# Consistent Earnings Surprises and Behavioral Biases in Analyst Forecasts

**Guojin Gong** *
University of Iowa

January 24, 2005

## ABSTRACT

The behavioral assumption that individuals overreact to a series of consistent information signals has been widely used in behavioral finance theories to explain return momentum and return reversal. This paper aims to evaluate the descriptive validity of this behavioral assumption by examining whether security analysts overreact to a series of consistent *extreme* earnings surprises. I find that analysts appear to extrapolate the consistent pattern in consecutive earnings surprises to revise earnings forecasts. However, analysts do not overreact to consistent earnings surprises in forecasting future earnings. Although analysts' initial underreaction to bad earnings surprises *diminishes* as bad earnings surprises continue to arrive, analysts' initial underreaction to good earnings news *magnifies* following consecutive good earnings surprises. This asymmetric forecasting behavior of analysts is inconsistent with the conjecture that analysts overreact to consistent earnings surprises. The future abnormal return behavior following consistent earnings surprises suggests that the biased processing of consistent good earnings signals by analysts influences market expectations. In supplementary tests, I document contrasting forecasting behavior of analysts in response to consistent *small* earnings surprises. Overall, the evidence challenges the widely accepted behavioral assumption that individuals overreact to a series of consistent information signals in financial markets.

**JEL Classifications:** G14, M41
**Keywords:** Earnings Surprise, Analysts' Forecasts, Heuristic and Biases, Behavioral Finance
**Data Availability:** The data used in this study are publicly available from the sources indicated.

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* Correspondence: Guojin Gong, Department of Accounting, Henry B. Tipple College of Business, Iowa City, IA 52242, phone: (319) 335-1813, email: guojin-gong@uiowa.edu. This paper is based on my dissertation at University of Iowa. I would like to thank Dan Collins for his consistent guidance and support. I am also grateful to Bruce Johnson, Richard Tubbs, Cristi Gleason, Haidan Li, Sonja Rego, and workshop participants at University of Iowa for many valuable suggestions. I would like to thank I/B/E/S for providing data on financial analysts' forecasts, as part of a broad academic program to encourage earnings expectations research. Finally, financial support from the University of Iowa is greatly acknowledged.

## 1. Introduction

Over the past two decades, a large body of finance and accounting research has documented intermediate-horizon momentum and long-horizon reversal in stock returns.[1] Recently developed behavioral finance theories attempt to reconcile these seemingly contradictory return patterns using assumptions about investor behavior. Few studies have evaluated the descriptive validity of these behavioral assumptions in financial markets (as opposed to experimental laboratories). This paper intends to fill this gap in the literature. I focus on one particular behavioral assumption that individuals overreact to a series of consistent information signals in forming expectations. This behavioral assumption has been widely used in behavioral finance theories to explain return momentum and return reversal (Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998).

Specifically, in this study I examine whether analysts overreact to consistent information signals by using earnings surprises as the stimuli for their forecasting activity. Analysts are usually recognized as sophisticated financial information users, and serve as important intermediaries in disseminating value-relevant information to investors. Although analysts' earnings forecasts may not fully capture investors' earnings expectations,[2] analysts' forecasting activity significantly influences investors' expectations and market prices (e.g. Givoly and Lakonishok, 1984; La Porta, 1996). However, analysts' forecasts exhibit considerable biases (See Kothari (2001) for a summary), which may mislead investment decisions and distort

[1] The intermediate-horizon momentum refers to the phenomena that past winners (defined as stocks with high returns over the past 3-12 months or good earnings news) outperform past losers (See Jegadeesh and Titman, 1993; Foster, Olsen, and Shevlin, 1984; Bernard and Thomas, 1989). The long-horizon reversal refers to the phenomena that past winners (defined as stocks with high returns over the past 3-5 years, low book-to-market ratio, or high sales growth) underperform past losers (See DeBondt and Thaler, 1985; Lakonishok, Shleifer, and Vishny, 1994).

[2] For example, prior studies have shown that investors fail to fully incorporate value-relevant information contained in analysts' forecasts (Elgers, Lo, and Pfeiffer, 2001; Stickel, 1991). In addition, due to analysts' forecast biases, investors (especially sophisticated investors) unlikely follow analysts' opinions blindly (e.g. Malmendier and Shanthikumar, 2004).

efficient pricing. Extant literature proposes that the source of analysts' biases may relate to incentive reasons (e.g. desire to boost investment-banking business and/or maintain good relationship with the management) and/or psychological factors.[3] This paper investigates analysts' behavioral biases in processing earnings signals by testing the prediction that analysts overreact to a series of consistent earnings surprises. Providing evidence on whether analysts exhibit behavioral biases should help investors better interpret earnings projections disseminated by analysts.

In extant literature, the behavioral assumption that individuals overreact to a series of consistent signals is often linked to *representativeness heuristic* (Barberis, Shleifer, and Vishny, 1998; Chan, Frankel, and Kothari, 2004; Frieder, 2004). Representativeness heuristic leads individuals to generalize about a population of future outcomes after observing only a small sample (Kahneman and Tversky, 1973, Tversky and Kahneman, 1974). In the case of earnings announcements, individuals who have viewed only a short sequence of earnings often conclude that theses are representative of future earnings. As described in Barberis, Shleifer, and Vishny (1998, p. 316), "while a consistent pattern of high growth may be nothing more than a random draw for a few lucky firms, … (investors) infer from the in-sample growth path that the firm belongs to a small and distinct population of firms whose earnings just keep growing". As a result, if analysts exhibit the representativeness bias, I predict they will over-extrapolate the consistent pattern in earnings series and become overly optimistic (pessimistic) in forecasting earnings subsequent to consistent good (bad) earnings news signals.

[3] Studies addressing incentive biases of analysts' forecasts include Lin and McNichols (1998), Das, Levine, and Sivaramakrishnan (1998), Chan, Karceski, and Lakonishok (2003), Bradshaw, Richardson, and Sloan (2003), among others. Studies showing analysts' overreaction or underreaction to price and earnings changes include DeBondt and Thaler (1987), Mendenhall (1991), Ali, Klein, and Rosenfeld (1992), Easterwood and Nutt (1999), Doukas, Kim, and Pantzalis (2002), Zhang (2004), among others. These latter studies typically do not specify the underlying cognitive factors driving analysts' overreaction or underreaction. In addition, a few recent studies argue that the observed analysts' biases maybe an artifact of skewed earnings distribution (Gu and Wu, 2003) or earnings management (Abarbanell and Lehavy, 2000).

In addition to the representativeness bias, self-deception biases like *overconfidence* and *biased self-attribution* could also induce individuals to overreact to consistent information signals (Daniel, Hirshleifer, and Subrahmanyam, 1998). In Daniel et al. (1998), the confidence of the investor in their model grows when public information (e.g. earnings announcements) is in agreement with his private information. As a series of consistent pubic information signals arrives, the investor's personal view shifts towards the direction of the observed public signals. Hence, as good (bad) earnings signals continue to arrive, the investor tends to overreact to the later earnings signals in the consistent earnings series.

Although researchers rely on quite different cognitive biases to motivate similar behavioral assumptions, the consensus is that individuals overreact to consistent information signals. Several recent studies attempt to test the descriptive validity of this behavioral assumption by examining investors' trading activities and market prices, but these studies provide conflicting results (Frieder, 2004; Shanthikumar, 2004; Swaminathan and Lee, 2000; Chan, Frankel and Kothari, 2004).[4] This paper complements prior studies by testing whether overreaction to consistent earnings signals is descriptive of analysts' forecasting activity. In this particular setting (i.e. examining analysts' earnings forecasts conditional on a series of consistent earnings signals), the representativeness bias is observationally indistinguishable from overconfidence and biased self-attribution. Hence, I do not intend to distinguish between these alternative cognitive biases proposed in behavioral finance theories, but rather focus on testing the human behavior that results from these biases – i.e., overreaction to consistent earnings signals.

[4] Frieder (2004) and Shanthikumar (2004) examine investors' trading activities in response to a series of consistent earnings surprises. Swaminathan and Lee (2000) and Chan, Frankel and Kothari (2004) examine pricing implications of consistent earnings signals. Chan et al. (2004) fail to find supporting evidence on this behavioral assumption, while all the other three studies provide consistent evidence on investors' overreaction to a series of consistent earnings surprises.

