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Time Variation in Analyst Optimism: An Investor Sentiment Explanation

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Many studies have documented that analyst forecasts are overly optimistic on average. Using quarterly observations from 1984 to 2002, this article shows that forecasts exhibit optimism for most of the quarters under examination, but the level of optimism varies substantially over time. More important, after correcting the measurement problem caused by price, this article does not find optimism greatly diminished during most of the 1990s. However, consistent with previous findings, the period of 1999 to 2000 displays pessimistic forecasts, especially for large firms and growth firms. The macroeconomic factor does not have significant impact on analyst optimism. In contrast, the time-varying investor sentiments measured by 2 Chicago Board Options Exchange (CBOE) put-call ratios, and the cross-sectional skewness in the forecast errors, play an important role in explaining the time variation in analyst optimism. Finally, analysts track institutional investor sentiment more closely, except for small firms.

Keywords: Analyst forecast, Forecast bias, Analyst optimism, Investor sentiment, Time variation

INTRODUCTION

Financial analysts' forecasts tend to be overly optimistic. Some recent studies report that analyst optimism appeared to be waning after 1992 (Brown [1997], Chopra [1998], Richardson et al. [2004]). However, these studies typically scale the forecast errors by price to get a measure of optimism. Since the price level was unusually high during the 1990s, it is likely that analyst optimism may appear to have vanished during this period because of the scaling effect, but in reality analyst forecasts may have continued to be biased. To avoid this measurement problem caused by price, I choose total asset per share as the deflator. The result confirms the conjecture. Analysts' forecasts continued to show optimistic bias throughout most of the 1990s, though the mean was only slightly lower in the 1990s than in the 1980s. The exception occurred in 1999–2000, during which analyst forecasts showed some pessimism.

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Previous studies have provided some explanations as to why analyst optimism exists, mainly from 3 perspectives: analysts' misaligned incentives, their cognitive bias, and the negative skewness of earnings (see Kothari [2001] for a good review). The economic incentive-based explanations argue that sell-side analysts issue upward-biased forecasts to help generate investment banking businesses or commissions for their brokerage houses (Lin and McNichols [1998], Michaely and Womack [1999], Dechow et al. [2000]), as well as to facilitate access to firm insiders (Das et al. [1998], Lim [2001]). Other than issuing overly optimistic forecasts directly, analysts may also withhold the unfavorable news (McNichols and O'Brien [1997]). Whatever causes the observed optimistic bias in analysts' forecasts, the incentive-based explanations rely on the assumption that analysts are rational and their forecasts are optimal from their point of view. In contrast, the cognitive-bias view holds that analysts are irrational and make systematic mistakes when they process the information (DeBondt [1992], Easterwood and Nutt [1999]). In particular, analysts underreact to negative news and overreact to positive news. Finally, Gu and Wu [2003] propose that analyst forecast bias can exist in the absence of either cognitive bias or misaligned incentives. Earnings skewness is what leads to forecast bias.

Most of these studies have focused on cross-sectional analyses to explain analyst forecast optimism. To my knowledge, Chopra [1998] is the only author who examines time variation in analyst optimism. He presents some evidence that analyst optimism diminishes when economic growth strengthens. He also predicts that analysts' forecasts will continue to be inaccurate as long as business cycles exist.

This article attempts to investigate whether the time variation in analyst optimism is related to the time-varying investor sentiments after controlling for the macroeconomic factor. The primary task of financial analysts is to come up with accurate forecasts and help clients make sound investment decisions. However, sell-side analysts will deviate from this objective if they expect to get a higher payoff by issuing optimistic forecasts. For example, analysts can time the market by tracking investor sentiments. When investors are optimistic about the market, analysts will be less likely to report true forecasts; when investors are pessimistic, analysts will be more likely to stick to truth telling. When investor sentiments are high, investors overvalue the company. It is easier for analysts to convince their clients with optimistic forecasts without hurting their own reputation much. Meanwhile, analysts receive extra reward either in the form of increased compensation or improved career opportunities, which encourages them to deviate from reporting true forecasts. Conversely, when investor sentiments are low, investors undervalue the company. Little room is left with analysts for upward-biased forecasts. Consequently, we see less bias in analyst forecasts when investors feel pessimistic about future market. The extent to which analysts deviate from truth telling varies as investor sentiments fluctuate over time.

The empirical results support the hypothesis that analyst optimism co-moves with investor sentiments. In addition, for small firms that are more sensitive to investor sentiments, the level of analyst optimism is higher; whereas for large firms, analyst forecasts exhibit virtually no optimistic bias. During 1999–2000, however, large and mid-cap firms saw pessimism in the forecast bias, but small firms continued to show optimistic bias. Obviously, other factors such as policy shift also have strong impact on analyst optimism. Analysts significantly reduced the optimistic bias after the regulations took off that aimed at strengthening the "Chinese wall" between the brokerage and investment banking divisions within a brokerage house.

The remainder of the paper is organized as follows. The second section develops the hypothesis. The third section describes the research design and the data. The fourth section presents the empirical results. The final section concludes.

HYPOTHESIS DEVELOPMENT

When maximizing their payoff, sell-side analysts have two major concerns. First, they care about their reputation. This concern drives them to minimize forecast errors and be as accurate as possible. Forecast accuracy is important to analysts because not only do their employers evaluate their performance partly on forecast accuracy, public media such as *Institutional Investors*' annual poll also pays much attention to forecast accuracy. Second, as economic agents, analysts ultimately want to seek for their self-interests. Recent investigations by regulators and numerous studies by researchers (Lin and McNichols [1998], Michaely and Womack [1999], Dechow et al. [2000]) have produced ample evidence that analysts' compensation is tied to the generation of investment banking fees and brokerage commissions. Moreover, Hong and Kubik [2003] find that controlling for accuracy, analysts who issue relatively optimistic forecasts are more likely to move up to more prestigious brokerage houses or get promoted within their brokerage houses. In sum, analysts are concerned with getting some extra reward if they can make it. Therefore, I will refer to this type of concern as the "extra-reward concern." This concern drives analysts to bias their forecasts upward for their own benefit. Analysts constantly have to face a tradeoff between the reputation concern and the extra-reward concern. The level of analyst optimism that analysts set results from such a trade-off. Analyst optimism is high when the extra-reward concern dominates and low or even disappears when the reputation concern dominates.

