurate and issuing overly optimistic forecasts in exchange for better private signals from firm management.

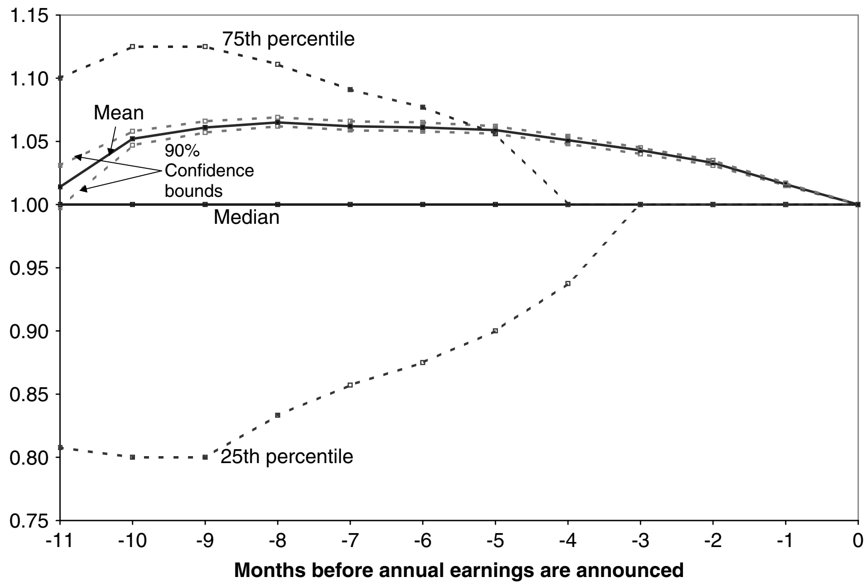

Figure 1. Analyst coverage through the fiscal year. In each month, the number of analysts issuing current fiscal year's earnings forecasts is scaled by the number of analysts issuing earnings forecasts in the final month before the annual earnings are announced. These fractions are then averaged across firms and the number of months remaining until the earnings announcement month and the statistics of the distribution plotted.

year earnings per share forecasts in the last 3 months. I focus on earnings forecasts, rather than recommendations, for two reasons. First, the accuracy of earnings forecasts is evaluated regularly, which should discourage analysts from reporting overly optimistic estimates. Second, for some of the tests, I parameterize the extent of missing negative information, and earnings forecasts constitute an appropriate context in which to do so.

The evolution of analyst coverage through the fiscal year is described in Figure 1. The figure plots the number of analysts who issue annual earnings per share forecasts as a fraction of the number of analysts who issue forecasts in the final month before earnings are announced, with the number of months remaining until the earnings announcement month on the X-axis. It can be seen that, for an average firm, analyst coverage increases slightly in the early part of the fiscal year, then declines later in the year. But considerable variability is observed in coverage patterns across firms. Computing the 75th and 25th percentiles of coverage reveals that, for some firms, initial coverage is high and declines significantly as the year progresses, and, for other firms, starts out low and increases later in the year.

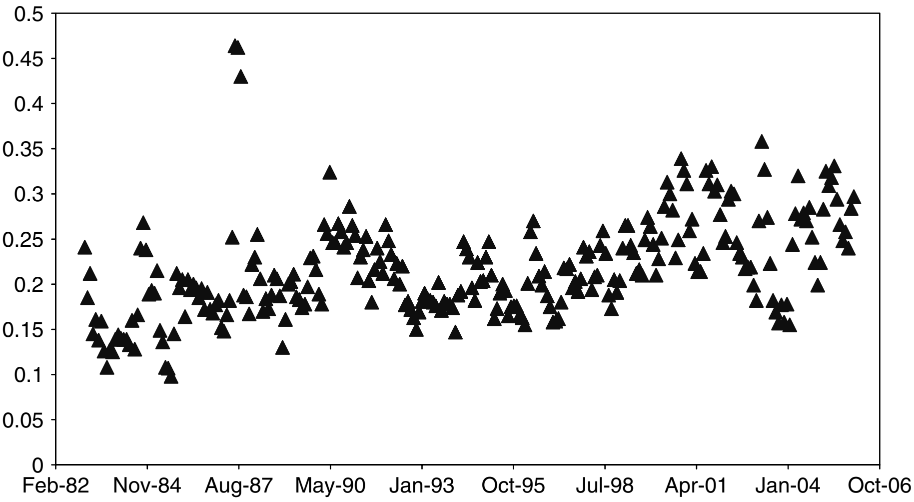

Figure 2. Fraction of firms for which analyst coverage has declined. This figure plots the fraction of firms in the I/B/E/S universe for which the number of analysts issuing current fiscal year's earnings forecasts has declined relative to the number 3 months ago.

Figure 2 plots the fraction of firms in the I/B/E/S universe for which I conclude analyst coverage has declined. Computing changes in coverage relative to the number of analysts who issued earnings per share forecasts for the current fiscal year 3 months ago automatically excludes from the sample firms in the first 3 months of their fiscal year. But because the sample comprises of firms with different fiscal year-ends, it contains observations in every month of the calendar year. The figure reveals that, by this measure, in any given month, roughly 10–35% firms in the cross-section have experienced diminished analyst coverage. This number increases somewhat over the sample period. The fraction of firms for which coverage has declined appears unusually high in 3 months of 1987 (July, August and September), which is caused by the permanent decline in coverage in July 1987. An I/B/E/S representative suggested that this decline was likely caused by an I/B/E/S policy change. Whereas presently, I/B/E/S research staff contact analysts 105 days post-issue to confirm the accuracy of outstanding forecasts, and deletes forecasts 180 days after the issue date, these periods might have been longer before June 1987. Excluding July, August and September 1987 from the analysis to reduce noise in the data does not significantly affect the results.

To minimize the problem of bid–ask bounce I restrict the sample to stocks priced at no less than $5 per share (following Jegadeesh and Titman (2001)). Partly because of this restriction, and partly because analysts do not typically cover small stocks, the sample used in this paper is composed predominantly of large stocks. The sample is described in Table I, which, as the portfolio strategies subsection, subdivides it into five equal quintiles based on firms' market capitalization. In January 1983, even the smallest size-based quintile contains relatively large firms with an average Center for Research in Security Prices (CRSP) market capitalization decile assignment of 5.50 (decile 10 containing the largest stocks). As of January 1983, the smallest size quintile contains none of the firms in the lowest two CRSP size deciles, only 3.63% of firms in the third size decile, and 10.23% in the fourth size decile.

Over time, analyst coverage has expanded to smaller firms. The average CRSP market capitalization decile assignment for the smallest quintile firms dropped to 4.17 in January 1995 and 3.83 in January 2005. But the 25th percentile distribution statistics indicate that coverage has not expanded sufficiently to include very small firms. As of January 1995, the smallest size quintile contains none of the firms in the smallest CRSP size decile, 4.73% of firms in the second, 12.23% in the third, and 33.95% in the fourth decile. In January 2005, among the firms in the lowest size quintile, 1.35% are in the smallest CRSP decile, 9.64% in the second, 22.14% in the third, and 38.71% in the fourth decile.