Earnings signals are measured as quarterly earnings minus analysts' recent consensus forecasts (i.e. earnings surprises). To ensure that earnings signals are salient to analysts (Tversky and Kahneman, 1974; Hirshleifer, 2001; Hirshleifer and Teoh, 2003), the empirical tests focus on extreme earnings surprises. Firms with consistent earnings surprises likely differ systematically from the other firms in terms of earnings performance (e.g. return on assets) and information environment (e.g. firm size, book-to-market ratio, analysts' forecast dispersion). Hence, I control for related firm characteristics in the empirical tests.

I first examine analysts' reactions to consistent earnings surprises as exhibited in forecast revisions. As elaborated later in the paper (see subsection 2.3), although analysts' forecast revisions alone do not reflect analysts' forecast *bias,* the test based on analysts' forecast revisions is critical to demonstrating an association between analysts' forecast bias and consistent earnings surprises. Results show that analysts' forecast revisions are more positive (more negative), per unit of earnings surprise, following a longer sequence of consistent good (bad) earnings surprises. This documented pattern in analysts' forecast revisions is consistent with analysts extrapolating the consistent pattern in consecutive earnings surprises to forecast earnings.

Next, I test whether analysts' reactions to consistent earnings surprises exhibit *overreaction*. Specifically, I examine the association between consistent earnings surprises and analysts' forecast errors, a measure of analysts' underreaction or overreaction to earnings surprises. Consistent with prior literature, analysts on average underreact to earnings surprises (Abarbanell and Bernard, 1992; Ali, Klein and Rosenfeld, 1992). More relevant to the primary research question, I find that analysts' underreaction to bad earnings surprises *diminishes* as consecutive bad earning surprises continue to arrive, consistent with analysts' overreacting to the consistent pattern in consecutive bad earnings news. However, analysts' underreaction to good earnings news *magnifies* as a series of good earnings surprises develops, contrary to the prediction implied in behavioral finance theories.[5] The evidence indicates that analysts become more pessimistic about future earnings prospects following a series of consistent good or bad earnings surprises. Thus, the evidence does not support the behavioral assumption that analysts overreact to consistent earnings signals.

Prior studies have shown a distinct price premium related with consistent positive earnings signals (e.g. Barth, Elliott, and Finn, 1999; Myers and Skinner, 2002; Kasznik and McNichols, 2002; Bartov, Givoly, and Hayn, 2002). Prior research also finds that firms have greater incentives to issue (repurchase) equity when market values are high (low), and equity issuance is associated with greater forecast optimism (Baker and Wurgler, 2002; Bradshaw, Richardson, and Sloan, 2004). Therefore, equity issuance activities may contaminate the tests on analysts' forecast biases in terms of consistent earnings signals. However, I do not find a significant influence of equity issuance activities on the associations between analysts' forecast errors and consistent earnings surprises.

I also provide preliminary evidence on market consequences of analysts' biased earnings forecasts. The abnormal return behavior around future earnings announcements suggests that analysts' biased processing of consistent good earnings surprises influences market expectations. For completeness, I examine analysts' reactions to consistent *small* earning surprises. In contrast to analysts' more pessimistic view following consistent extreme earnings surprises, analysts appear more optimistic following consecutive small positive earnings surprises, and largely ignore the consistent pattern in consecutive small negative earnings surprises in forecasting

[5] The more positive forecast reversions and greater *underreaction* of analysts following consistent good earnings surprises are not necessarily contradictory. The evidence suggests that consistent good earnings surprises are much more persistent than analysts' *perceived* persistence level. Hence, even though analysts' forecast revisions are more positive, their revised forecasts still fall behind the realized future earnings.

earnings. Overall, the evidence poses a challenge to the widely accepted behavioral assumption that individuals overreact to a series of consistent earnings signals in financial markets.

This paper contributes to extant literature in several ways. First, I conduct empirical tests of one widely held assumption in behavioral finance theories – namely, that individuals overreact to consistent information signals. Evidence presented in the paper suggests that cognitive biases associated with processing consistent signals documented in laboratory settings is not revealed in analyst earnings forecast behavior. Therefore, researchers should be cautious in extrapolating behavioral biases observed in a controlled laboratory setting to real market settings. Second, I add to the literature on potential biases in financial analysts' earnings forecasts by testing a particular behavioral bias (i.e. overreaction to consistent earnings signals). Prior research shows that investors fail to fully incorporate value-relevant information contained in analysts' forecasts (Elgers, Lo, and Pfeiffer, 2001; Stickel, 1991). Hence, evidence presented in this paper should help investors better understand analysts' forecasting process, which potentially facilitates market efficiency.

Finally, this paper complements several recent studies that assess the implications of consistent earnings signals on investors' trading activities and market prices (Frieder, 2004; Shanthikumar, 2004; Swaminathan and Lee, 2000; Chan, Frankel and Kothari, 2004). Since various market frictions (transactions costs, short-selling constraints, etc.) may impede investors' trading activities and distort security prices, tests based on trading and pricing are joint tests of investors' expectations and arbitrage risks due to market frictions. This paper largely avoids this identification problem. To the extent that analysts' forecasts mirror investors' earnings expectations, tests based on analysts' forecasts provide more direct evidence on the validity of this behavioral assumption in financial markets.

The rest of the paper proceeds as follows. The next section reviews related literature and develops hypotheses. Section 3 describes the measurement of key variables used in the analysis, and presents the sample. Section 4 discusses the research design and empirical findings. The last section concludes with suggestions for future research.

## 2. Related Literature

In behavioral finance theories, investors' biased information processing is the source of systematic mispricing (under the maintained assumption of limited arbitrage) (Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999). Researchers typically draw upon psychology literature to justify the behavioral assumptions underlying their models. In this section, I first discuss related literature on the behavioral assumption that individuals overreact to a series of consistent information signals. I then review studies on analysts' forecast biases, and develop hypotheses.

### 2.1 Overreaction to a Series of Consistent (Earnings) Information Signals

Over the past two decades, the evidence concerning medium-horizon return momentum and long-horizon return reversal has attracted enormous attention in the empirical finance and accounting literature (DeBondt and Thaler, 1985; Bernard and Thomas, 1989; Jegadeesh and Titman, 1993; Chan, Jegadeesh and Lakonishok, 1996, among others). Recent behavioral finance theories attempt to explain these seemingly contradictory return patterns using assumptions about investor behavior (Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999). Barberis, Shleifer, and Vishny (1998) assume investors believe that earnings are either mean reverting or trending, even though the underlying earnings process follows a random walk. As earnings continue to increase (decrease), investors incorrectly conclude a trending performance, thus overreact to the later earnings changes in the series. Barberis et al. (1998) justify this trend-chasing behavior based on representativness heuristic documented in the psychology literature (Kahneman and Tversky, 1972).

Daniel, Hirshleifer, and Subrahmanyam (1998) present a model that combines overconfidence and biased self-attribution to explain return momentum and reversal. In their model, investors underreact to news that disagrees with their opinions and overreact to news that agrees. As a sequence of consistent earnings signals develops, investors' personal views shift towards the direction of the observed signals. Therefore, the later earnings signals in a consistent series cause a stronger reaction than the earlier earnings signals in the same series, or investors overreact to consistent earnings signals.

Despite different cognitive factors underlying these models, the consensus in Barberis et al. (1998) and Daniel et al. (1998) is that individuals overreact to a series of consistent earnings signals.[6] Several recent studies attempt to evaluate the validity of this behavioral assumption in real market settings (Frieder, 2004; Shanthikumar, 2004; Swaminathan and Lee, 2000; Chan, Frankel and Kothari, 2004). Frieder (2004) and Shanthikumar (2004) find that investors tilt their trades more heavily to the buy-side as the number of consecutive positive earnings surprises increases, consistent with investors overreacting to consistent earnings signals. Swaminathan and Lee (2000) find that the post-earnings-announcement drift, a measure of investors' underreaction to earnings news, is attenuated when the most recent earnings surprises confirm the previous earnings surprises. This finding suggests that return reversal following investors' overreactions to consistent earnings surprises diminishes return momentum arising from investors' underreaction to individual earnings news. Nevertheless, Chan, Frankel and Kothari (2004) find

[6] Hong and Stein (1999) propose an alternative model to explain return momentum and reversal, but do not directly appeal to any behavioral biases on the part of investors. In Hong and Stein (1999), two groups of investors who trade based on different sets of information interact to produce the momentum and reversal return patterns.

little, if any, stock price evidence that investors overreact to consistent earnings signals.[7] To better understand the influence of a consistent pattern in earnings series on market expectations, this study complements prior studies by examining analysts' earnings forecast behavior in response to consistent earnings surprises.[8]

### 2.2 Analysts' Forecasting activity

There is considerable evidence suggesting analysts' earnings forecasts are optimistically biased, and analysts fail to fully incorporate information contained in prior earnings and stock prices in forecasting future earnings. DeBondt and Thaler (1985, 1987, 1990) propose that analysts systematically *overreact* to earnings information, which imparts an optimistic bias in their forecasts and leads to market overreaction. More recent studies suggest that analysts *underreact* to information contained in prior earnings changes and stock returns (Abarbanell and Bernard, 1992; Lys and Sohn, 1990; Ali, Klein and Rosenfeld, 1992). Easterwood and Nutt (1999) attempt to reconcile these two conflicting views by showing that analysts overreact to good earnings news, but simultaneously underreact to bad earnings news. However, Ahmed, Lobo, and Zhang (2000) show that results in Easterwood et al. (1999) are sensitive to outliers. Gu and Xue (2004) find that analysts' overreaction to good earnings news can be explained away by the associated high earnings uncertainty. These more recent findings cast doubt on the conclusion in Easterwood et al. (1999) that analysts exhibit systematic optimism with respect to past information.