What factors may influence the weight analysts put on the two concerns and the way analysts issue forecasts? A large body of literature has centered on the debate as to whether systematic mispricing exists in the market. Behavioral finance theories were motivated by attempts to explain such market overreactions and underreactions. Brown and Cliff [2005] provide further evidence that excessive optimism, or high investor sentiment, is associated with market overvaluation. They divide investors into two groups: fundamentalists and speculators. Fundamentalists price the stock based on its intrinsic value, whereas speculators are influenced by their sentiment when forming their expectations. Speculators tend to overvalue stocks in times of high sentiment and undervalue stocks when their sentiment is low. Brown and Cliff argue that the market price of a stock is a weighted average of the valuations of the two groups. As a result, the market price is above fundamentals when speculators are overly optimistic and below fundamentals when they are overly pessimistic. The periods of mispricing can be protracted because of limits to arbitrage (Shleifer and Vishny [1997]). It is widely known that investors underreact to earnings announcements (Ball and Brown [1968], Bernard and Thomas [1989]). The post-earnings-announcement drift is longer for negative surprises than for positive surprises. If market mispricing does exist and is somewhat skewed, and if such mispricing is associated with investor sentiments, then analysts may be able to take advantage of the biased investor expectation by issuing optimistic forecasts on average.

When investors' expectation of a stock deviates more or less from its intrinsic value, analysts may intend to "time the market" by tracking investor sentiments. When investors themselves are overly optimistic, they tend to value the company above its intrinsic value. As a result, analysts are able to set their forecasts above the true value. For example, Hong and Kubic [2003] report that accuracy matters less for career concerns such as in the period of 1996–2000 when investor sentiments are high. By contrast, when investors are bearish and undervalue stocks, analysts have less room to be optimistic. Therefore, they have to minimize forecast bias to keep their reputation untarnished. Based on these arguments, I form the following hypothesis:

H1: Analyst optimism is positively associated with investor sentiments.

RESEARCH DESIGN AND DATA DESCRIPTION

Analyst Optimism

Analysts' forecast data come from the Institutional Brokers Estimate Systems (I/B/E/S) detail database[1]. Several papers have shown that forecast accuracy improves as forecast age decreases (Richardson et al. [2004], Lim [2001]). To address the issue of forecast recency, I take the mean of all analysts' latest forecasts for a firm's forecast period end as the consensus forecast for that firm and that forecast period end[2]. To exclude stale forecasts, I restrict the forecasts to be no more than 90 days before the report dates. The forecast error is computed as the difference between consensus forecast and actual earnings. Since I/B/E/S forecasts generally exclude extraordinary items and some special items, for consistency, actual earnings are taken from I/B/E/S instead of Compustat. To control for the cross-sectional scale differences, I deflate the forecast error by total asset per share so that the measure of optimistic bias is comparable across different firms[3] . One-year-ahead total asset, one-quarter-ahead shares outstanding, and price are obtained from CRSP/Compustat-merged database. Formally, the scaled forecast errors for firm j's forecast period end τ , $\mathrm{SFE}_{\tau,j}$, is calculated as follows:

$$SFE_{\tau,j} = \frac{Consensus_{\tau,j} - Actual_{\tau,j}}{TotalAsset_{\tau,j} \div Shrout_{\tau,j}} \times 1000\% \qquad (1)$$

I eliminate those observations whose forecast errors are greater than total asset per share[4] as well as those observations whose prices are less than 2 dollars. Finally, I limit my sample to December fiscal year-end firms, which are the majority of I/B/E/S coverage. To get a quarterly measure of analyst optimism, I take the average of SFE across different firms (j) for the same forecast period end (τ):

$$AOMEAN_{\tau} = \frac{1}{J}\sum_{j=1}^{J} SFE_{\tau,j} \qquad (2)$$

Table 1 tabulates the summary statistics of the scaled forecast errors $\mathrm{SFE}_{\tau,j}$. The sample contains 178,999 firm-quarter observations from 1984 to 2002. The number of firms per quarter increased slowly from 1,246 in the second quarter of 1984 to about 3,400 in the late 1990s and then decreased considerably to 2,500 at the end of 2002[5]. Over time, analyst optimism seemed to decline. During most of the 1990s, however, analyst forecasts were still far above actual earnings. This result questions the findings in previous studies, which scaled the forecast errors by price and concluded that analyst optimism became substantially smaller after 1992 (Brown [1997], Chopra [1998], Richardson et al. [2004]). Given that the average price level was much higher during the 1990s, their results are suspicious. Interestingly, mean analyst forecasts exhibit pessimism during 1999–2000. Richardson et al. [2004], using annual forecasts, have verified the claim by the press that analysts "walk down" their estimates to a level the firm is likely to beat by the end of the year because investors react too strongly to the small negative earnings surprise on earnings announcement dates. This seems to apply to the quarterly forecasts during 1999–2000. Finally, forecast bias became insignificant after 2000. This may be attributed to the enactment of Regulation Fair Disclosure (FD) by the Securities and Exchange Commission (SEC) in October 2000, which prohibits companies from disclosing selectively to analysts and institutional investors. If analysts can not get more information from companies by favorably biasing their forecasts, we would expect the optimism to vanish as Lim [2001] predicts. Alternatively, as my hypothesis argues, the diminished forecast bias may be attributed to low investor sentiments during this period. Overall, the medians of $\mathrm{SFE}_{\tau,j}$ are much smaller than the means and are close to zero, as was found in the previous studies (Brown [1997], Easterwood and Nutt [1999]). For most quarters, the cross-sectional distributions of the forecast errors are positively skewed[6]. Like the means, the skewness also varies greatly over time.

Investor Sentiments

A series of studies have explored the role of investor sentiments in the stock market. Among them, Brown and Cliff [2004] examine the most comprehensive group of sentiment measures and the correlation between them. They find that many popular sentiment proxies are correlated with direct measures of sentiments obtained from surveys. Here I employ two publicly available indirect measures of sentiments that have been in existence since 1987.

The Chicago Board Options Exchange (CBOE) provides two put-call ratios. The CBOE equity put-call ratio tracks individual trades, whereas the S&P 100 index put-call ratio reflects professional and institutional strategies. Both ratios are bearish indicators. Like many other investor sentiment indicators, they are interpreted in a contrary fashion. That is, when the put-call ratio is high, it implies that investors

TABLE 1
Summary Statistics for the Scaled Forecast Errors Over Time.
This table presents summary statistics for the scaled forecast errors ($SFE_{\tau,j}$) for the sample period of third-quarter 1984 to fourth-quarter 2002. The scaled forecast error for forecast period end τ and firm j ($SFE_{\tau,jt}$) is calculated as the difference between the consensus forecast (mean of all analysts' last forecasts for τ and j in I/B/E/S detail database) and the actual earnings divided by the one-year ahead total asset per share.