3.2 PORTFOLIO STRATEGIES BASED ON DECLINES IN ANALYST COVERAGE

To check whether firms that have experienced declines in analyst coverage underperform in the future I first construct portfolios based on whether or not coverage has recently declined. Each month, I subdivide the sample into five equal groups based on firms' market capitalization as of the end of the previous month, then subdivide each size group into two portfolios based on whether or not the number of analysts who issue current fiscal year's earnings forecasts has declined relative to that number 3 months ago. Stocks are held in the portfolio for 1 month, starting at the beginning of the following month, such that all information used in portfolio construction is publicly known for roughly 2 weeks. Portfolio returns are value-weighted. Since the reference point for calculating changes in analyst coverage is set to 3 months ago, a stock that has experienced a permanent decline in analyst coverage will be highlighted as such 3 months in a row and remain in the decreased-analyst-coverage portfolio for 3 months. I could have computed changes in coverage relative to 1 month ago and held stocks in the portfolio for 3 months, but with this alternative methodology, monthly fluctuations in analyst coverage that might have been caused by data errors would have greater effect on the results. Trying both methods, nevertheless, yielded quite similar results.

Table I. Sample Description

This table presents sample statistics for the sample of firms used in the paper. At each date presented in the table, the firms in the I/B/E/S universe are subdivided into five groups based on their market capitalization. NYSE market capitalization deciles are obtained from CRSP. Firms priced at less than $5 a share are excluded.

January 1983
Total number of firms: 1,515

	Size quintile				
	Small				Large
	S1	*S2*	*S3*	*S4*	*S5*
Average market capitalization (in millions of $)	32.62	78.22	163.75	380.88	2, 301.76
CRSP market capitalization decile:					
—Average	5.50	7.40	8.47	9.29	10.00
—Median	6	7	8	9	10
—25th percentile	5	7	8	9	10
—75th percentile	6	8	9	10	10
Average number of analysts issuing EPS forecasts	1.97	2.94	5.04	8.90	17.23

January 1995
Total number of firms: 2,960

	Size quintile				
	Small				Large
	S1	*S2*	*S3*	*S4*	*S5*
Average market capitalization (in millions of $)	42.84	104.29	224.13	590.62	4, 960.29
CRSP market capitalization decile:					
—Average	4.17	6.30	7.69	8.94	10.00
—Median	4	6	8	9	10
—25th percentile	4	6	7	9	10
—75th percentile	5	7	8	9	10
Average number of analysts issuing EPS forecasts	2.06	2.80	4.43	7.59	16.87

January 2005
Total number of firms: 3,320

	Size quintile				
	Small				Large
	S1	*S2*	*S3*	*S4*	*S5*
Average market capitalization (in millions of $)	146.81	380.12	814.65	1, 919.75	18, 670.30
CRSP market capitalization decile:					
—Average	3.83	5.98	7.51	8.74	9.90
—Median	4	6	8	9	10
—25th percentile	3	6	7	8	10
—75th percentile	5	6	8	9	10
Average number of analysts issuing EPS forecasts	2.41	4.32	6.11	8.53	15.66

Table II reports risk-adjusted portfolio returns and portfolio return differentials. I adjust portfolio returns relative to the Fama and French (1993) three-factor model (market, size, and book-to-market factors are downloaded from French's website) as well as to price momentum factor of Jegadeesh and Titman (1993) and earnings momentum factor of Chan, Jegadeesh and Lakonishok (1996). The price momentum factor is long stocks in the highest decile based on the past 12 months' cumulative return, and short stocks in the lowest decile (and is also downloaded from French's website). I construct the earnings momentum factor as the return differential between the value-weighted portfolios of stocks in the highest decile based on the change in the mean earnings forecast for the current fiscal year over the past 6 months, and stocks in the lowest decile, as described in Chan et al. (1996). As can be seen from the table, stocks in the smallest and next smallest size quintiles that have experienced declines in analyst coverage earn significantly negative risk adjusted returns (−0.54 and −0.40% per month, respectively) and underperform other stocks in their size group by, respectively, 0.57 and 0.46% per month.

Table III presents factor loadings for the long-short portfolio of the smallest quintile stocks, that is, short stocks that have experienced declines in coverage and long rest. The generally low R^2s suggest that the pricing factors used cannot explain the return differential. Moreover, the *Market* factor seems to have a significantly negative risk premium since firms for which analyst coverage has recently declined tend to have somewhat larger betas than firms for which coverage has been stable, but end up underperforming in the future. It is worth noting that the loading on the *Price Momentum* factor is significantly positive. Firms that have experienced declines in coverage have suppressed the negative information, which will be revealed gradually in the future, at which point their prices will adjust downward. The relation between returns on these stocks and momentum portfolio returns is not surprising if the price momentum phenomenon is also caused by the slow adjustment to new information.

3.3 PORTFOLIO STRATEGIES BASED ON SKEW IN THE FORECAST DISTRIBUTION

Analysts might withhold negative opinions not only by deciding not to issue new forecasts, but also by not initiating coverage in the first place, or by choosing not to revise initially optimistic estimates. Hence, I also employ an alternative measure of missing opinions based on the shape of the reported forecast distribution. If analysts' private signals are symmetrically distributed around true future earnings, reported forecasts should also be symmetrically

Table II. Estimated bias due to self-selection in coverage and portfolio returns

The top table reports portfolio alphas after regressing portfolio excess returns on the Fama and French (1992) three factors and price momentum and earnings momentum factors for the period January 1983–December 2005. Every month, stocks in the I/B/E/S universe are first sorted into five size groups based on the previous month's market capitalization and then, within each size group, into two further sub-groups based on whether analyst coverage has declined or not relative to 3 months ago. If analyst coverage has declined, the number of missing analysts (*missing*) is equal to the number of analysts that have stopped coverage. Portfolios are re-formed monthly and value-weighted. Stocks valued at less than \$5 per share are excluded; *t*-statistics are adjusted for autocorrelation. The bottom table reports average portfolio characteristics at the time of portfolio formation. Due to changes in I/B/E/S reporting, portfolios formed in July, August, and September 1987 and, hence, portfolio returns for August, September, and October 1987 are not considered.

Portfolio alphas

	Size					
	Small *S1*	*S2*	*S3*	*S4*	Large *S5*	All stocks
missing = 0	0.03	0.05	−0.03	−0.11	0.04	0.02
	(0.23)	(0.57)	(−0.27)	(−1.22)	(0.50)	(0.21)
missing > 0	−0.54[a]	−0.40[a]	−0.04	−0.11	−0.01	−0.02
	(−2.54)	(−2.51)	(−0.26)	(−0.84)	(−0.07)	(−0.23)
return difference	0.57[a]	0.46[a]	0.02	0.01	0.05	0.04
	(3.22)	(3.34)	(0.12)	(0.07)	(0.42)	(0.33)

Portfolio statistics

		Size				
		Small *S1*	*S2*	*S3*	*S4*	Large *S5*
missing= 0	Size ($\times 10^6$ \$)	52.91	143.15	313.54	772.30	6,808.65
	Number of missing analysts	0.00	0.00	0.00	0.00	0.00
missing> 0	Size ($\times 10^6$ \$)	58.50	146.67	317.09	793.97	8,020.77
	Number of missing analysts	1.16	1.25	1.33	1.44	1.70

Table III. Factor loadings

This table reports alphas and factor loadings for the return differential between the value-weighted portfolios of stocks with zero estimated bias and with positive estimated bias, formed of stocks in the smallest-quintile of stocks in the I/B/E/S universe (*S1*) as in Table II. The Fama and French (1992) three factors—market (Market), size (SMB), and book-to-market (HML)—as well as the price momentum factor of Jegadeesh and Titman (1993) (Price Mom) are downloaded from Kenneth French's website. The earnings momentum factor, based on Chan, Jegadeesh and Lakonishok (1996), is constructed as a return differential in value-weighted returns between stocks that are in the highest decile based on revision of the mean earnings forecast relative to 6 months ago and the stocks in the lowest decile. The sample period is January 1983–December 2005, but due to changes in I/B/E/S reporting, portfolios formed in July, August, and September 1987 and, hence, portfolio returns for August, September, and October 1987 are not considered; *t*-statistics are adjusted for autocorrelation.