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[7] Several recent studies also investigate this behavioral assumption in non-equity markets. For example, Poteshman (2001) find consistent evidence in options market, and Durham, Hertzel, and Martin (2004) report scant evidence supporting this behavioral assumption using data from the college football wagering market.

[8] Without testing a particular behavioral bias, several accounting studies document a significant price premium for firms consistently beating earnings benchmarks (proxied by last period earnings or analysts' consensus forecasts) (Barth, Elliott, and Finn, 1999; Myers and Skinner, 2002; Kasznik and McNichols, 2002; Bartov, Givoly, and Hayn, 2002). Barth, Elliott and Finn (1999) and Myers and Skinner (2002) look at a series of increasing (non-decresing) earnings; while Bartov, Givoly, and Hayn (2002) and Kasznik and McNichols (2002) examines firms beating analysts' consensus forecasts consistently. None of these studies examine firms with a series of *negative* earnings signals. This paper includes both good and bad earnings signals in the empirical analysis.

Given conflicting views on analysts' overreaction or underreaction to past information, alternative explanations are offered to account for analysts' biased information processing. Many studies propose incentive-based explanations, arguing that investment-banking relationships and analysts' desire to gain or maintain access to management's private information motivate analysts to issue overly optimistic forecasts (Lin and McNichols, 1998; Das, Levine and Sivaramakrishnan, 1998; Bradshaw, Richardson and Sloan, 2004).[9] However, incentive bias seems at odds with analysts' underreaction to positive information signals. In addition, reputation concerns should deter analysts from issuing intentionally biased forecasts. Ultimately, analysts' ability to generate trades and attract investment banking business depends on their credibility.[10]

Other studies documenting analysts' biased information processing typically do not specify the underlying cognitive factors that drive analysts' biases. DeBondt and Thaler (1985, 1987) argue that the long-horizon return reversal phenomenon is attributable to analysts' overreacting to past earnings performance.[11] In contrast, Abarbanell and Bernard (1992) suggest analysts underreact to past earnings information by showing positive serial correlations in analysts' forecast errors. Mendenhall (1991) shows that analysts appear to underestimate the persistence of prior earnings forecast errors in revising earnings forecasts. None of these studies attempt to examine whether analysts overreact to *consistent* earnings signals, which is the primary question addressed in this paper.

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[9] More recent studies provide inconsistent evidence regarding the incentive-bias explaination. Cowen, Groysberg and Healy (2004) find that analysts at firms with underwriting and trading businesses are actually less optimistic than those at pure brokerage houses, who perform no underwriting. Kolasinski and Kothari (2004) fail to find supporting evidence on analysts' incentive biases using a sample of merger and acquisitions. Agrawal and Chen (2004) examine a unique dataset that contains the revenue breakdown of analysts' employers among investment banking, brokerage, and other business. They do not find any relation between bias in quarterly earnings forecasts and several measures of incentive conflict severity.

[10] Indeed, Cowen, Groysberg and Healy (2004) find that analysts' one-quarter ahead earnings forecasts are less optimistic for bulge (i.e. largest and most reputed) investment banks than for non-bulge underwriting firms.

[11] Klein (1990) reexamines the return reversal phenomena, but fails to find evidence supporting analysts' overreaction to earnings information.

## 2.3 Hypotheses Development

To test whether analysts *overreact* to consistent earnings signals, I first examine whether analysts *react* to the consistent pattern in earnings surprises. It is important to demonstrate that analysts indeed *utilize* the consistent pattern in earnings surprises to forecast future earnings before testing the relationship between consistent earnings surprises and analysts' forecast errors (proxy for analyst forecast bias). The reason is the relationship between consistent earnings surprises and analysts' forecast errors depends on both analysts' forecasting process and the underlying earnings process (since forecast errors are measured as realized earnings minus analysts' consensus forecasts). Since consistent earnings surprises likely contain information about future earnings (Barth, Elliott, and Finn,1999; Bartov, Givoly, and Hayn, 2004), forecast errors could be systematically related with consistent earnings surprises even when analysts do not heed the consistent pattern in earnings surprises at all.[12] Therefore, to evaluate analysts' forecast efficiency/bias with respect to consistent earnings surprises, I need to show that the consistent pattern in earnings surprises does influence analysts' forecasting process.

To test whether analysts react to consistent earnings surprise, I examine the association between analysts' forecast revisions and associated consistent earnings surprises. If, as argued in behavioral finance theories, analysts extrapolate the consistent pattern in earnings series, then the later earnings signals in a consistent earnings series should trigger greater revision in earnings expectations than the initial earnings signals in the same series. Specifically, as good earnings surprises continue to arrive, analysts will hold a stronger belief that the trend will continue in the next period. Thus, analysts revise their earnings forecasts upward more aggressively (per unit of

[12] An alternative possibility is that analysts *choose* to disregard the consistent pattern in earnings surprises if they believe the consistent pattern in earnings surprises contain irrelevant information about future earnings. However, this alternative explanation is empirically indistinguishable from the argument that analysts do not heed the consistent pattern in earnings surprises at all.

earnings surprise) following a longer string of good earnings surprises. A similar story holds for a string of bad earnings surprises. As bad earnings surprises continue to arrive, analysts expect a greater portion of current earnings surprises to continue. Hence, they revise earnings forecasts downward more aggressively (per unit of earnings surprise). This reasoning leads to the first hypothesis, stated below in alternative form:

*$H_1$: Analysts' forecast revisions are more positive (more negative), per unit of earnings surprise, following a longer sequence of consecutive good (bad) earnings surprises.*

Forecast revisions reflect analysts' perceived permanence of earnings surprises. To examine whether analysts *efficiently* process information contained in earnings surprises, I next examine analysts' forecast errors subsequent to a string of consecutive good (bad) earnings surprises. If, as suggested in behavioral finance theories, analysts *overreact* to a series of consistent earnings signals, then analysts' forecasts will contain greater optimism (pessimism) bias following a longer sequence of consecutive good (bad) earnings surprises. This reasoning leads to the second hypothesis, stated below in alternative form:

*$H_2$: Analysts' forecasts exhibit greater optimism (pessimism) bias, per unit of earnings surprise, following a longer sequence of consecutive good (bad) earnings surprises.*

Consistent good (bad) earnings signals usually accompany favorable (unfavorable) market reactions. For example, Barth, Elliott, and Finn (1999) and Myers and Skinner (2002) find a significant price premium among firms that experience consistent earnings increases. Similarly, Bartov, Givoly, and Hayn (2002) and Kasznik and McNichols (2002) find that the market assigns a higher value to firms that beat analysts' consensus forecasts consistently. Since firms have greater incentives to undertake equity financing when their market values are high, and to repurchase equities when their market values are low (Baker and Wurgler, 2002), corporate equity financing likely accompanies consistent earnings surprises. Bradshaw, Richardson and Sloan (2004) show that equity issuance activities introduce pervasive optimistic bias in analysts' forecasts.[13] Therefore, it is plausible that equity issuance activities induce greater optimistic bias in analysts' forecasts following consistent good earnings surprises. To mitigate the potential confounding effect of equity financing, I also test $H_2$ controlling for equity issuance (repurchase) activities.