Date	Number	Mean	Median	t	Skewness	Date	Number	Mean	Median	t	Skewness
1984.1	80	5.81	0.54	1.46	−0.29	1993.3	2335	3.49	0.00	3.44	6.63
1984.2	1246	5.30	0.24	2.90	−0.28	1993.4	2363	7.46	0.00	5.75	7.53
1984.3	1201	3.10	0.50	2.02	0.11	1994.1	2586	3.35	−0.15	4.28	7.75
1984.4	1304	10.90	0.65	5.04	0.78	1994.2	2721	3.20	−0.21	3.40	5.66
1985.1	1235	10.37	1.07	5.23	0.90	1994.3	2770	2.44	−0.26	2.84	4.35
1985.2	1326	9.84	0.57	5.66	0.75	1994.4	2778	4.73	−0.26	4.10	3.71
1985.3	1187	5.53	0.87	3.01	1.12	1995.1	2763	1.59	−0.29	2.08	−7.70
1985.4	1495	13.43	0.31	6.56	1.98	1995.2	2769	2.08	−0.21	2.45	−1.24
1986.1	1453	14.35	0.70	7.47	6.66	1995.3	2878	2.03	−0.22	3.33	5.77
1986.2	1334	11.79	0.49	6.21	6.38	1995.4	2896	4.18	−0.16	4.77	1.35
1986.3	1317	8.43	0.44	5.54	4.09	1996.1	3025	1.63	−0.34	2.65	6.50
1986.4	1544	11.50	0.24	5.87	3.59	1996.2	3060	1.50	−0.41	2.21	5.08
1987.1	1108	8.65	0.26	5.03	5.22	1996.3	3242	3.18	−0.27	3.57	4.89
1987.2	1475	11.97	0.20	6.83	4.91	1996.4	3239	3.40	−0.42	3.33	3.74
1987.3	1377	5.60	0.14	3.07	0.66	1997.1	3349	1.59	−0.48	2.47	6.53
1987.4	1478	13.27	0.58	6.95	2.95	1997.2	3389	1.94	−0.56	2.16	7.48
1988.1	1348	2.41	−0.20	1.88	4.76	1997.3	3437	0.55	−0.63	0.77	4.91
1988.2	1476	5.87	0.00	5.14	8.88	1997.4	3385	5.59	−0.32	5.61	4.99
1988.3	1559	7.12	0.11	5.44	6.40	1998.1	3405	1.15	−0.44	2.09	−1.10
1988.4	1609	8.36	0.14	5.52	6.23	1998.2	3451	1.69	−0.45	2.13	1.77
1989.1	1556	2.73	0.02	2.63	−0.36	1998.3	3377	1.29	−0.18	1.45	−0.26
1989.2	1649	7.94	0.18	5.97	9.48	1998.4	3325	4.01	−0.49	4.17	4.56
1989.3	1619	9.99	0.96	7.48	7.93	1999.1	3173	−0.21	−0.84	−0.33	7.56
1989.4	1639	12.62	0.64	8.15	6.72	1999.2	3154	−0.41	−0.75	−0.54	−2.12
1990.1	1595	5.13	0.31	6.02	3.33	1999.3	3166	−0.58	−0.71	−0.83	1.29
1990.2	1630	5.97	0.42	5.20	4.61	1999.4	2929	0.68	−0.94	0.66	1.21
1990.3	1684	7.71	0.61	6.74	6.35	2000.1	3173	−2.98	−1.41	−4.50	−1.82
1990.4	1690	13.05	0.56	8.20	6.92	2000.2	3074	−2.31	−1.07	−2.97	−0.55
1991.1	1643	2.97	0.24	3.52	−7.80	2000.3	2924	−2.98	−0.90	−3.04	−2.70
1991.2	1709	5.58	0.06	5.36	4.45	2000.4	2696	1.61	−0.58	1.40	3.00
1991.3	1773	4.13	0.12	3.70	2.04	2001.1	2685	0.24	−0.52	0.37	1.68
1991.4	1837	5.89	0.10	4.58	1.16	2001.2	2688	0.37	−0.71	0.66	4.54
1992.1	1856	2.24	0.00	2.61	11.71	2001.3	2725	−0.87	−0.60	−1.17	−10.75
1992.2	1935	3.03	−0.03	2.94	6.72	2001.4	2656	0.70	−0.95	0.87	4.67
1992.3	1979	2.96	0.00	3.20	2.06	2002.1	2740	−1.62	−1.07	−2.46	0.84
1992.4	2059	6.65	0.00	5.28	3.85	2002.2	2702	0.01	−0.93	0.02	1.34
1993.1	2047	3.19	0.00	4.37	5.30	2002.3	2627	−0.03	−0.83	−0.05	5.64
1993.2	1658	7.90	0.00	5.66	9.45	2002.4	2500	−0.46	−0.89	−0.76	10.03

think the market is going down. Weekly put-call ratios are hand-collected from *Barron's*. To convert the data into quarterly series, I take the average of the weekly data for each quarter. Due to data availability, the measures of sentiments range from 1987 to 2002.

Prior literature typically refer investor sentiments to the sentiments of individual investors. Institutional investors are often considered as sophisticated or rational investors. However, not all institutional investors make wise decisions on the market. The performance of money mangers varies greatly. We do not have convenient data to distinguish among different groups of institutional investors. Nevertheless, both the study by Brown and Cliff [2004] and the correlation between the two put-call ratios used in this study indicate that institutional investor sentiment is different from individual investor sentiment. Therefore, I distinguish the two groups of investors by the two put-call ratios, respectively.

Finally, to closely proxy sentiments, we need to eliminate the rational component in the put-call ratios. When an individual investor or an institutional investor says she is bullish on the market, her expectation may be rational, irrational, or some combination of the two. Therefore, to isolate the irrational component from the rational component, I project each of the put-call ratios on the space of