Return difference between zero-bias and positive-bias portfolios for the smallest-quintile stocks

	Fama–french factors			Price	Earnings	R^2
Alpha	Market	SMB	HML	Mom	Mom	(%)
0.66[a]	−0.11[b]	−0.056	−0.01	–	–	1.93
(4.10)	(−2.29)	(−1.07)	(−0.09)	–	–	
0.55[a]	−0.08[c]	−0.067	0.02	0.10[b]	–	3.85
(3.11)	(−1.75)	(−1.23)	(0.27)	(2.18)	–	
0.57[a]	−0.08[c]	−0.09	0.01	0.13[b]	−0.05	4.31
(3.22)	(−1.77)	(−1.64)	(0.14)	(2.64)	(−1.18)	
0.67[a]	−0.11[b]	−0.06	−0.01	–	−0.01	1.61
(4.18)	(−2.26)	(−1.15)	(−0.14)	–	(0.26)	

[a,b,c] Statistically significant at the 1, 5, and 10 percent levels, respectively

distributed. When negative opinions are withheld, the forecast distribution is right-skewed. If investors do not adjust their valuations based on the shape of the reported forecast distribution, the right skew in the distribution will predict future stock underperformance. I construct portfolios based on the skew in the reported forecast distribution to check whether it predicts returns.[4] Skew is defined as the difference between the mean and the median forecast scaled by the absolute value of the mean forecast (scaling by stock price, instead, does not significantly affect the results). A mean forecast being higher than the median forecast implies more positive than negative outliers.

[4] I thank Dick Thaler for suggesting this test.

One concern about making cross-sectional comparisons of earnings forecast distributions at any given time is that firms in the I/B/E/S dataset can have different fiscal year ends. Most of the sample firms, 66.35%, have a December fiscal year end, 7.99%, a June fiscal year end, 6.24%, a September fiscal year end, and 5.66%, a March fiscal year end. Between 1 and 2% of firms have fiscal year ends in each of the other months. Signals about future earnings are likely to be less certain the further they are in time from the earnings announcement day. Annual earnings are the sum of four quarterly earnings numbers: $EPS = EPS^{Qtr_1} + EPS^{Qtr_2} + EPS^{Qtr_3} + EPS^{Qtr_4}$. If quarterly earnings are independent of each other, and the total uncertainty of the signal about the annual earnings number is equal to the sum of the uncertainty about each of the quarterly earnings signal: $\sigma^2_{EPS} = \sigma^2_{EPS^{Qtr_1}} + \sigma^2_{EPS^{Qtr_2}} + \sigma^2_{EPS^{Qtr_3}} + \sigma^2_{EPS^{Qtr_4}}$. If, in addition to being independent, quarterly earnings have the same level of uncertainty, $\sigma^2_{EPS^{Qtr}}$, the annual earnings signal has four times the uncertainty of the quarterly earnings signals: $\sigma^2_{EPS} = 4\sigma^2_{EPS^{Qtr}}$ and, after each quarterly announcement, the uncertainty about annual earnings falls by $\sigma^2_{EPS^{Qtr}}$. Assuming that the dispersion of analysts' signals about future earnings reflects the level of underlying uncertainty, reported forecasts will also be more spread out the further away they are from the annual earnings announcement day. Skew in the forecast distribution, forecast dispersion and a measure of withheld negative opinions, used later in the paper, depend on the degree to which outstanding earnings forecasts are spread out. One way to standardize these variables across firms with different fiscal year ends is to scale them by the square root of the number of quarterly announcements remaining in the year. I employ this scaling for skew, forecast dispersion, and the parameterized measure of withheld negative opinions. However, not scaling these variables does not significantly affect the results.

Each month, I subdivide the sample with at least three outstanding earnings forecasts into five groups based on the stocks' market capitalization as of the end of the previous month. Each size group is further subdivided into five groups based on the skew of the forecast distribution. Stocks are assigned portfolios as of the beginning of the following month, such that the information used in portfolio construction is publicly known for about 2 weeks. Stocks are held in the portfolio for 1 month and their returns value-weighted.

Table IV reports portfolio returns and the return differentials between negative and positive-skew portfolios adjusted, as in the earlier tests, for the three factors of Fama and French (1993) and the price momentum and earnings momentum factors. Consistent with my hypothesis, positive skew portfolios earn significantly negative returns (stocks with a symmetric forecast distribution appear to earn the highest returns, possibly because negative

Table IV. Skew in analyst forecast distribution and portfolio returns

The first part of the table reports portfolio alphas after regressing portfolio excess returns on the Fama and French (1992), three factors, and price momentum and earnings momentum factors for the period January 1983–December 2005. Every month, stocks in the I/B/E/S universe with at least three outstanding analysts' earnings forecasts are sorted first into five size groups based on the previous month's market capitalization and then, within each size group, into five further groups based on skewness in the earnings forecast distribution. Skew is defined as the difference between the mean and median outstanding forecast scaled by the absolute value of the mean forecast. To facilitate comparison across firms with different fiscal year-ends, the skew is divided by the square root of the number of quarters remaining until the month in which annual earnings are announced (this methodology assumes that news about annual earnings are revealed evenly and independently across quarters). Portfolios are re-formed monthly and value-weighted. Stocks valued at less than $5 per share are excluded; *t*-statistics are adjusted for autocorrelation. The second part of the table reports average portfolio characteristics at the time of portfolio formation.

Portfolio alphas

Skew	Size: Small S1	S2	S3	S4	Large S5	All stocks
Skew1 (low)	−0.06	0.22	0.06	0.06	−0.02	−0.01
	(−0.42)	(1.64)	(0.50)	(0.49)	(−0.18)	(−0.06)
Skew2	0.432	0.20	0.32[a]	0.04	0.09	0.11
	(2.14)	(1.51)	(2.35)	(0.36)	(0.83)	(1.30)
Skew3	0.09	0.20	0.13	−0.01	0.18[a]	0.12[c]
	(0.62)	(1.66)	(1.26)	(−0.13)	(2.64)	(1.97)
Skew4	0.20	0.16	−0.02	0.12	0.17[c]	0.06
	(1.23)	(0.93)	(−0.12)	(0.71)	(1.72)	(0.75)
Skew5 (high)	−0.42[a]	−0.08	−0.34[a]	−0.05	−0.23[b]	−0.22[c]
	(−3.25)	(−0.61)	(−2.51)	(−0.44)	(−2.11)	(−1.76)
Skew1–Skew5	0.36[a]	0.30[a]	0.40[a]	0.11	0.21	0.20
	(2.61)	(1.87)	(2.48)	(0.82)	(1.46)	(1.59)

Table IV. (Continued)

Portfolio statistics

Skew		Size: Small *S1*	*S2*	*S3*	*S4*	Large *S5*
Skew1	Skew	−0.12	−0.07	−0.06	−0.05	−0.02
	Dispersion	0.38	0.26	0.20	0.19	0.10
	Coverage	4.47	5.88	7.64	11.03	21.11
Skew2	Skew	−0.01	−0.01	−0.00	−0.00	−0.00
	Dispersion	0.04	0.03	0.03	0.02	0.02
	Coverage	4.50	5.80	7.60	11.12	23.20
Skew3	Skew	0.00	0.00	0.00	0.00	0.00
	Dispersion	0.05	0.04	0.04	0.03	0.02
	Coverage	4.55	5.87	7.74	11.54	24.07
Skew4	Skew	0.01	0.01	0.01	0.00	0.00
	Dispersion	0.04	0.03	0.03	0.03	0.02
	Coverage	4.56	5.85	7.72	11.20	23.01
Skew5	Skew	0.11	0.08	0.06	0.05	0.03
	Dispersion	0.35	0.28	0.21	0.20	0.12
	Coverage	4.63	6.18	8.11	11.54	21.34

outliers in the forecasts and, consequently, negatively skewed distributions also contain negative information). For example, the highest skewed portfolio in the smallest size quintile earned a negative risk-adjusted monthly return of −0.42%, which is highly statistically significant. Interestingly, the predictive power of skew for future returns does not gradually diminish with firm size, as in the previous portfolio test, possibly because skew is measured more precisely when there are more outstanding forecasts, and analyst coverage is highly correlated with size.