## 3. Variable Measurements and The Sample

### 3.1 Analysts' Forecast Revision and Forecast Error

To avoid stale forecasts maintained in the IBES Summary History File, I construct analysts' consensus forecasts based on the IBES Detail History File, following the methodology proposed in Diether, Malloy, and Scherbina (2002). The Detail History File contains individual analysts' forecasts by issue date. Each record also contains a review date, which is the date that the forecast was last confirmed as valid. A forecast is deemed valid from its issue date until its review date.[14] Analysts' consensus forecast over a specified period of time is the mean of all valid forecasts during that particular period.[15]

Analysts' forecast revision for quarter q+1 earnings is measured as the revision in the consensus forecast around quarter q earnings announcements ($REVISION_{i,q}^{q+1}$). Analysts'

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[13] Bradshaw et al. (2004) offer three explanations for their findings. First, analysts could self-select into covering issuing firms because they consider them to have the best future growth prospects, thus leading to an (unintentional) upward bias in published forecasts. Second, management could self-select into issuing securities during periods in which their inside information indicates that analysts' forecasts are most optimistic. Third, conflicts stemming from incentives to generate investment banking or brokerage business could lead analysts to intentionally bias their forecasts. The first two explanations are consistent with analysts exhibiting cognitive biases in forecasting earnings.

[14] For example, if a forecast was issued on October 15, 2000 and its review date is November 20, 2000, then it is deemed valid from October 15, 2000 until November 20, 2000. In some circumstances, the review date lags far behind the issued date, suggesting that these forecasts are likely to be stale and erroneous. Hence, I extend the issued date for a maximum of 90 days (Zhang, 2004).

[15] In laboratory experiments, psychology researchers typically draw inferences based on consensus responses from the subjects. Consistent with this practice, I use mean analysts' forecasts in the empirical analysis. Empirical results are qualitatively similar based on *median* analysts' forecasts.

consensus forecast *subsequent* to quarter q earnings announcements, $FC_{i,q,post}^{q+1}$, is measured as the mean of valid individual analysts' forecasts within 30 days after quarter q earnings announcements. Analysts' consensus forecast *prior* to quarter q earnings announcements, $FC_{i,q,prior}^{q+1}$, is measured as the mean of valid individual analysts' forecasts within 30 days (excluding the most recent week) before quarter q earnings announcements.[16] If an analyst makes more than one forecast during the specified period, only the last forecast is used in calculating the consensus. Forecast revision ($REVISION_{i,q}^{q+1}$) and forecast errors ($ERROR_{i,q}^{q+1}$) for quarter q+1 are computed as follows:

$$REVISION_{i,q}^{q+1} = \frac{FC_{i,q,post}^{q+1} - FC_{i,q,prior}^{q+1}}{P_{i,q}}; \quad ERROR_{i,q}^{q+1} = \frac{EPS_{i,q+1} - FC_{i,q,post}^{q+1}}{P_{i,q}},$$

where $P_{i,q}$ is stock prices at the end of quarter q, and $EPS_{i,q+1}$ is quarter q+1 earnings (as reported in IBES). Figure 1 further illustrates the measurement of analysts' forecast variables using a time-line.

### 3.2 Earnings Surprise and A Series of Consistent Earnings Surprises

To measure quarter q earnings surprise ($SURP_{i,q}$), I first construct analysts' consensus forecast for quarter q prior to quarter q earnings announcements ($FC_{i,q,prior}^{q}$) as the mean of valid individual analysts' forecasts within 30 days (excluding the most recent week) before quarter q earnings announcements. Earnings surprise ($SURP_{i,q}$) for quarter q is computed as follows:

$$SURP_{i,q} = \frac{EPS_{i,q} - FC_{i,q,prior}^{q}}{P_{i,q-1}},$$

[16] The 1-week exclusion criterion mitigates the influence of earnings guidance on analysts' earnings expectations since managers have incentives to guide analysts' forecasts closer to earnings announcements dates. Results based on a 2-week exclusion criterion are qualitatively similar.

where $EPS_{i,q}$ is quarter q earnings (as reported in IBES), and $P_{i,q-1}$ is share price at the end of quarter q-1.[17]

Since "salience" is central to individuals' biases and expectation formation (Tversky and Kahneman, 1974; Hirshleifer, 2001; Hirshleifer and Teoh, 2003), the main empirical analysis focuses on *extreme* earnings surprises under the assumption that more extreme earnings surprises are more salient.[18] To identify extreme earnings surprises, I rank $SURP_{i,q}$ into deciles within each quarter. The top three deciles (decile 8-10) include positive $SURP_{i,q}$ with relatively large magnitudes, hereafter referred to as *good* earnings surprises. The bottom three deciles (decile 1-3) include relatively large negative $SURP_{i,q}$, hereafter referred to as *bad* earnings surprises. The remaining $SURP_{i,q}$ with small magnitudes (decile 4-7) are identified as *neutral* earnings surprises. I argue that both good and bad earnings surprises are more salient than neutral earnings surprises, and are more likely to influence analysts' judgments. Thus, the empirical tests of the hypotheses focus on consistent good or consistent bad earnings surprises.

I classify firms with consistent earnings surprises based on a rolling horizon of four quarters. Specifically, once a series of earnings surprises is formed, I create four binary variables, D($N$ =1), D($N$ =2), D($N$ =3), and D($N \geq 4$), to indicate the number of consistent earnings surprises preceding an extreme earnings surprise.[19] Specifically, if quarter q earnings surprise, $SURP_{i,q}$, is neutral, then all the four dummies have values of zero. If $SURP_{i,q}$ is good (bad) and

[17] Results are similar if I eliminate firms with a share price below $1 (to mitigate small denominator problem). Using standard deviation of individual forecasts as an alternative deflator also does not change results qualitatively.
[18] A side-benefit of using extreme earnings surprises is mitigated influence of earnings guidance on analysts' expectations. The reason is managers have greater incentives to guide analysts' earnings expectations downwards when unmanaged earnings fall short of earnings forecasts by a *small* margin.
[19] Behavioral finance theory does not specify the *length* of the earnings series that induce individuals' biased expectation. Psychology literature on representativeness heuristic suggests that individuals tend to ignore sample size, and extrapolate patterns from *a few* data points (or a *short* sequence of data). To mitigate greater measurement errors in classifying firms based on too few earnings observations and maintain a reasonable sample size, I arbitrarily choose four quarters' earnings to form earnings sequences in testing analysts' forecasting behavior.

$SURP_{i,q-1}$ was *not* good (bad), then D($N$ =1) equals one, and all the other three dummies have values of zero. If both $SURP_{i,q}$ and $SURP_{i,q-1}$ are good (bad), and $SURP_{i,q-2}$ is *not* good (bad), then D($N$ =2) equals one, and all the other three dummies have values of zero, and so on. If a series of earnings surprises ($SURP_{i,q-3}$, $SURP_{i\ q-2}$, $SURP_{i,q-1}$, $SURP_{i,q}$) comprises of all good (bad) earnings surprises, then D($N \geq 4$)=1, and the other three dummies all equal zero. In the empirical analysis, I examine sequences of good and bad earnings surprises separately.

**3.3 The Sample**

Analysts' forecasts are extracted from the IBES Detail History File over a 16-year horizon, extending from 1987 to 2002. Quarterly earnings announcement dates are collected from COMPUSTAT. To allow reasonable sample size, I require firms to have at least four quarters' earnings per share (EPS) available on IBES to form an earnings surprise series. The primary sample includes 4,345 firms and 53,599 firm-quarter observations with available analysts' forecasts and earnings surprise series.

Table 1 summarizes descriptive statistics and correlations for selected variables. As shown in Panel A, the median (price scaled) earnings surprise is positive (0.02%), suggesting the sample is predominated by firms beating analysts' consensus forecasts. The mean (median) of (price scaled) forecast revision for quarter q+1 earnings around quarter q earnings announcements ($REVISION_{i,q}^{q+1}$) is -0.09% (-0.01%), consistent with analysts revising earnings forecasts downwards (Richardson, Teoh, and Wysocki, 2004). Despite the downward revisions, analysts' mean forecast is still too high relative to reported earnings, as evidenced by the negative mean of –0.19% for (price scaled) forecast errors ($ERROR_{i,q}^{q+1}$). However, analysts' median forecast error is about zero, suggesting the negative mean forecast error (–0.19%) is due to some extreme negative values from a skewed forecast error distribution (Gu and Wu, 2002).

The sample is comprised mostly of large firms, with mean (median) market value of $6,957 ($906) million, reflecting the selection bias inherent in requiring analyst coverage. The median level of net equity financing (*ΔEQUITY*) is near zero, suggesting the sample is not populated by equity issuing firms or equity repurchasing firms.