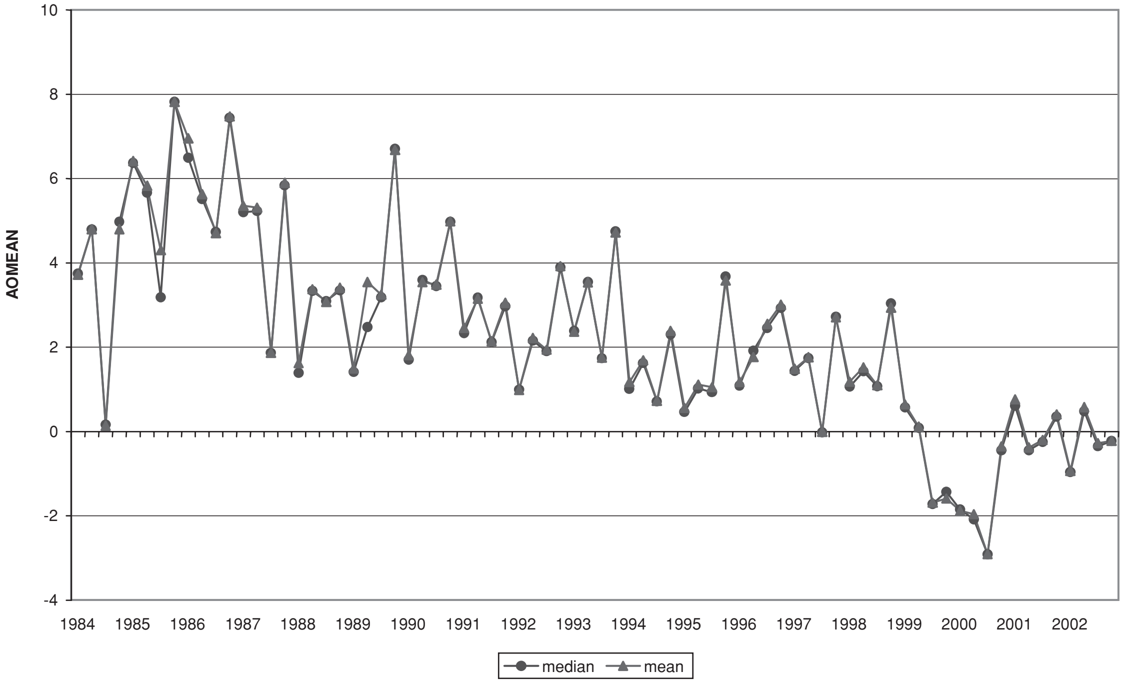

FIGURE 1 Analyst optimism over time. This figure plots the quarterly analyst optimism measures (AOMEAN_{τ}) over the sample period of 1984:1–2002:4, using mean and median estimates, respectively. The quarterly analyst optimism mean (median) measure is calculated as the average of the scaled mean (median) forecast errors ($\text{SFE}_{\tau,j}$) across firms in each quarter. The scaled mean (median) forecast error for forecast period end τ and firm j ($\text{SFE}_{\tau,j}$) is calculated as the difference between the consensus forecast and the actual earning, divided by the total asset per share. Consensus forecast is the average of all analysts' last forecasts for forecast period end τ and firm j.

two variables: the growth in the industrial production index and a dummy variable for NBER recessions[7]. The former is collected from the website of the Federal Reserve Bank of St. Louis (http://research.stlouisfed.org), while the NBER dummy follows the NBER definition of business cycles (see the Appendix). I use the othogonalized series as cleaner proxies for sentiments.

Control Variables

Chopra [1998] examines analysts' forecasts for the earnings growth rate of S&P 500 stocks and documents that analyst optimism varies across business cycles. More important, companies tend to take a bath when performance is poor. During recessions, many companies like to engage in major restructurings and discontinue unprofitable operations, writing off a significant fraction of fixed assets and the corresponding expenses involved with such restructuring programs. These are unexpected events. It is possible that forecasts are above actual earnings during recessions because companies have taken significant hits, not because analysts intentionally bias forecasts upward. For the above two reasons, it is necessary to control for the macroeconomic factor. I choose the percentage growth in Gross Domestic Product (GDP) to proxy for macroeconomic conditions. Quarterly GDP data are taken from the Federal Reserve Bank of St. Louis.

The second control variable I consider is the skewness in the cross-sectional distribution of the forecast errors (SKEW). A number of papers have documented that although the mean analysts' forecasts are far above actual earnings, the median is much closer to actual earnings (Brown [1997], Easterwood and Nutt [1999]). The summary statistics in Table 1 also indicates that the cross-sectional distribution of SFE is positively skewed and varies over time. Therefore, I assume the time variation in the cross-sectional distribution of the forecast errors is likely to be associated with analyst optimism, which is the mean forecast error. In particular, analyst optimism is higher if forecast errors are more positively skewed.

EMPIRICAL RESULTS

Subsample Analyses

As seen in Figure 1, consensus forecasts are, on average, above the actual value. In other words, analysts' forecasts are generally overly optimistic. Moreover, the level of optimism varies over time. The correlogram indicates that the time series AOMEAN (1987.1–2002.4) is serially correlated. The Dickey-Fuller test rejects that it is nonstationary at a 5% significance level.