One potential concern is that the predictive power of skew for future stock returns might be related to the predictive power of dispersion in analysts' forecasts (Diether, Malloy and Scherbina (2002)). The subtable Portfolio Statistics lists average dispersion (defined, as in Diether, Malloy and Scherbina (2002), as the standard deviation in outstanding forecasts scaled by the absolute value of the mean forecast). Since dispersion is high for stocks with both positive and negative skew, the significance of the return differential between the two portfolios does not appear to be caused by stocks with a positively skewed distribution having higher analyst disagreement.

3.4 QUANTIFYING THE MAGNITUDE OF THE SUPPRESSED INFORMATION

Having established that the unreported negative information is not fully reflected in prices, I attempt to quantify its magnitude. Pessimistic analysts who withhold their views introduce an optimistic bias in the average outstanding forecast. I quantify the withheld negative information as the magnitude of this bias. The simplest and most intuitive assumption for assessing the magnitude of the bias is that analysts who stopped issuing earnings forecasts (missing analysts) would have issued a forecast 1 cent below the lowest outstanding forecast. As before, I define "missing analysts" as those who stopped issuing current fiscal year's earnings forecasts in the past 3 months (I could, as noted earlier, set the reference point to the past month without significantly affecting the results). Denoting the average outstanding forecast by EPS, the lowest outstanding forecast by EPS^{min}, the number of analysts who have issued forecasts by N, and the number of missing analysts by $missing$, the true average forecast is equal to $\frac{N*EPS+missing*(EPS^{min}-\$0.01)}{N+missing}$. The upward bias in the current average outstanding forecast can thus be denoted as:

$$\widehat{bias} = EPS - \frac{N * EPS + missing * (EPS^{min} - \$0.01)}{N + missing} \tag{1}$$

To make comparisons across firms, I scale this estimate by the stock prices as of the end of the previous month, and by the square root of the number of earnings forecasts remaining in the fiscal year.

Figure 3, which plots the monthly series of average estimated bias for all firms for which analyst coverage has declined, shows that the bias fluctuates, on average, between 0.6 and 1.9% of the price. The average number of missing analysts, on which the estimates are based, fluctuates between 1.2 and 2.0, with two outliers in early 1999.

I will show that $\widehat{bias}$ and skew in the reported forecast distribution are negative significant predictors of earnings surprises and market reaction around the earnings announcement days, consistent with my claim that they reflect suppressed negative information. The summary statistics for the variables used in these regressions are provided in panel A of Table V. Earnings surprise (*surprise*) is defined as the difference between the actual earnings number and the latest average forecast, scaled by stock price as of the most recent month-end. Although the median surprise is zero, the average surprise is negative, which is consistent with the previously documented evidence of analyst optimism. Cumulative returns around the earnings announcement days will be discussed later in the paper. As previously mentioned, $\widehat{bias}$, *skew*, and *dispersion* are scaled by the recent month-end stock price, and by the square root of the number of quarterly earnings announcements remaining in the fiscal year. Both the median $\widehat{bias}$ and the median *skew* observations are zero; the mean *skew* observation is slightly positive, indicating that there are, on average, more optimistic than pessimistic outliers in the distribution of reported forecasts. The average and median revisions in the mean forecast over the past 3 months are negative, consistent with the evidence from Bradshaw et al. (2003) that analysts prefer to issue optimistic forecasts early on and revise them downward gradually throughout the year. The distribution of market capitalization (ME) is highly right-skewed, which explains why, in the specifications in which market capitalization is the only independent variable, the regression R^2s are low despite the regression coefficients being statistically significant. The regressions were rerun using the $log(ME)$ specification because a logarithm tightens a variable's distribution. When the log transformation is used, the regression R^2s increase and the coefficients on size variable often become more significant, but, qualitatively, the results do not change. Throughout the paper, I report the results with the nontransformed ME variable.

Panel B of Table V also shows the correlations between the predictive variables. A quick look at the table reveals most variables to be significantly correlated. It is thus important to ensure that regression results are not being affected by the collinearity problem, which I do by including regression