Panel B of Table 1 presents Pearson and Spearman correlations between selected variables for the full sample. Earnings surprise ($SURP_{i,q}$) and forecast revision ($REVISION_{i,q}^{q+1}$) are positively correlated (Pearson correlation is 0.43), consistent with analysts revising forecasts upwards (downwards) upon good (bad) earnings news. The positive correlation between earnings surprise ($SURP_{i,q}$) and subsequent forecast error ($ERROR_{i,q}^{q+1}$) (Pearson correlation is 0.35) is consistent with analysts' underreaction to earnings news (Abarbanell and Bernard, 1992; Ali, Klein and Rosenfeld, 1992). In other words, analysts' forecasts are too low (too high) following good (bad) earnings news, resulting in positive (negative) forecast errors.

**4. Research Design and Empirical Results**

The empirical analysis reported below focuses on analysts' forecasting behavior in response to extreme earnings surprises. I first show that firms with consistent extreme earnings surprises differ systematically (in terms of earnings performance and information environment) from the other firms (Chevis, Das, and Sivaramakrishnan, 2002). Subsection 4.2 describes the univariate associations between consistent earnings surprises and analysts' forecasting behavior (forecast revisions and forecast errors). Subsection 4.3 and subsection 4.4 test the same associations in a regression framework,[20] controlling for firm characteristics associated with consistent earnings surprises. The results suggest that analysts extrapolate the consistent pattern

[20] I estimate all regressions using GMM (Generalized Method of Moments) to provide heteroscedasticity-consistent standard errors. Since I classify sample firms based on a rolling-window of four quarters, overlapping horizons can introduce serial-correlation in the error structure. Hence, I assume a fourth-order serial correlation structure in residuals when estimating standard errors using GMM.

in earnings surprises series to revise earnings forecasts, but do *not* overreact to consistent earnings surprises. In fact, the evidence is more consistent with analysts being more pessimistic following a longer sequence of consistent earnings surprises. Additional analysis in subsection 4.5 examines the influence of equity financing activities on analysts' forecast biases with respect to consistent earnings surprises. Subsection 4.6 provides preliminary evidence on the market consequence of analysts' forecast biases related with consistent earnings surprises. In the final analysis, I examine analysts' forecasting behavior in response to consistent small earnings surprises.

### 4.1 Characteristics of Firms with Consistent Earnings Surprises

Several studies document a distinct price premium among firms consistently meeting or beating earnings expectations (proxied by prior period earnings or analysts' forecasts) (Barth, Elliott and Finn, 1999; Myers and Skinner, 2002; Kasznik and McNichols, 2002; Bartov, Givoly, and Hayn, 2002). If managers are aware of the potential market consequences of consistent earnings signals, then maintaining a consistent earnings series may be a conscious choice made by firms that have the incentive and ability to achieve this goal. Hence, firms with consistent earnings surprises may differ systematically from the other firms (Chevis et al., 2002).

Panel A of Table 2 summarizes firm characteristics related with earnings performance and information environment across sample firms with consistent good and bad earnings surprises. As shown, consecutive good (bad) earnings surprises lead to improving (deteriorating) earnings performance ($ROA_{q+1}$). Firms with longer series of good (bad) earnings surprises appear to issue more (less) equity securities ($\Delta EQUITY_q$), although the overall (debt and equity) financing activities ($\Delta FIN_q$) are roughly stable.

It is worth noting that extreme earnings surprises are associated with greater dispersion in analysts' forecasts (measured as standard deviation of all valid individual forecasts within 30 days after quarter q earnings announcements) than small earnings surprises (i.e. D($N$=1)=0), suggesting that extreme earnings surprises cause greater disagreements among analysts concerning future earnings prospects. The consistent pattern in consecutive good earnings surprises reduces analysts' dispersion (decreasing from 8.41% to 5.22%), but a series of bad earnings surprises heightens dispersion in analysts' forecasts (rising from 5.51% to 12.04%). In other words, the sample variance of analysts' forecasts is negatively (positively) related with the consistent pattern in consecutive good (bad) earnings surprises.

Also as shown in Table 2, firms with consistent earnings surprises are smaller than the other firms. Prior studies have shown that analysts' forecast biases are systematically related with analysts' forecast dispersion, firm size, book-to-market ratio and earnings performance (Scherbina, 2004; Doukas, Kim, and Pantzalis, 2002; DeBondt and Thaler, 1987).[21] To mitigate correlated omitted variable problem, I control for these firm characteristics in testing the relationship between consistent earnings surprises and analysts' forecast behavior.

**4.2 Consistent Earnings Surprises and Analysts' Forecasts – Univariate Results**

Panel B of Table 2 presents variables related with analysts' forecasts across subsamples of firms with consecutive good and bad earnings surprises. Recall that D($N$ =i) equals 1 for firms with good (bad) earnings surprises preceded by *i*-1 consecutive good (bad) earnings surprises. As shown, analysts' forecast revisions increase from –0.01% to 0.06% as good earnings surprises continue to arrive over the most recent four quarters. Likewise, forecast revisions monotonically

[21] For example, Scherbina (2004) documents that analysts' consensus forecasts exhibit greater optimistic biaes as forecast dispersion increases. Doukas, Kim, and Pantzalis (2002) find that analysts make larger forecast errors (defined as median consensus forecast minus actual earnings) in predicting future earnings for small-cap and value (low book-to-market) stocks than large-cap and growth (low book-to-market) stocks. DeBond and Thaler (1987) provide evidence consistent with analysts over-extrapolate past earnings growth in forecasting future earnings.

decline from –0.21% to -0.34% following a longer series of bad earnings surprises. These patterns suggest that the later earnings surprises in a consistent series cause greater revisions in analysts' expectations about next quarter earnings, consistent with analysts' extrapolating the consistent pattern in earnings series to forecast earnings.

Recall that in Panel A of Table 2, the evidence shows better (worse) future earnings performance ($ROA_{q+1}$) following a longer sequence of consistent good (bad) earnings surprises, suggesting that the consistent pattern in earnings surprise series contains information about future earnings. To see whether analysts *fully* appreciate the future earnings implications of consistent earnings surprises, Panel B of Table 2 presents the associations between the duration of consistent earnings surprises and analysts' forecast errors (measured as actual earnings minus analysts' recent consensus forecast). As the duration of consecutive good earnings surprises increases, analysts' forecast errors increase monotonically from -0.04% to 0.25%, consistent with analysts being increasingly *pessimistic* subsequent to a longer series of good earnings news. On the other hand, analysts' forecast errors decline monotonically from –0.44% to -0.95% as consecutive bad earnings surprises continue to arrive. This result suggests that analysts become more *optimistic* following a longer series of bad earnings surprises. These patterns are inconsistent with the behavioral assumption that analysts overreact to consistent earnings signals. The following subsections reexamine these associations in multivariate regression tests.

### 4.3 Consistent Earning Surprises and Analysts' Forecast Revisions

To test $H_1$ that analysts' forecast revisions are more positive (negative), per unit of earnings surprises, following a longer consistent sequence of good (bad) earnings surprises, I estimate equation (1) below (for simplicity, firm subscripts are suppressed hereafter). To allow analysts' asymmetric reactions to good and bad earnings news, I estimate equation (1) among firms having positive earnings surprises (hereafter, the Positive *SURP* subsample) and non-positive earnings surprises (hereafter, the Non-positive *SURP* subsample) separately. To mitigate nonlinearities induced by extreme observations, as in Abarbanell and Bernard (1992) and others, variables in the regressions are percentile rankings, instead of the actual values.[22]

$$\begin{aligned} REVISION_q^{q+1} &= a_0 + a_1 |SURP_q| + a_{11} |SURP_q| * D(N=1) + a_{12} |SURP_q| * D(N=2) \\ &+ a_{13} |SURP_q| * D(N=3) + a_{14} |SURP_q| * D(N \geq 4) + a_2 DISP_q + a_3 MVE_q + a_4 BM_q + a_5 ROA_q + \delta_{q+1} \end{aligned} \quad (1)$$

In equation (1), the coefficients on earnings surprises reflect analysts' forecast revisions in response to one unit change in the magnitude of earnings surprises. Specifically, $a_1$ measures analysts' forecast revisions associated with one unit change in a neutral (i.e. small positive or small negative) earnings surprise. The coefficients, $a_1 + a_{1i}$ (where $i = 1, 2, 3$, or 4), measure analysts' forecast revisions in response to one unit change of a good (bad) earnings surprise preceded by ($i$-1) consecutive good (bad) earnings news. If analysts perceive the later earnings surprises in a consistent earnings surprise series as more permanent or persistent, they would revise earnings forecasts upward (downward) more aggressively following a longer sequence of consistent good (bad) earnings surprises. Thus, under this condition, I expect $a_{11} < a_{12} < a_{13} < a_{14}$ for Positive *SURP* subsample, and $a_{11} > a_{12} > a_{13} > a_{14}$ for Non-positive *SURP* subsample.