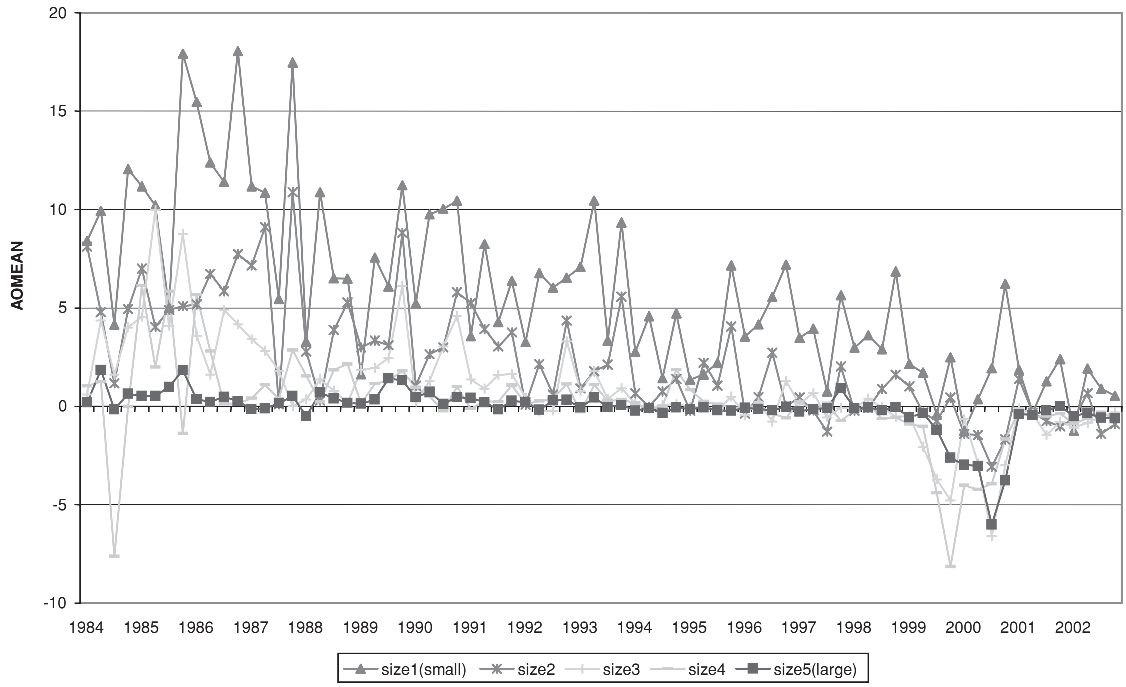

FIGURE 2 Analyst optimism over time grouped by size. This figure plots the quarterly analyst optimism measures ($AOMEAN_\tau$) for 5 groups of firms over the sample period of 1984:1–2002:4. In each quarter, firms are grouped by market capitalization (size) using French's quintile size breakpoints. The quarterly analyst optimism mean (median) measure is calculated as the average of the scaled mean (median) forecast errors ($SFE_{\tau,j}$) across firms in each quarter. The scaled mean (median) forecast error for forecast period end τ and firm j ($SFE_{\tau,j}$) is calculated as the difference between the consensus forecast and the actual earning, divided by the total asset per share. Consensus forecast is the average of all analysts' last forecasts for forecast period end τ and firm j.

Morgan and Stocken [2003] suggest that policies which change either the degree or probability of bias by analysts reduce the optimism. In 1988, Congress amended U.S. securities laws to strengthen the "Chinese wall" separating the brokerage and investment banking divisions. Following suit, the SEC issued guidelines, while the National Association of Securities Dealers (NASD) and NYSE issued a joint memorandum in 1991 endorsing this separation. These regulations impose a restriction on the binding relationship between analysts' compensation and investment banking business, and therefore lower the probability of analysts' bias. According to Morgan and Stocken, analyst optimism will be reduced after such regulations. Because forecast bias turned negative or insignificant after 1999, those quarters are excluded. I then divide the rest of the sample into two subperiods at the third quarter of 1991 and test the difference in analyst optimism before and after the regulation shift. The choice of third-quarter 1991 is rather ad hoc[8]. I assume by then the legislation effect had been fully realized. The result of the Wilcoxon test shows that analyst optimism decreases significantly (p-value <0.001) and substantially from 8.11 to 3.24 after the stringent regulations, which is consistent with Morgan and Stocken's prediction.

To take a closer look at the cross-sectional characteristics of the optimism, I conduct 2 more subsample analyses. First, I rank the size of the firms in each quarter with respect to Fama and French's quintile size breakpoints (French's online data library, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Size is calculated by the price times the shares outstanding. Note that the number of firms in each group differs greatly. The smallest size group has a particularly large number of firms, about one-third of the whole sample for each quarter. The rest of the groups more or less evenly share the other two-thirds. Next, I average analyst optimism across the firms in each of the 5 groups. Figure 2 clearly shows that analyst optimism of the small-firm group is much higher than that of the others. Forecasts for large-firm group show hardly any bias except during 1999–2000. The differentiation among groups can be explained by the cross-sectional different degrees of information asymmetry. In particular, investors watch large firms more closely and so obtain a greater amount of public information. Therefore, analysts have less incentive to give biased forecasts. Brown [1997] has pointed out that optimistic bias was absent for S&P 500 firms for the 11 quarters from the first quarter of 1993 to third quarter 1995. Das et al. [1998] and Lim [2001] use size as a cross-sectional measure of information asymmetry and find evidence that analyst optimism increases as information asymmetry increases. My result is consistent with theirs. Alternatively, the strong bias in small-size firms

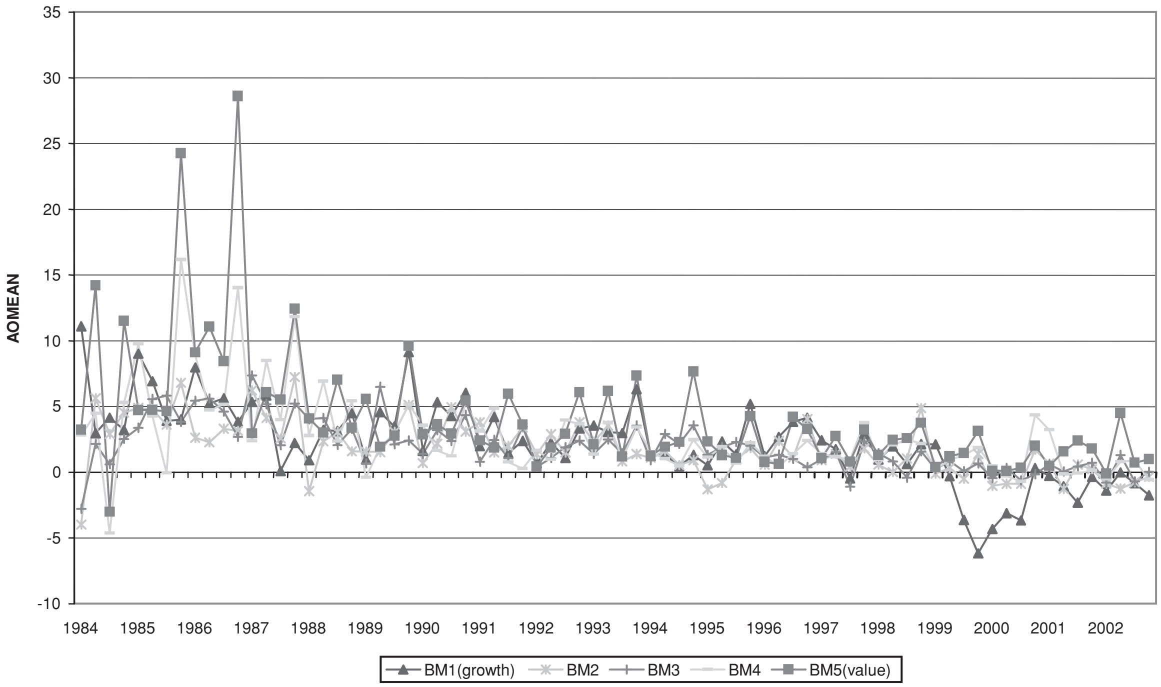

FIGURE 3 Analyst optimism grouped by book-to-market. This figure plots the quarterly analyst optimism measures (AOMEAN$_\tau$) for 5 groups of firms over the sample period of 1984:3–2002:4. In each quarter, firms are grouped by book-to-market ratios using French's quintile book-to-market breakpoints. The quarterly analyst optimism mean (median) measure is calculated as the average of the scaled mean (median) forecast errors (SFE$_{\tau,j}$) across firms in each quarter. The scaled mean (median) forecast error for forecast period end τ and firm j (SFE$_{\tau,j}$) is calculated as the difference between the consensus forecast and the actual earning, divided by the total asset per share. Consensus forecast is the average of all analysts' last forecasts for forecast period end τ and firm j.

may be because pricing of these firms is more influenced by investor sentiments. As investor sentiments fluctuate, analyst forecasts deviate more or less from the true value. By contrast, the pricing of large firms is determined by more rational investors. Therefore, analysts are more likely to stick to the true forecasts. The pessimism shown in the forecasts of large and mid-cap firms during 1999–2000 is consistent with the findings in Richardson et al. [1999]. They argue that larger companies make more effort in beating analyst forecasts during this period because investors react too strongly to the small negative earnings surprise in such firms.