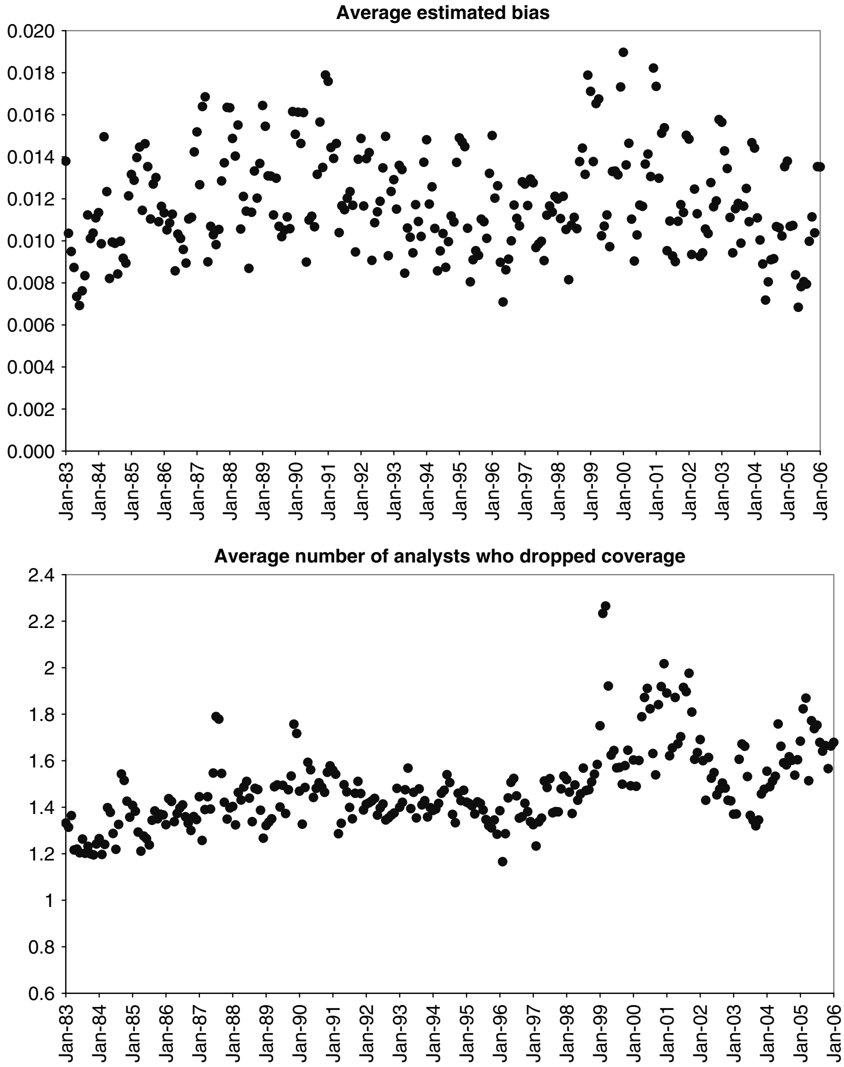

Figure 3. Average bias and drop in coverage for firms with reduced coverage. For the subset of firms for which the number of analysts issuing current fiscal year's earnings forecasts has declined relative to 3 months ago, the figures plot average estimated bias due to self-selection in analyst coverage and the average number of analysts who dropped coverage. The bias is estimated under the assumption that analysts who dropped coverage would have issued a forecast 1 cent below the current lowest earnings forecast: $\widehat{bias} = EPS - \frac{N * EPS + missing * (EPS^{min} - \$0.01)}{N + missing}$, where EPS is the current mean outstanding earnings forecast, EPS^{min} is the current lowest outstanding earnings forecast, N is the number of analysts currently issuing forecasts, and $missing$ is the number of analysts who dropped coverage. For each firm, the estimated bias is scaled by the end-of-previous-month price. Stocks priced at less than \$5 per share are excluded.

Table V. Variable description

This table reports summary statistics and correlations of the variables used in the subsequent regressions. Annual earnings surprise (*surprise*) is defined as realized annual earnings per share minus the latest average forecast, scaled by stock price as of the previous month-end. Cumulative abnormal return around the earnings announcement date (CAR) is the difference between the log-return on the stock and log-return on the CRSP value-weighted portfolio cumulated from 1 day before to 1 day after the quarterly earnings announcement day. Optimistic bias in the mean outstanding forecast resulting from self-selection in analyst coverage ($\widehat{bias}$) is estimated under the assumption that analysts who dropped coverage would have issued a forecast 1 cent below the current lowest earnings forecast: $\widehat{bias} = EPS - \frac{N * EPS + missing * (EPS^{min} - \$0.01)}{N + missing}$, where EPS is the current mean outstanding earnings forecast, EPS^{min} is the current lowest outstanding earnings forecast, N is the number of analysts currently issuing forecasts, and $missing$ is the number of analysts who dropped coverage. Skew in the reported forecast distribution (*skew*) is the difference between the mean and median outstanding forecast. Forecast dispersion (*dispersion*) is the standard deviation of the outstanding earnings per share forecasts. $\widehat{Bias}$, *skew*, and *dispersion* are estimated based on the latest available forecasts before the announcement date and scaled by price as of the previous month-end as well as by the square root of the number of quarterly earnings announcements remaining in the fiscal year in order to facilitate comparison across firms with different fiscal year-ends. Past-quarter forecast revision (*revision*) is the difference between the latest mean forecast preceding the earnings announcement day and the mean forecast 3 months ago, scaled by price. Market capitalization (*ME*) is the dollar value of all common equity as of the previous month. Book-to-market ratio (*BE*/*ME*) is the ratio of book value of equity to the market value of equity as of the last annual report. Book equity is defined as the Compustat book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, redemption, liquidation, or par value (in that order) are used to estimate the book value of preferred stock. Panel B reports Pearson correlation coefficients and their significance levels expressed as the probability of the true coefficient being zero. Stocks priced at less than \$5 per share are excluded. The sample period is January 1983–December 2005.

Panel A: Descriptive statistics

	Mean	Median	Standard deviation
Annual earnings surprise ($\times 10^{-2}$) (*surprise*)	-0.53	0.00	3.59
3-day cumulative abnormal return ($\times 10^{-3}$) (CAR)	−0.53	0.19	24.23
Estimated bias due to self-selection ($\times 10^{-2}$) ($\widehat{bias}$)	0.24	0.00	0.78
Skew in the forecast distribution ($\times 10^{-2}$) (*skew*)	0.01	0.00	0.45
Forecast dispersion ($\times 10^{-2}$) (*dispersion*)	0.47	0.19	1.33
Past-quarter forecast revision ($\times 10^{-2}$) (*revision*)	−0.64	−0.03	2.99
Market capitalization (in millions of \$) (*ME*)	2, 420.38	382.80	11, 550.62
Book-to-market ratio (*BE*/*ME*)	0.68	0.58	0.49

Table V. (Continued)

Panel B: Pearson correlation coefficients

	$\widehat{bias}$	*skew*	*dispersion*	*revision*	*ME*	*BE/ME*
$\widehat{bias}$	1	−0.01 (0.004)	0.23 (<.0001)	−0.21 (<.0001)	−0.04 (<.0001)	0.06 (<.0001)
skew		1	0.08 (<.0001)	−0.11 (<.0001)	−0.01 (0.1094)	0.03 (<.0001)
dispersion			1	−0.49 (<.0001)	−0.05 (<.0001)	0.27 (<.0001)
revision				1	0.03 (<.0001)	−0.11 (<.0001)
ME					1	−0.11 (<.0001)

specifications with subsets of predictive variables and with one predictive variable at a time. It can be seen that regression coefficients do not significantly change across specification, and therefore, variable collinearity does not pose a problem for the tests performed here.

That $\widehat{bias}$ and *skew* are negatively correlated might seem to contradict the view that both capture the missing negative opinions. But in the case that it is the initially more optimistic analysts who tend to drop coverage, firms for which coverage has recently declined would have more negative than positive outliers in the distribution of the reported earnings forecasts. This would explain the negative correlation between these variables. Therefore, *bias* and *skew* could be seen as complementary indicators of the withheld negative views. The positive correlation of $\widehat{bias}$ with *dispersion* is not surprising given its definition in Equation (1). The $\widehat{bias}$ estimate would be higher the further the lowest outstanding forecast is from the mean, and this distance would increase with forecast dispersion. The positive correlation between *skew* and *dispersion* is also expected inasmuch as the optimistic outliers will be further from the median the more spread out the forecast distribution. Analyst disagreement, declines in coverage, and the positive skew in the forecast distribution often increase in response to bad news, which is usually accompanied by downward forecast revisions. Therefore, $\widehat{bias}$, *skew* and *dispersion* are significantly negatively correlated with revisions in the mean forecast over the past 3 months. Finally, all three variables tend to be higher for smaller firms (which are less transparent) and for value firms.

Indicators of withheld opinions as the negative predictors of the earnings surprise

To validate $\widehat{bias}$ and *skew* as measures of the negative information suppressed by analysts, I check whether they are negative predictors of earnings surprises relative to mean reported forecasts. I use the latest set of outstanding forecasts before the annual earnings announcement is made and require that observations included in the regression have valid stock market data and defined observations of $\widehat{bias}$, which would be equal to zero if none of the analysts stopped issuing estimates during the prior quarter. This requirement leaves 56,021 eligible firm-year observations. This number is reduced to 40,963 firm-year observations in regression specifications that require that *skew* and *dispersion* are defined (recall that for *skew* to be defined, at least three analysts must issue forecasts).