Table 3 tabulates the estimation results. Figure 3, Panel A plots coefficient estimates of ($a_1 + a_{1i}$) for $i = 1, 2, 3$, and 4. For the Positive *SURP* subsample, analysts' forecast revisions, per unit of earnings surprise, increase monotonically from 0.164 to 0.279 as a series of consistent good earnings surprises develops over the most recent four quarters. The increasing pattern in forecast revisions preserves after controlling for earnings performance ($ROA_q$) and other related firm characteristics ($DISP_q$, $MVE_q$, $BM_q$). Thus, consistent with $H_1$, analysts appear to revise

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[22] Results are qualitatively similar based on the actual values of the variables. For ease of interpretation of coefficients on earnings surprises, I use absolute values of earnings surprises in estimating equation (1).

forecasts upward more aggressively, per unit of good earnings surprise, following a longer sequence of consistent good earnings news.

Results are weaker in supporting $H_1$ for the Non-positive *SURP* subsample. Analysts' forecast revisions, per unit of earnings surprises, are more negative following consistent bad earnings surprises than following "isolated" bad earnings news. However, forecast revisions following *four* consecutive bad earnings news are not more negative, but more positive, than forecast revisions following *three* consecutive bad earnings surprises. Indeed, analysts' forecast revisions following "isolated" bad earnings surprises (-0.329) are statistically indistinguishable from forecast revisions following four consecutive bad earnings surprises (-0.334). Controlling for earnings performance ($ROA_q$) and other related firm characteristics ($DISP_q$, $MVE_q$, $BM_q$) does not change these results qualitatively. Overall, the evidence is consistent with analysts extrapolating the consistent pattern in good earnings surprise series in revising earnings forecasts. Analysts' revision behavior following bad earnings surprise series only weakly supports $H_1$. Next, I examine whether these observed patterns in analysts' forecast revisions reflect analysts' efficient/inefficient information processing of consistent earnings surprises, or whether consistent patterns of earnings surprises lead to systematically biased earnings forecasts.

### 4.4 Consistent Earning Surprises and Analysts' Forecast Errors

To test $H_2$ that analysts' forecasts are overly optimistic (pessimistic) following a series of consistent good (bad) earnings surprises, I estimate equation (2) below for the Positive *SURP* and Non-positive *SURP* subsamples separately. Similar to equation (1), I estimate equation (2) using percentile rankings to control for non-linear relationship.

$$\begin{aligned} ERROR_q^{q+1} &= b_0 + b_1 SURP_q + b_{11} SURP_q * D(N=1) + b_{12} SURP_q * D(N=2) \\ &+ b_{13} SURP_q * D(N=3) + b_{14} SURP_q * D(N \geq 4) + a_2 DISP_q + a_3 MVE_q + a_4 BM_q + a_5 ROA_q + \varepsilon_{q+1} \end{aligned} \quad (2)$$

In equation (2), the coefficients on earnings surprises measure the degree to which analysts underreact/overreact to earnings surprises. As argued in Abarbanell and Bernard (1992), if analysts underreact to earnings surprises, then analysts' forecasts would be too low (high) following good (bad) earnings surprises. Thus, a positive (negative) association between analysts' forecast errors (measured as actual earnings minus analysts' consensus forecasts) and earnings surprises indicates analysts' underreaction (overreaction) to earnings news.

The coefficient, $b_1$, represents the extent that analysts underreact (overreact) to neutral earnings surprises. The coefficients, $(b_1 + b_{1i})$ (where $i$ = 1, 2, 3, or 4), reflect the degree to which analysts underreact (overreact) to good (bad) earnings surprises preceded by $i$-$1$ consecutive good (bad) earnings surprises. If, as predicted in $H_2$, analysts overreact to consistent earnings surprises, I expect to observe less underreaction (or more overreaction) of analysts following a longer series of consistent earnings surprises. Less underreaction (or more overreaction) of analysts implies a less positive (or more negative) association between forecast errors and earnings surprises. Hence, I expect $b_{11} > b_{12} > b_{13} > b_{14}$ for both the Positive *SURP* subsample and the Non-positive *SURP* subsample.

Table 4 summarizes the estimation results. Figure 3, Panel B plots coefficient estimates of $(b_1 + b_{1i})$ for $i$ = 1, 2, 3, and 4. Consistent with prior studies, analysts appear to underreact to prior earnings news as shown by the positive coefficients on earnings surprises (Abarbanell and Bernard, 1992; Ali, Klein and Rosenfeld, 1992). Consistent with $H_2$, $(b_1 + b_{1i})$ is monotonically decreasing from 0.334 to 0.228 as a series of bad earnings surprises develops, suggesting analysts' underreaction to bad earnings news diminishes following consistent bad earnings surprises. However, analysts' underreaction to good earnings surprises appears to be exacerbated following a longer string of good earnings news, as evidenced by the increasing coefficients on good earnings surprises ($(b_1 + b_{1i})$ increases from 0.164 to 0.279 as $i$ goes from 1 to 4). These patterns remain qualitatively similar with control variables.[23]

It is possible that the control variables (forecast dispersion, size, book-to-market and return-on-asset) included in equation (1) do not fully capture the distinction between firms having consistent and isolated extreme earnings surprises. Thus, some un-identified variables may account for the observed pattern in coefficients on consistent earnings surprises as reported in Table 4. To lessen the correlated omitted variable problem, I also test $H_2$ based on a subsample of firms having four consecutive good or bad earnings surprises (i.e. firms with D($N \geq 4$)=1). Specifically, I run separate regressions of forecast errors on an intercept and earnings surprises across the four consecutive earnings surprises. Since the regressions are estimated based on a constant subsample, the pattern in coefficient estimates on consistent earnings surprises is unlikely driven by un-identified differences across sample firms. Figure 4 plots the coefficient estimates on earnings surprises for the four consecutive good or bad earnings surprises. As shown in Figure 4, coefficient estimates on consecutive good earnings surprises increase monotonically, suggesting analysts underreact more as consistent good earnings news arrives. The coefficient estimates on consecutive bad earnings surprises are similar in magnitude, inconsistent with the declining pattern reported in Table 4. Hence, tests of $H_2$ based on a constant subsample of firms strengthen the conclusion that the behavioral assumption of overreaction to consistent earnings signals is not descriptive of analysts' forecasting behavior.

In summary, results reported in this subsection fail to support the conjecture that analysts overreact to a series of consistent earnings surprises. Although analysts may underreact *less* to

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[23] Prior studies have shown that the fourth quarter earnings have differential persistence levels from the other quarters, possibly due to more frequent special items, strategic asset sales, earnings management, and end-of-the-year audit adjustments (e.g. Rangan and Sloan, 1996; Livnat, 2003). Hence, it is possible that analysts forecast the forth quarter earnings in a different fashion, compared with their forecasts for the other quarters. As a robustness check, I estimate equation (1) and (2) among the forth quarter and non-fourth quarter earnings forecasts separately. Results for these two subsamples remain qualitatively similar as those reported in Table 3 and Table 4.

bad earnings news as consecutive bad earnings surprises continue to arrive, analysts' underreaction to good earnings news appear exacerbated following a longer sequence of good earnings surprises. Analysts' asymmetric behavior in response to consistent good and bad earnings news is intriguing. Presumably, managers would take greater efforts (including discretionary accrual management) to sustain the consistent pattern in good earnings surprises since other things equal, consistent good earnings news looks more favorable to managers than consistent bad earnings news. As a result, analysts would react more cautiously to consistent good earnings news, leading to increasing underreaction to consecutive good earnings surprises. Untabulated results show that firms with consistent good (bad) earnings surprises mostly have income-increasing (income-decreasing) abnormal working capital accruals.[24] Interestingly, the magnitude of income-increasing accruals accompanying consistent good earnings surprises is significantly larger than the magnitude of income-decreasing abnormal accruals associated with consistent bad earnings surprises, suggesting greater extent of accrual management for firms having consistent good earnings surprises. A thorough investigation of the implications of accrual management on analysts' forecasting behavior is left for future research.