In the second subsample analysis, I rank the firms' book-to-market ratios in each quarter with respect to Fama and French's quintile book-to-market breakpoints (French's online data library, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Book value of common equity (BE) is data item #60 in Compustat. Those observations of which BE is unavailable or negative are eliminated before grouping. Again, each group has different numbers of firms, with the lowest book-to-market group having a disproportionately large number. Next, I average analyst optimism across the firms in each of the 5 groups. Figure 3 suggests that for nearly all periods, value-firm group has the highest optimism. However, the difference between the value-firm group and other groups vanished during later periods. Intuitively, we would expect analyst optimism to be high for low book-to-market firms because such firms are typically considered growth firms, for which earnings are hard to predict. However, it is also true that investors may have difficulty accessing firms that are under financial distress or such firms may be more reluctant to disclose bad news (Lang and Lundholm [1993]). Hence, analysts distort their forecasts to facilitate access to nonpublic information from management. Alternatively, growth firms may actively engage in the game of beating analyst forecasts. Skinner and Sloan [2002] report that stock prices drop by a greater amount when a firm misses a forecast compared to when it beats a forecast, and this asymmetry is largest for growth firms. This gives the growth firms strong incentive to beat analysts' forecasts, as we see the pessimism in the forecasts for such firms during 1999–2000.

Regression Analyses

To test the main hypothesis, the regression model is specified as follows:

$$\begin{aligned}\text{AOMEAN}_t &= \beta_0 + \beta_1\text{RCBOE}_t + \beta_2\text{RSP100}_t + \beta_3\text{DGDP}_t \\ &\quad + \beta_4\text{SKEW}_t + \varepsilon_t \qquad (3)\end{aligned}$$

where AOMEAN is the quarterly average forecast errors across firms, RCBOE is the CBOE equity put-call ratio orthogonal to the growth in the industrial production index (DINV) and a dummy variable for NBER recessions

TABLE 2
Time-series Regressions of Quarterly Analyst Optimism: 1987.1–2002.4.
This table investigates the factors that affect the magnitude of analyst optimism over time. Pearson correlations are presented in panel A. Regression results are reported in panel B. The dependent variable, AOMEAN, is the average level of analyst optimism, calculated as the average of the scaled forecast errors across firms in each quarter. The rest are independent variables. RCBOE is the CBOE equity put-call ratio orthogonal to growth in the industrial production index (DINV) and a dummy variable for NBER recessions (NBER), RSP100 is the CBOE S&P100 index put-call ratio orthogonal to DINV and NBER, DGDP is the growth rate of GDP, and SKEW is the skewness in the cross-sectional distribution of the scaled forecast errors. The sample ranges from first-quarter 1987 to fourth-quarter 2002. AR(1) model is employed to correct for the serial correlation.

Panel A: Pearson Correlation

	AOMEAN	RCBOE	RSP100	DGDP	SKEW
AOMEAN	1.00				
RCBOE	−0.46	1.00			
RSP100	−0.54	0.33	1.00		
DGDP	−0.02	−0.01	0.00	1.00	
SKEW	0.56	−0.26	−0.30	−0.14	1.00

Panel B: Regression

	(1) sentiment	(2) macro	(3)skewness	(4) all
constant	1.76***	2.00***	1.18***	1.23***
	(7.49)	(3.72)	(3.12)	(3.41)
RCBOE	−5.43**			−4.61**
	(−2.23)			(−2.19)
RSP100	−5.19***			−4.37***
	(−3.23)			(−3.04)
DGDP		−0.55		0.01
		(−1.47)		(0.02)
SKEW			0.09***	0.10***
			(3.60)	(3.83)
AR(1)	0.15	0.57***	0.48***	0.08
	(1.16)	(5.49)	(4.18)	(0.60)
Adj. R^2	0.33	0.31	0.41	0.45

Notes: t-statistics are provided in the parenthesis.
***,**,* represent significance at 1%, 5%, 10%, respectively.

(NBER), RSP100 is the CBOE S&P100 index put-call ratio orthogonal to DINV and NBER, DGDP is the growth rate of GDP, and SKEW is the skewness in the cross-sectional distribution of the scaled forecast errors. AR(1) model is applied to correct for serial correlations.

Table 2 reports the results of the regressions. Because the whole sample has only 64 observations, the results could be sensitive to the number of independent variables and the correlations among them. To avoid multicollinearity, I examine the Pearson correlations first. Panel A of Table 2 shows that the correlations between the independent variables are relatively low. RCOBE and RSP100 have a correlation of 0.33, which is relatively high. The two series are, however, still distinguishable from each other. Column 1 of panel B investigates the importance of the investor sentiment hypothesis. Both RCBOE and RSP100 show significantly negative relation with AOMEAN, implying that analyst optimism rises as investor sentiments climb and wanes as sentiments fall. Moreover, the coefficient on RSP100 is at a higher level than the coefficient on RCBOE, suggesting that analyst optimism is more closely related to institutional investor sentiment. By contrast, DGDP, the proxy for macroeconomic conditions, does not seem to be significantly related to AOMEAN, though the negative sign on its coefficient is consistent with the prediction that analyst optimism is low when the economy expands. The univariate regression result of analyst optimism on skewness variable shows that the more positively skewed the cross-sectional distribution of the scaled forecast errors, the higher the level of the mean. The last column of panel B presents the result of the multiple regression. After we control for the macroeconomic and skewness factors, the coefficients on RCBOE and RSP100 remain significant at the 5% and 1% levels, respectively, strongly supporting the investor sentiment hypothesis. Overall, the four variables account for 45% of the change in analyst optimism over time.