Common earnings shocks caused, for example, by unanticipated industry-wide or economy-wide events would affect many firms simultaneously and induce cross-sectional correlations in earnings surprises across firms. If not accounted for in the pooled-cross-section-and-time-series regressions, the cross-sectional correlations would lead one to underestimate the ex-ante variability of the earnings surprise and produce upwardly biased significance levels for the coefficient estimates. To deal with the potential issue of the cross-sectional correlation, I employ the Fama and MacBeth (1973) methodology. Regression coefficients are estimated in two steps. First, I run for each calendar quarter, each year, cross-sectional regressions for the subset of firms that made annual earnings announcements at that time (i.e. I run separate regressions for the sets of firms that made earnings announcements from January 1, 1983, to March 31, 1983, from April 1, 1983, to June 30, 1983, and so on). Having obtained a time series of the regression coefficients from the set of cross-sectional regressions, I report the average and its *t*-statistic adjusted for the potential time series correlation in the estimates with the Newey and West (1987) correction.

The regression results, reported in Table VI, support the conjecture that the variables that measure unreported negative information are, indeed, negative and significant predictors of the earnings surprise. The regression intercept is always negative, consistent with the evidence presented in Table V that the average earnings surprise is negative. In the regression specification with only the constant term, the intercept is lower than the mean estimate reported in Table V. The reason is that these are not pooled regressions; the intercept is obtained by averaging earnings surprises first within each calendar quarter and then across quarters.

When $\widehat{bias}$ is included in addition to the intercept, its coefficient estimate is -0.53 (with the *t*-statistics of -3.28). That it is roughly half of the expected

Table VI. Predictors of the earnings surprise

This table reports results of the Fama and MacBeth (1973) regressions of annual earnings surprises on a set of predictive variables, defined as in Table V. Regressions are implemented as follows. First, in each calendar year-quarter, regression coefficients are obtained from the cross-sectional regression for firms making annual earnings announcements in that quarter (i.e., January 1–March 31, 1983, April 1–June 30, 1983, and so on). The regression coefficients are then averaged across quarters and the *t*-statistics adjusted for autocorrelation. Average adjusted R^2 of the cross-sectional regressions are reported. Stocks priced at less than \$5 per share at the end of the month prior to the earnings announcement are excluded. The sample period is January 1983–December 2005.

intercept ($\times 10^{-2}$)	$\widehat{bias}$	*skew*	*dispersion*	*revision*	*ME* ($\times 10^{-12}$)	*BE/ME* ($\times 10^{-2}$)	*Adjusted* R^2 (%)
−0.43[a]	−0.18[b]	−0.39[b]	−0.91[a]	0.20[a]	−0.03	0.59[a]	22.70
(−4.91)	(−2.59)	(−2.02)	(−9.97)	(4.13)	(−0.04)	(3.60)	
− 0.73[b]	−0.39[a]	–	–	0.18[a]	0.48[a]	0.17	8.42
(−2.58)	(−3.67)	–	–	(2.96)	(2.80)	(0.33)	
− 0.50[a]	–	−0.52[a]	–	0.39[a]	0.20[b]	0.14	15.22
(−6.01)	–	(−3.06)	–	(5.48)	(2.03)	(1.15)	
−0.91[a]	–	–	–	–	–	–	0.00
(−7.68)	–	–	–	–	–	–	
−0.72[a]	−0.53[a]	–	–	–	–	–	1.64
(−7.20)	(−3.28)	–	–	–	–	–	
−0.67[a]	–	−0.65[a]	–	–	–	–	8.51
(−6.82)	–	(−3.05)	–	–	–	–	
−0.28[a]	–	–	−1.05[a]	–	–	–	16.39
(−4.87)	–	–	(−7.70)	–	–	–	
−0.71[a]	–	–	–	0.22[a]	–	–	5.45
(−7.73)	–	–	–	(3.72)	–	–	
−0.96[a]	–	–	–	–	0.94[a]	–	−0.00
(−7.46)	–	–	–	–	(3.31)	–	
−0.91[b]	–	–	–	–	–	0.03	2.02
(−2.61)	–	–	–	–	–	(0.05)	

[a,b,c] Statistically significant at the 1, 5, and 10 percent levels, respectively

value of -1 implies that the estimate of bias is about twice the actual magnitude. The assumption that missing analysts would have issued a forecast \$0.01 below the lowest outstanding forecast is thus an aggressive one; in fact, some would have issued estimates that are equal to or even above the lowest outstanding forecast. The economic magnitude of the coefficient is significant. When bias increases from its median value of zero to its median value, conditional on being positive, of 1.31% of the stock price, the earnings surprise decreases by 0.69% of the price.

The skew in the forecast distribution is also a robust and significant negative predictor of the earnings surprise. When it is the only predictive variable, the coefficient is -0.65, with the t-statistics of -3.05. Therefore, a one standard deviation increase in *skew*, equal to 0.45% of the stock price, on average, leads to a decrease in the earnings surprise of 0.29% of the stock price.

Analyst disagreement is also a highly significant negative predictor of the earnings surprise. As explained earlier, analysts' incentives to issue optimistic forecasts are kept in check by their reputational concerns. Because reputational costs are likely to be lower when earnings are highly uncertain, and, consequently, earnings forecasts more dispersed, optimistic bias in the mean forecast will be correlated with forecast dispersion. Lim (2001) proposes an alternative explanation. He conjectures that the quality of information analysts receive from the firms they cover increases in the degree of their optimism. Inside information is more valuable when earnings are uncertain, hence, optimistic bias will increase in earnings uncertainty and, therefore, in the dispersion of analysts' forecasts. Jackson (2005), who formally solves the analysts' optimization problem, obtains a similar prediction. Consistent with the evidence of the optimistic bias increasing with forecast dispersion, Gebhardt, Lee and Swaminathan (2001) find that the firm cost of capital implied by analysts' forecasts of earnings and the earnings growth rates increase in the dispersion of the earnings forecasts. To the extent that biases in analysts' forecasts influence market prices, a strong positive relationship between optimistic forecast bias and dispersion might explain to some degree the future underperformance of high-dispersion stocks documented by Diether et al. (2002).

The revision of the mean forecast over the past quarter is a positive and significant predictor of the earnings surprise. This relationship is even stronger for the subsample with negative revisions (results are available upon request), suggesting that the average analyst tends to underreact to news, and more so to bad news.

That earnings forecasts tend to be more optimistic for smaller firms is, again, consistent with the Lim (2001) conjecture, inasmuch as smaller firms tend to be less transparent. Additionally, analysts tend to be slightly more optimistic about growth than value firms, but the relationship is not very significant.

Indicators of withheld opinions as the negative predictors of returns around earnings announcements

Although suppressed negative opinions introduce an upward bias in the mean outstanding earnings forecast, they will not predict returns if the marginal investor properly adjusts for them in his valuation. I have already shown this not to be the case by documenting that stocks with missing negative opinions underperform otherwise similar stocks in the future. Here I use earlier proxies for missing negative opinions to predict underperformance around earnings announcements, further confirming the conjecture that the marginal investor learns the full extent of suppressed negative information about earnings only at the time it becomes public. Note that if the underperformance documented in Tables II and IV were evenly spread throughout the year, the tests for predicting cross-sectional return differences in the short window around earnings announcements would not yield statistically significant results. Hence, underperformance must be more pronounced around earnings announcements to be detectable.

I compute abnormal cumulative returns around quarterly earnings announcement days in the following way. I assume that all returns can be described by the market model with $\beta = 1$:

$$r_{it} = r_{mt} + \varepsilon_{it} \tag{2}$$

where r_{it} and r_{mt} are daily log-returns on an individual stock and the CRSP value-weighted index, respectively.[5] Assuming day 0 to be the announcement date, the cumulative abnormal return (CAR) is estimated as:

$$CAR_{it} = \sum_{\tau=-1}^{\tau=1} (r_{i\tau} - r_{m\tau}) \tag{3}$$

Even though Equation (3) takes the market return out of the estimation of the price reaction, *CAR*s could still be cross-sectionally correlated if the 3–day estimation windows overlapped and the return loadings on the market factor were not equal to 1 as assumed in the formula. The significance of the regression coefficients would thus be overstated if regressions with CAR as the dependent variable were pooled over the cross-section and time-series. To deal with cross-sectional correlations in the *CAR*s, I once again employ the Fama and MacBeth (1973) methodology. As before, I subdivide the sample into calendar quarters (January 1 1983 through March 31 1983;

[5] Brown and Warner (1985) find this model to perform as well as the more sophisticated models.