**4.5 Equity Financing, Consistent Earnings Surprises, and Analysts' Forecast Errors**

The primary focus of this paper is to test for possible analysts' behavioral bias associated with consistent earnings signals. In addition to behavioral bias, pressures to generate investment banking business and/or desire to maintain good relationships with the management may also bias analysts' forecasting activity (e.g. Lin and McNichols, 1998; Das, Levine and Sivaramakrishnan, 1998). A recent study by Bradshaw, Richardson and Sloan (2004) argues that both affiliated analysts (defined as analysts working for firms having investment banking ties to

[24] Abnormal working capital accruals are estimated as residuals from cross-sectional regressions of working capital accruals on changes in revenue (adjusted for changes in accounts receivable), book-to-market and return-on-assets.

the corporations that they cover) and unaffiliated analysts have incentives to issue overly optimistic forecasts for security issuing firms in order to maintain or increase their chances of generating investment-banking business. Supporting their argument, Bradshaw et al. (2004) show that external financing activity dominates investment banking affiliation as a determinant of analyst optimism. More important to this study, Bradshaw et al. (2004) find a strong positive relation between net external financing and over-optimism in analysts' forecasts.

All else equal, firms have greater incentive to issue equity when their market values are high, and to repurchase equity when their market values are low (Baker and Wurgler, 2002). Since consistent earnings news likely accompanies improving or deteriorating stock performance (Barth et al., 1999; and Myers and Skinner, 2002; Kasznik and McNichols, 2002; Bartov et al., 2002), equity financing activities may be systematically correlated with consistent earnings surprises.[25] Thus, analysts' incentive bias induced by equity financing activities may contaminate the analysis on analysts' behavioral bias related with consistent earnings surprises.

To isolate the influences due to equity financing activities, I reexamine the associations between consistent earnings surprises and analysts' forecast errors within equity issuing firms and equity repurchasing firms separately. The classification of equity issuance and repurchase is based on information provided in the statement of cash flows.[26] A dummy variable, *ISSUE,* equals 1 for equity issuing firms (i.e. $\Delta EQUITY_q > 0$) and 0 for equity repurchasing firms (i.e. $\Delta EQUITY_q \leq 0$). I augment equation (2) by including interaction terms of *ISSUE* and earnings

[25] As shown in Table 2, firms having longer sequences of consistent good (bad) earnings surprises do issue greater (lower) amount of equity securities.

[26] Following Bradshaw et al. (2003), net equity financing ($\Delta EQUITY_q$) is measured as equity issuance (quarterly data item #84) minus equity repurchase (data item #93) minus dividends (data item #89), scaled by lagged total assets (data item #44), for the period immediately before the measurement of analysts' forecast errors.

surprises, and estimate the following equation for the Positive *SURP* and Non-positive *SURP* subsamples separately.

$$\begin{aligned} ERROR_q^{q+1} &= c_0 + c_1 SURP_q + c_{11} SURP_q * D(N=1) + c_{11F} SURP_q * D(N=1) * ISSUE + c_{12} SURP_q * D(N=2) \\ &+ c_{12F} SURP_q * D(N=2) * ISSUE + c_{13} SURP_q * D(N=3) + c_{13F} SURP_q * D(N=3) * ISSUE \\ &+ c_{14} SURP_q * D(N \geq 4) + c_{14F} SURP_q * D(N \geq 4) * ISSUE + c_2 DISP_q + c_3 MVE_q + c_4 BM_q + c_5 ROA_q + \gamma_{q+1} \end{aligned} \quad (3)$$

The interpretation of coefficients on earnings surprises is similar as before. The coefficients, $c_1 + c_{1i}$ (where $i$ = 1, 2, 3, or 4), represent the degree to which analysts underreact to consistent earnings surprises of equity *repurchasing* firms; and ($c_1 + c_{1i} + c_{1iF}$) represents the extent that analysts underreact to consistent earnings surprises of equity *issuing* firms. Assuming equity issuance activities induce greater analysts' optimism, I expect to observe less underreaction to good earnings surprises and greater underreaction to bad earnings surprises among equity issuing firms than equity repurchasing firms. Furthermore, examining analysts' forecasting behavior within equity repurchasing firms should provide clearer evidence regarding analysts' behavioral biases *per se*.

Table 5 summarizes the regression results. Recall that a more positive coefficient on earnings surprises indicates greater underreaction to earnings news. Within the Positive *SURP* subsample, I find that the coefficients on earnings surprises monotonically increase as consecutive good earnings surprises continue to arrive for both equity issuing and equity repurchasing firms. Furthermore, the coefficients on earnings surprises are similar across equity issuing and equity repurchasing firms, suggesting that compared with equity repurchase, equity issuance does not lead to less underreaction (or greater overreaction) to extreme positive earnings surprises among analysts. Hence, equity issuance does not appear to bias previous inferences regarding analysts' greater underreaction to consistent good earnings surprises.

For the Non-positive *SURP* subsample, equity issuance is associated with analysts' less underreaction to bad earnings surprises, as shown by the smaller (i.e. less positive) coefficients on earnings surprises among equity issuing firms than those among equity repurchasing firms. This finding contradicts the argument that equity issuance induces analysts to be more optimistic, hence underreact more to bad earnings news. More relevant to the primary question of this paper, across both equity issuing and equity repurchasing firms, the coefficients on earnings surprises monotonically decline as consecutive earnings surprises continue to arrive, confirming the general pattern observed in Table 4. Overall, equity financing activities do not significantly influence the relationship between analysts' forecast errors and consistent earnings surprises documented in the previous subsection.

**4.6 Consistent Earnings Surprises and Future Stock Return Behavior**

The evidence thus far suggests that analysts underreact *more* to consistent good earnings surprises, and underreact *less* to consistent bad earnings surprises. Prior studies have shown that the optimistic bias in analysts' earnings forecasts is reflected in stock prices (e.g. Scherbina, 2004). Thus, it is possible that investors are misled by analysts' biased forecasts with respect to consistent earnings surprises, resulting in exacerbated (attenuated) market underreaction to consistent good (bad) earnings news. On the other hand, market prices may not fully reveal analysts' forecast biases. Besides trading constraints, it is unlikely that investors rely solely on analysts' opinions to make investment decisions (Abarbanell and Bernard, 1992; Malmendier and Shanthikumar, 2004).[27] In this section, I provide preliminary evidence regarding the market consequence of analysts' forecast biases related with consistent earnings surprises.

[27] For example, Abarbanell and Bernard (1992) suggest that analysts' behavior is at best a partial explanation for stock price underreaction to earnings, and may be unrelated to stock price overreaction. In addition, sophisticated investors may be able to discern biases in analysts' forecasts (e.g. Malmendier and Shanthikumar, 2004).

Extant research commonly attributes the price drift that is in the same direction as the initial price reaction (upon information signals such as earnings announcements) to investors' *underreaction* to information (e.g. Bernard and Thomas, 1989). If investors naively follow analysts' biased earnings forecasts in shaping earnings expectations, investors would underreact *more* (*less*) to consistent good (bad) earnings surprises. Assuming pricing errors correct over time, I would observe greater or prolonged (less or short-lived) price drift for firms having consistent good (bad) earnings surprises. In addition, abnormal returns around future earnings announcements should be more pronounced

To examine pricing implications of consistent earnings surprises, I first group firms into four portfolios – (1) firms having isolated good earnings surprises (i.e. $SURP_q > 0$ and D($N = 1$) = 1); (2) firms having three or four consecutive good earnings surprises (i.e. $SURP_q > 0$, and D($N = 3$) = 1 or D($N \geq 4$) = 1); (3) firms having isolated bad earnings surprises (i.e. $SURP_q \leq 0$ and D($N = 1$) = 1); and (4) firms having three or four consecutive bad earnings surprises (i.e. $SURP_q \leq 0$, and D($N = 3$) = 1 or D($N \geq 4$) = 1). I then calculate cumulative abnormal (size-adjusted) returns (CARs) beginning the day after quarter q earnings announcement, and extending through the fourth subsequent earnings announcement for each portfolio of firms.[28]

Figure 2 graphically depicts the future return behavior following extreme earnings surprises. Consistent with the conjecture that analysts' biased earnings forecasts lead investors to underreact more to consistent good earnings news, the post-earnings-announcement drift is more pronounced for firms with three or more consecutive good earnings news, relative to firms with isolated good earnings news. In addition, the 3-day CARs around the subsequent two quarters'

[28] The abnormal returns are calculated by subtracting from each firm's daily return, the equally weighted return on a control portfolio of all firms within the same NYSE/AMEX size decile as of the beginning of the calendar year. This daily abnormal return is then summed over time to compute a cumulative abnormal return (CAR). Only firms listed on NYSE and AMEX are retained in the analysis (Swaminathan and Lee, 2000).

earnings announcements are significantly higher for firms with consistent good earnings surprises. This result is consistent with the notion that investors underreact more to consistent good earnings news, and thus the market is "surprised" to a greater extent that future realized earnings are better than initial expectations.