TABLE 3
Time-series Regressions of Quarterly Analyst Optimism for Small Firms: 1987.1–2002.4.
This table investigates the sources of time variation in analyst optimism for small firms. In each quarter, small firms are picked from the whole sample using French's quintile size breakpoints. Any the firm whose market capitalization is below French's 20% breakpoint is identified as small firm. Pearson correlations are presented in panel A. Regression results are reported in panel B. The dependent variable, AO_S1, is the average level of analyst optimism, calculated as the average of the scaled forecast errors across all small firms in each quarter. The rest are independent variables. RCBOE is the CBOE equity put-call ratio orthogonal to growth in the industrial production index (DINV) and a dummy variable for NBER recessions (NBER), RSP100 is the CBOE S&P 100 index put-call ratio orthogonal to DINV and NBER, DGDP is the growth rate of GDP, and SKEW_S1 is the skewness in the cross-sectional distribution of the scaled forecast errors. The sample ranges from first-quarter 1987 to fourth-quarter 2002. AR(1) model is employed to correct for the serial correlation.

Panel A: Pearson Correlation

	AO_S1	RCBOE	RSP100	DGDP	SKEW_S1
AO_S1	1.00				
RCBOE	−0.46	1.00			
RSP100	−0.50	0.33	1.00		
DGDP	−0.13	−0.01	0.00	1.00	
SKEW_S1	0.48	−0.18	−0.19	−0.06	1.00

Panel B: Regression

	(1) sentiment	(2) macro	(3)skewness	(4) all
constant	4.77***	5.73***	3.45***	4.18***
	(16.03)	(6.46)	(5.67)	(7.40)
RCBOE	−14.18***			−12.42***
	(−4.01)			(−3.80)
RSP100	−10.19***			−8.47***
	(−4.08)			(−3.64)
DGDP		−1.62**		−0.50
		(−1.97)		(−0.89)
SKEW_S1			0.31***	0.25***
			(3.84)	(3.69)
AR(1)	−0.26**	0.37***	0.25**	−0.25**
	(−2.02)	(3.10)	(1.99)	(−1.85)
Adj. R^2	0.33	0.12	0.25	0.45

Notes: t-statistics are provided in the parenthesis.
***,**,* represent significance at 1%, 5%, 10%, respectively.

Tables 3 and 4 report the results of the regressions for the group of small size firms (small firms) and the group of firms with highest book-to-market ratio (value firms), respectively. The groupings are based on the subsample analyses. The basic results remain the same as in Table 2. For both small firms and value firms, investor sentiments play an important role in explaining the time variation in analyst optimism. The coefficient on RCBOE is significant at a higher level in the regressions for small firms, suggesting that individual investor sentiment is more related to analyst forecasts for small firms. This is not surprising because the pricing of small firms is more affected by individual investor sentiment. The coefficient on the macroeconomic factor, DGDP, turns significant (at 5% level) in the single-hypothesis regression for small firms. However, it remains insignificant in multiple regression. Unlike DGDP, the cross-sectional skewness remains an important control variable. Overall, the adjusted R^2 remains 0.45 for small firms but decreases substantially for value firms to 0.36. As has been mentioned in the subsample analysis, analyst optimism of value firms differentiates from that of other firms only in the early periods. The flattening of analyst optimism of value firms in the later periods may help explain why the adjusted R^2 is lowered.

CONCLUSION

Using quarterly analyst forecast data for the sample period 1984–2002, I document noticeable variations in analyst optimism over time. Unlike the findings in prior literature, the level of analyst optimism was only a little lower in the 1990s than in the 1980s but still far from vanishing. Because I use total asset per share as the scalar, this measure of optimism is less sensitive to the changes in price. So I suspect previous findings of substantially decreased optimism in the 1990s may have been induced by the higher price level in that period. Subsample analyses suggest that analyst optimism decreases monotonically by firm size. However, there is no

TABLE 4
Time-series Regressions of Quarterly Analyst Optimism for Value Firms: 1987.1–2002.4.
This table investigates the sources of time variation in analyst optimism for value firms. In each quarter, value firms are picked from the whole sample using French's book-to-market breakpoints. Any firm whose book-to-market ratio is less than French's 20% breakpoint is identified as value firm. Pearson correlations are presented in panel A. Regression results are reported in panel B. The dependent variable, AO_B5, is the average level of analyst optimism, calculated as the average of the scaled forecast errors across all value firms in each quarter. The rest are independent variables. RCBOE is the CBOE equity put-call ratio orthogonal to growth in industrial production index (DINV) and a dummy variable for NBER recessions (NBER), RSP100 is the CBOE S&P 100 index put-call ratio orthogonal to DINV and NBER, DGDP is the growth rate of GDP, and SKEW_B5 is the skewness in the cross-sectional distribution of the scaled forecast errors. The sample ranges from first-quarter 1987 to fourth-quarter 2002. AR(1) model is employed to correct for the serial correlation.

Panel A: Pearson Correlation

	AO_B5	RCBOE	RSP100	DGDP	SKEW_B5
AO_B5	1.00				
RCBOE	−0.26	1.00			
RSP100	−0.41	0.33	1.00		
DGDP	0.03	−0.01	0.00	1.00	
SKEW_B5	0.41	0.16	0.05	0.06	1.00

Panel B: Regression

	(1) sentiment	(2) macro	(3)skewness	(4) all
constant	3.04***	2.97***	1.40***	1.70***
	(13.32)	(5.45)	(2.65)	(3.66)
RCBOE	−4.70*			−5.94**
	(−1.75)			(−2.31)
RSP100	−6.90***			−6.70***
	(−3.67)			(−3.78)
DGDP		0.03		0.16
		(0.05)		(0.36)
SKEW_B5			0.26***	0.20***
			(4.94)	(4.17)
AR(1)	−0.21*	0.11	0.36***	−0.10
	(−1.67)	(0.87)	(2.94)	(−0.76)
Adj. R^2	0.20	−0.02	0.24	0.36

Notes: t-statistics are provided in the parenthesis.
***,**,* represent significance at 1%, 5%, 10%, respectively.

distinct difference between firms with varied book-to-market ratios. With the fluctuating mean forecast errors and the relatively stable medians, the skewness of the cross-sectional distribution also changes over time.

Next, this paper explores the sources of time variation in analyst optimism. In particular, I investigate whether analyst optimism is related to investor sentiments after controlling for the macroeconomic factor and the cross-sectional skewness. Analysts' incentive is not always aligned with investors' because analysts have two conflicting concerns: the reputation concern and the extra-reward concern. Forecast bias is the equilibrium result of the tradeoff between these two concerns. The degree of misalignment varies over time as investor sentiments change, so does the level of bias. When investors are subject to excessive optimism, they tend to overvalue the stock. It is relatively easy for analysts to convince investors with optimistic forecasts. As a result, the extra-reward concern dominates in times of high investor sentiments. Conversely, when investors are pessimistic about firms' prospect, analysts' reputation concern dominates and consequently forecast bias decreases. The empirical results strongly support the investor sentiment hypothesis.