April 1 1983 through June 30 1983, and so on) and then run cross-sectional regressions of CAR on a set of explanatory variables for the quarterly earnings announcement observations in each calendar quarter. Having obtained the time series of regression coefficients from the cross-sectional regressions, I compute the average estimate and corresponding $t-$statistics, adjusted for autocorrelation.[6]

The regression results reported in Table VII are based on 98,568 firm-quarter observations in the specifications in which both *skew* and *dispersion* variables are defined, and on 109,813 observations in the specifications that require only $\widehat{bias}$ variable to be defined. It can be seen that both $\widehat{bias}$ and *skew*, the variables that capture missing negative information, are robust and significant negative predictors of returns around quarterly earnings announcement days. In the regression specification in which $\widehat{bias}$ is the only predictive variable, the regression coefficient is −0.1560 with the *t*-statistic of −3.85. This means that when *bias* increases from 0 to its median value, conditional on being positive, of 1.31% of the stock price, the 3-day return around the earnings announcement day declines by 0.20%. Similarly, in the specification in which *skew* is the only predictor, the coefficient is −0.3335 with the *t*-statistic of −2.89, implying that a one-standard deviation increase *skew* of 0.45% of the stock price leads to a 0.15% decrease in the 3-day cumulative return around the earnings announcement.

Another significant negative predictor of returns around earnings announcements is $dispersion$. Its predictive power is tied to the resolution of uncertainty at the time of the announcement. Invoking the Miller (1977) hypothesis, Diether et al. (2002) argue that analyst disagreement proxies for the general level of disagreement about stock value, and that in the presence of short-sale constraints prices tend to reflect the more optimistic views. The optimistic views should be corrected down when the uncertainty about firm valuation is resolved. The initial overpricing of high-dispersion stocks could be also explained by the positive relationship between the optimistic bias in analysts' earnings forecasts and dispersion documented in Table VI.

Past-quarter forecast revision is a positive and significant predictor of returns around earnings announcements. This suggests that the news to which analysts were reacting was not fully incorporated into prices at the time of the announcement, and is consistent with the earnings momentum phenomenon described by Chan et al. (1996).

Size is a somewhat positive predictor of announcement-day returns. Although the argument advanced by Chari, Jagannathan and Ofer (1988)

[6] I have also run pooled regressions. The results are qualitatively similar, but, the regression coefficients, as expected, are generally more statistically significant.

Table VII. Predictors of cumulative abnormal returns around quarterly earnings announcement days

This table reports results of the Fama and MacBeth (1973) regressions of CARs on a set of predictive variables, defined as in Table V. The intercept coefficient is not reported. Regressions are implemented as follows. First, in each calendar year quarter, regression coefficients are obtained from the cross-sectional regression for firms making quarterly earnings announcements in that quarter (i.e., Jan 1–Mar 31, 1983, Apr 1–Jun 30, 1983, and so on). The regression coefficients are then averaged across quarters and the *t*-statistics adjusted for autocorrelation. Average adjusted R^2 of the cross-sectional regressions are reported. Stocks priced at less than \$5 per share at the end of the month prior to the earnings announcement are excluded. The sample period is January 1983–December 2005.

$\widehat{bias}$ ($\times 10^{-2}$)	*skew* ($\times 10^{-2}$)	*dispersion* ($\times 10^{-2}$)	*revision* ($\times 10^{-2}$)	*ME* ($\times 10^{-12}$)	*BE/ME* ($\times 10^{-2}$)	*adjusted* R^2 (%)
−9.09[b]	−20.68[c]	−17.05[a]	6.22[a]	0.51	0.47[a]	1.06
(−2.28)	(−1.78)	(−3.20)	(2.64)	(1.01)	(4.06)	
−16.90[a]	–	–	–	0.99[c]	0.41[a]	0.27
(−4.13)	–	–	–	(1.96)	(3.81)	
–	−32.48[a]	–	–	1.17[b]	0.40[a]	0.34
–	(−2.83)	–	–	(2.35)	(3.67)	
−15.60[a]	–	–	–	–	–	0.12
(−3.85)	–	–	–	–	–	
–	−33.35[a]	–	–	–	–	0.19
–	(−2.89)	–	–	–	–	
–	–	−19.52[a]	–	–	–	0.17
–	–	(−3.95)	–	–	–	
–	–	–	7.49[a]	–	–	0.32
–	–	–	(4.53)	–	–	
–	–	–	–	1.07[b]	–	−0.00
–	–	–	–	(2.23)	–	
–	–	–	–	–	0.39[a]	0.20
–	–	–	–	–	(3.61)	

[a,b,c] Statistically significant at the 1, 5, and 10 percent levels, respectively

suggests that smaller firms, which are less transparent, should earn higher returns around announcement days as compensation for risk, the sample used in this paper does not contain the very small firms to which this argument most applies. Finally, book-to-market appears to be a positive predictor of returns in this sample.

The evidence presented in this section confirms that negative news withheld from market participants is generally not reflected in market prices. Proxies for withheld negative information predict future underperformance and negative price reaction around quarterly announcements.

4. Do Sophisticated Investors Ameliorate the Mispricing? Evidence from Institutional Trades

I have argued that the underperformance of stocks for which negative information has been withheld is caused by their initial mispricing rather than lower riskiness. If this is the case, I should also be able to show that sophisticated investors trade against the mispricing. Unlike retail investors, institutions commit substantial resources to buying and processing information. For example, mutual funds employ in-house analysts, and have been shown to act on their recommendations (Cheng, Liu and Qian (2005)). Here, I test whether institutions as a group tend to sell their stock holdings when the unreported negative information begins to accumulate.

I use the same measures of unreported negative information as before, namely, $\widehat{bias}$ and *skew*. Institutional trades are calculated quarterly and defined as the change in the fraction of shares outstanding held by all institutions relative to the previous quarter. Total institutional stock holdings are aggregated from holdings reported by individual institutions on their quarterly SEC 13F reports. Because I run explanatory regressions of the quarterly change in a stock's institutional holdings, I need to include on the left-hand side the stock-related variables that change from quarter to quarter. Since Grinblatt, Titman and Wermers (1995) have shown that 77% of mutual funds buy stocks that are past winners, I include the cumulative return over the past quarter as an additional predictor of trade.[7] Earnings forecast revisions capture analysts' response to news events during the quarter, which will also likely influence institutional trades, and are included in the regressions. Finally, I include *dispersion*, as it has been shown to predict future stock underperformance.

As before, I need to control for potential cross-sectional correlations in institutional trades. For example, institutions might be hit by an industry-wide

[7] See also Wermers (1997), who documents mutual funds' reliance on momentum strategies.

shock such as a mutual fund scandal and forced to sell a fraction of all holdings to meet redemption demand. Alternatively, they might experience an increase in retirement investing due to change in regulations. Because cross-sectional correlation in trades will lower the volatility of the dependent variable and raise the significance of the coefficient estimates in pooled regression specifications, I once again employ the Fama and MacBeth (1973) methodology by running regressions in two steps. For each quarter, I run a set of cross-sectional regressions of institutional trades on a set of predictive variables to obtain a time-series of regression coefficients, and then compute the average estimates and their $t-$statistics, adjusted for autocorrelation.