Obviously, some other factors may help explain the observed fluctuations in analyst optimism. For example, after the Congress and the SEC strengthened the regulation to separate out the research division in brokerage houses, analyst optimism has been substantially reduced. In the new millennium, forecast errors almost vanished. However, it is not yet clear whether the decrease was due to the enactment of Regulation FD or some unknown factors. Interestingly, both large and mid-cap firms and growth firms even exhibit some pessimism during 1999–2000. In sum, investors have to bear in mind that when analysts issue forecasts, they do not simply report what they truly think. Oftentimes, they deviate from true forecasts depending on what circumstance they are in. Whatever strategy they may have, their final goal is to maximize their own profits.

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NOTES

1. Consensus forecasts provided by I/B/E/S suffer the staleness problem because I/B/E/S summary database are updated on a monthly basis.
2. I also tried the median as consensus forecasts. As can be seen from Figure 1, the two measures are very close to each other. So in later analyses, I use only the mean estimates.
3. I also tried book value of equity. The result is not reported here, but it is quite similar to that obtained by using total asset as deflator. Because we have to eliminate those observations with negative book value of equity, the sample selected may be less representative. I use the measure deflated by total asset for the rest of the analyses.
4. Previous studies usually eliminate those observations whose forecast errors exceed the price.
5. The first quarter of 1984 had extremely small number of observations, since I/B/E/S just started to record the quarterly forecasts around that time.
6. Opposite to most of forecast bias studies, I define the forecast error as forecast minus actual earnings per share. Therefore, the mean forecast errors are larger than the median forecast errors which are closer to zero, and the forecast errors are positively skewed in the cross-sectional distribution.
7. See Baker and Wugler [2003] for similar approach.
8. I tried three other breakpoints at 1990.1, 1991.2, 1991.4, the results are robust to these specifications. I also exclude the quarters from 1988 to 1991, the time when the new regulations took place, the result is still robust.

REFERENCES

Ball, R. and P. Brown. "An Empirical Evaluation of Accounting Income Numbers." *Journal of Accounting Research*, 6, (1968), pp. 159–178.

Bernard, V. and J. Thomas. "Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?" *Journal of Accounting Research*, 27, (1989), pp. 1–36.

Brown, G. and M. Cliff. "Investor Sentiment and the Near-term Stock Market." *Journal of Empirical Finance*, 11, (2004), pp. 1–27.

Brown, G. and M. Cliff. "Investor Sentiment and Asset Valuation." *Journal of Business*, 78, (2005), pp. 405–436.

Brown, L. "Analyst Forecasting Errors: Additional Evidence." *Financial Analysts Journal*, 53, (1997), pp. 82–88.

Chopra, V.K. "Why So Much Error in Analysts' Earnings Forecasts?" *Financial Analysts Journal*, 54, (1998), pp. 35–42.

Das, S., C. Levine and K. Sivaramakrishnan. "Earnings Predictability and Bias in Analysts' Earnings Forecasts." *Accounting Review*, 73, (1998), pp. 277–294.

DeBondt, W. "Earnings Forecasts and Share Price Reversals." *Research Foundation of CFA Institute Publications*, April, (1992), pp. 1–36.

Dechow, P., A. Hutton, and R. Sloan. "The Relation between Analysts' Long-term Earnings Forecasts and Stock Price Performance Following Equity Offerings." *Contemporary Accounting Research* 17, (2000), pp. 1–32.

Easterwood, J. and S. Nutt. "Inefficiency in Analysts' Earnings Forecasts: Systematic Misreaction or Systematic Optimism?" *Journal of Finance*, 54, (1999), pp. 1777–1797.

Gu, Z. and J. Wu. "Earnings Skewness and Analyst Forecast Bias." *Journal of Accounting and Economics*, 35, (2003), pp. 5–29.

Hong, H. and J. Kubik. "Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts." *Journal of Finance*, 58, (2003), pp. 313–351.

Kothari, S.P. "Capital Markets Research in Accounting." *Journal of Accounting and Economics*, 31, (2001), pp. 105–231.

Lang, M. and R. Lundholm. "Cross-sectional Determinants of Analyst Ratings of Corporate Disclosures." *Journal of Accounting Research*, 31, (1993), pp. 246–271.

Lim, T. "Rationality and Analyst Forecast Bias." *Journal of Finance*, 56, (2001), pp. 369–385.

Lin, H. and M. McNichols. "Underwriting Relationships, Analysts' Earnings Forecasts and Investment Recommendations." *Journal of Accounting and Economics*, 25, (1998), pp. 101–127.

McNichols, M. and P. O'Brien. "Self-selection and Analyst Coverage." *Journal of Accounting Research*, 35, (1997), pp. 167–208.

Michaely, R. and K. Womack. "Conflict of Interest and the Credibility of Underwriter Analyst Recommendations." *Review of Financial Studies*, 12, (1999), pp. 653–686.

Morgan, J. and P. Stocken. "An Analysis of Stock Recommendations." *RAND Journal of Economics*, 34, (2003), pp. 183–203.

Richardson, S., S. Teoh and P. Wysocki. "The Walkdown to Beatable Analyst Forecasts: The Roles of Equity Issuance and Insider Trading Incentives." *Contemporary Accounting Research*, 21, (2004), pp. 885–924.

Shleifer, A. and R. Vishny. "The Limits of Arbitrage." *Journal of Finance*, 52, (1997), pp. 35–55.

Skinner, D. and R. Sloan. "Earnings Surprises, Growth Expectations, and Stock Returns, or Don't Let an Earnings Torpedo Sink Your Portfolio." *Review of Accounting Studies*, 7, (2002), pp. 289–312.

APPENDIX: NBER BUSINESS CYCLES

This appendix explains how the quarters in the sample period are classified as expansions or contractions based on the NBER business-cycle dates. The expansions (contractions) begin at the peak (trough) of the cycles and end at the trough (peak). Periods and durations (in quarters) of each business cycle phase are provided during the sample period. The business cycle dates are available from the NBER Web site: www.nber.org/cycles.html. Among the full sample of 64 quarters, 59 quarters are classified as being in expansions and 5 quarters are in contractions.

Business Cycle Expansions		Business Cycle Contractions	
Periods	Durations	Periods	Durations
1987.1-1990.3	15	1990.4-1991.1	2
1991.2-2001.1	40	2001.2-2001.4	3
2002.1-2002.4	4		
	total: 59		total: 5

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