Table VIII reports the results. Regressions are based on 130,162 firm-quarter observations when both the *skew* and *dispersion* variables are defined, and on 186,807 observations when the specification requires that only $\widehat{bias}$ be defined. The results indicate that $\widehat{bias}$ is the reliably significant negative predictor of institutional trades. When it is the only predictive variable used, the coefficient is -0.12 with the t-statistic of -11.21. This means that when $\widehat{bias}$ goes from zero to its median value, conditional on being positive of 1.31% of the stock price, the fraction of shares outstanding held by the institutional sector decreases by 16%. Institutional response to an increase in skew in the forecast distribution is less significant, possibly due to the difficulty of statistically detecting it since *skew* is highly correlated with other explanatory variables. But when *skew* is the only explanatory variable used, the regression coefficient is -0.14 with the t-statistic of -2.41. This means that a one-standard deviation increase in *skew* of 0.45% of the stock price leads to a 6% decrease in the fraction of shares outstanding held by the institutional sector. Moreover, institutions seem to recognize that high analyst disagreement is associated with overpricing and future underperformance and sell high-dispersion stocks. Institutional trades are also significantly contemporaneously related to analysts' forecast revisions, as both react to the same news. Similarly, institutional trades are strongly related to contemporaneous stock price performance.

This evidence suggests that institutions trade against mispricing and push prices closer to fundamentals. The presence of sophisticated investors thus improves the informativeness of stock prices.[8] But even though institutions trade against it, the mispricing is not fully eliminated. There are several potential reasons. First, most institutions face short-sale restrictions; they can sell only holdings they have previously accumulated. Arbitrageurs, who are allowed to sell short, will avoid doing so when the costs of short selling are too high relative to the magnitude of mispricing. (Miller (1977) and

[8] The beneficial role of institutions in the financial markets is discussed by Metron and Bodie (2004).

Table VIII. Predictors of trades by institutional investors

This table reports results of the Fama and MacBeth (1973) regressions of cumulated trades by institutional investors on a set of predictive variables, defined as in Table V; *past-quarter stock return* is the cumulative return of the stock over the previous quarter. A trade is defined as the change in the fraction of shares outstanding held by all institutional investors relative to the previous quarter. The intercept coefficient is not reported. Regressions are implemented as follows. First, in each quarter, regression coefficients are obtained from the cross-sectional regression. The regression coefficients are then averaged across quarters and the *t*-statistics adjusted for autocorrelation. Average adjusted R^2 of the cross-sectional regressions are reported. The sample period is January 1983–December 2005.

$\widehat{bias}$	*skew*	*dispersion*	*forecast revision*	*stock return*	*adjusted* R^2 (%)
−0.12[a]	−0.03	0.03	0.12[a]	0.05[a]	4.76
(−5.02)	(−0.31)	(0.97)	(4.66)	(9.68)	
−0.07[a]	–	–	–	0.04[a]	3.11
(−6.01)	–	–	–	(10.37)	
–	0.06	–	–	0.06[a]	4.05
–	(−1.04)	–	–	(10.37)	
–	–	0.09[a]	–	0.05[a]	3.69
–	–	(−4.31)	–	(10.53)	
−0.12[a]	–	–	–	–	0.29
(−11.21)	–	–	–	–	
–	−0.14[b]	–	–	–	0.07
–	(−2.41)	–	–	–	
–	–	−0.15[a]	–	–	0.35
–	–	(−5.59)	–	–	
–	–	–	0.07[a]	–	0.51
–	–	–	(6.36)	–	
–	–	–	–	0.04[a]	2.93
–	–	–	–	(10.63)	

[a,b,c] Statistically significant at the 1, 5, and 10 percent levels, respectively

Viswanathan (2001) argue that optimistic bias in stock prices should be lower than the short-sale costs.) Finally, even if short-sale costs are low, trading costs might still be substantial. Stocks for which negative information can be suppressed are likely to be relatively less transparent. Lower transparency implies a potentially higher degree of informational asymmetry between the market maker and better informed traders, leading to higher trading costs to compensate for the adverse selection (Kyle (1985)). The too-high transaction costs might render arbitrage unprofitable (Sadka and Scherbina (2006)).

5. Conclusion

Managerial compensation is frequently tied to stock price in order to ensure that managers' incentives coincide with those of shareholders. The unfortunate side effect is that managers might try to maintain the stock price artificially high by withholding bad news. The sell-side analysts' job is to research firms and report the information to investors. But because they are typically compensated on the basis of trading volume and the investment banking business they help to generate, and because they often rely on inside information from the firms' managements, analysts face a strong disincentive to report bad news. Confronted with bad news, they frequently either fail to adjust down their earnings forecasts or stop issuing forecasts altogether. I develop indicators of missing negative information based on the properties of analysts' earnings forecasts and show that they predict future stock underperformance, which is especially pronounced around earnings releases. I show that the underperformance is caused by the initial mispricing by presenting evidence that sophisticated investors trade against it. But the intensity of sophisticated trading is not always sufficient to eliminate the mispricing.

The findings in this paper suggest that information is aggregated into prices only gradually, partly because it is slow to reach the market. The strong relation between the predictable stock underperformance documented here and price momentum suggests that the latter might also be caused by slow reaction to the predictable information flow. The evidence presented in this paper suggests that ensuring firm transparency and eliminating short-sale restrictions will help to improve stock market efficiency.

Appendix

Data for this paper were obtained from several datasets and cover the period January 1983-December 2005. Analysts' earnings forecasts data were obtained from the Institutional Brokers Estimate System (I/B/E/S) US Summary History

Unadjusted dataset, which includes mean, median, and standard deviation for outstanding analysts' earnings forecasts as well as the number of analysts issuing forecasts and lowest and highest estimates. These variables are typically calculated on the Thursday before the third Friday of each month. The Unadjusted dataset is used in order to avoid the rounding error present in the Adjusted dataset, which arises when historical earnings forecasts are divided by subsequent stock splits and rounded to the nearest cent. Data on realized earnings were obtained from the I/B/E/S Unadjusted Actuals file.

Information on stock returns, prices, and shares outstanding were obtained from the CRSP Daily and Monthly stock files. To minimize the problem of bid-ask bounce I used stocks priced at no less than \$5 per share.

The accounting data and report dates of quarterly earnings were obtained from the Merged CRSP/Compustat database, Industrial Quarterly and Annual files. If less than 3 months had elapsed since the latest fiscal year-end date, accounting data for the preceding year were used to ensure that the information from the latest annual report had become public. Book value of equity was calculated using the annual file as follows. I used total common equity, if available, plus balance sheet deferred taxes and investment tax credit. If total common equity was not available I used shareholders' equity minus the value of preferred stock. For preferred stock I used redemption value, liquidating value, or carrying value in that order, as available. The book-to-market ratio was defined as the ratio of book value to market value of equity, the latter calculated as the product of month-end share price and number of shares outstanding.

Finally, data on institutional holdings were obtained from the Spectrum database. Spectrum collects quarterly information on institutional stock holdings from 13F reports, which institutions are required to file if their holdings exceed \$100 million. I aggregated share holdings of a particular stock in a particular quarter across all institutions to arrive at the total fraction of shares outstanding held by institutional investors. Institutional trades were calculated as the change in the fraction of shares outstanding held by institutional investors.

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