The price drift following bad earnings surprises is less pronounced than the price drift following good earnings surprises.[29] In fact, the downward price drift following isolated bad earnings surprises starts to reverse shortly after the next quarter's earnings announcement, suggesting isolated bad earnings surprises tend to be followed by good news (possibly due to mean-reversion property of earnings process). Contrary to the conjecture that analysts' biased forecasts lead investors to underreact less to consistent bad earnings surprises, the downward price drift lasts longer following consistent bad earnings surprises, relative to isolated bad earnings surprises. Overall, the evidence reported in Figure 2 implies that analysts' biased processing of consistent good earnings news may mislead market expectations, resulting in more pronounced price drift following consistent good earnings surprises. However, analysts' forecast biases associated with consistent bad earnings surprises seem unrelated with the differential return behavior following consistent and isolated bad earnings news.

### 4.7 Consistent Small Earning Surprises and Analysts' Forecasting activity

For completeness, I also examine analysts' forecasting activities in response to consistent *small* earnings surprises. Griffin and Tversky (1992) provide experimental evidence suggesting that individuals focus on the strength or extremeness of the available evidence with insufficient regard for its weight or predictive validity in intuitive judgments. This mode of judgment yields overreaction when strength is high (e.g. a series of extreme earnings surprises) and predicative

[29] Prior studies have documented more pronounced downward price drifts following bad earnings news (e.g. Abarbanell and Bernard, 1992; Bernard and Thomas, 1990). The results in Figure 2 differ from prior findings, possibly due to different portfolio formation and/or measurement of earnings surprises.

validity is low, and underreaction when strength is low (e.g. a series of small earnings surprises) and predicative validity is high. Prior studies have shown that small earnings surprises are more persistent than extreme earnings surprises (Freeman and Tse, 1992). Hence, based on Griffin and Tversky (1992), I expect to observe greater underreaction following a longer sequence of consistent small earnings surprises.

To examine analysts' responses to consistent small earnings surprises, I first categorize consistent neutral earnings surprises based on a rolling window of four quarters. Recall that neutral earnings surprises are small positive or small negative earnings surprises, ranked in the middle range of the cross-sectional earnings surprise distribution (decile 4-7). I create four binary variables, ND($N$=1), ND($N$=2), ND($N$=3), and ND($N \geq 4$),with values zero or one, to categorize firms based on the consistent pattern in neutral earnings surprises over the most recent four quarters. Specifically, if quarter q's earnings surprise, $SURP_{i,q}$, is not neutral, then all the four dummies have values of zero. If $SURP_{i,q}$ is small positive (small negative) and $SURP_{i,q-1}$ is not, then I assign one to ND($N$=1), and zero to all the other three dummies. If both $SURP_{i,q}$ and $SURP_{i,q-1}$ are small positive (small negative), and $SURP_{i,q-2}$ is not, then I assign one to ND($N$=2), and zero to all the other three dummies, and so on. If a series of earnings surprises (e.g. $SURP_{i,q-3}$, $SURP_{i\ q-2}$, $SURP_{i,q-1}$, $SURP_{i,q}$) is comprised of all small positive (small negative) earnings surprises, then I assign one to ND$(N \geq 4)$, and zero to the other three dummies.

Similar to previous tests on extreme earnings surprises, I estimate the following equations (5) and (6) for the Positive *SURP* and Non-positive *SURP* subsamples separately, and use percentile rankings in estimating the regressions.

$$REVISION_q^{q+1} = a'_0 + a'_1 |SURP_q| + a'_{11} |SURP_q| * ND(N=1) + a'_{12} |SURP_q| * ND(N=2) + a'_{13} |SURP_q| * ND(N=3) + a'_{14} |SURP_q| * ND(N \geq 4) + a'_2 DISP_q + a'_3 MVE_q + a'_4 BM_q + a'_5 ROA_q + \delta'_{q+1} \quad (5)$$

$$ERROR_q^{q+1} = b'_0 + b'_1 SURP_q + b'_{11} SURP_q * ND(N=1) + b'_{12} SURP_q * ND(N=2) + b'_{13} SURP_q * ND(N=3) + b'_{14} SURP_q * ND(N \geq 4) + b'_2 DISP_q + b'_3 MVE_q + b'_4 BM_q + b'_5 ROA_q + \varepsilon'_{q+1} \quad (6)$$

The univariate associations between analysts' forecasting behavior and consistent small earnings surprises are summarized in Panel B of Table 6. As shown, there is no clear trend in analysts' forecast revisions as small positive earnings surprises continue to arrive. Analysts' forecast revisions become *less* negative following a longer sequence of small negative earnings surprises. There is weak evidence suggesting analysts are more optimistic (forecast errors decline in general from –0.02% to –0.05%) following a longer series of small positive earnings news. Analysts appear more pessimistic (forecast errors increase from –0.27% to –0.11%) following a longer series of small negative earnings surprises. Thus, the univariate associations between forecast revision/error and consistent small earnings surprises show quite different patterns, compared to the same associations based on consistent extreme earnings surprises as reported in Panel B of Table 2.

Table 7 reports regression results for estimating equation (5) and (6). As shown, analysts' forecast revisions, per unit of earnings surprise, appear to decline following consecutive small positive earnings surprises. There is no clear pattern in analysts' forecast revisions following consecutive small negative earnings surprises. These results suggest that analysts do not extrapolate the consistent pattern in small earnings surprises to revise earnings forecasts.

As for analysts' forecast bias, results in Table 7 suggest that analysts underreact less as small positive earnings surprises continue to arrive, as shown by the declining coefficients on consecutive small positive earnings surprises (from 0.407 to 0.277). The consistent pattern in consecutive small negative earnings surprises does not appear to influence analysts' forecast biases. Although the coefficients on consecutive small negative earnings surprises in general increase from 0.156 to 0.170, the magnitudes of the increases are small and highly insignificant.

Therefore, analysts appear to *overreact* to a series of small positive earnings surprises, but largely ignore the consistent pattern in small negative earnings surprise series.[30]

**5. Conclusions and Future Research**

Over the past two decades, the conventional efficient market hypothesis has been challenged by a host of studies documenting cross-sectional return predictability. Recent behavioral finance theories attempt to explain the seemingly anomalous return patterns based on assumptions about investors' biased information processing. However, empirical tests of these behavioral biases have been limited in scope. This paper seeks to test one widely used behavior assumption that individuals overreact to a series of consistent information signals using analysts' earnings forecast data. The overall evidence fails to support the conjecture that analysts overreact to a series of consistent earnings surprises. Findings in the paper are of interests to investors in evaluating analysts' forecasts. Since analysts' opinions are important inputs to investors' investment decision process, investors can make more informative investment decisions by gaining a better understanding of analysts' forecasting process. More important, the documented evidence poses a challenge to the entire class of behavioral finance theories that assume investors overreact to consistent earnings signals.

The findings in this study raise several issues. First, consistent earnings surprises unlikely result from a random process. Managers may intentionally manage earnings/expectations to achieve a sustained earnings pattern, for the purpose of signaling future performance or misleading investors temporarily to reap private benefits. As sophisticated financial information users, analysts may be able to discount unwarranted good/bad earnings news in forecasting

[30] Unlike extreme earnings surprises, earnings surprises with small magnitudes more likely motivate managers to engage in earnings management and/or earnings guidance activities (e.g. Dechow, Richardson and Tuna, 2003). The tools (earnings/expectation management) utilized by managers to sustain a consistent small earnings surprise series may as well influence analysts' forecasting behavior, a question left for future research.

earnings. The interaction between earnings/expectation management and analysts' forecasting behavior needs further investigation.

Second, given analysts' forecasts exhibiting behavioral biases, the question of how to de-bias analysts' forecasts needs further examination. A richer information environment (e.g. more frequent management forecasts, greater analysts following, less information uncertainty, etc.) potentially alleviates analysts' biases by providing higher quality information and more frequent feedbacks. As shown in the paper, consistent earnings surprises are associated with differential levels of analysts' forecast dispersion. How forecast dispersion (or more generally, information uncertainty) influences analysts' forecasting behavior (Zhang, 2004)? Further examination of these issues is left for future research.

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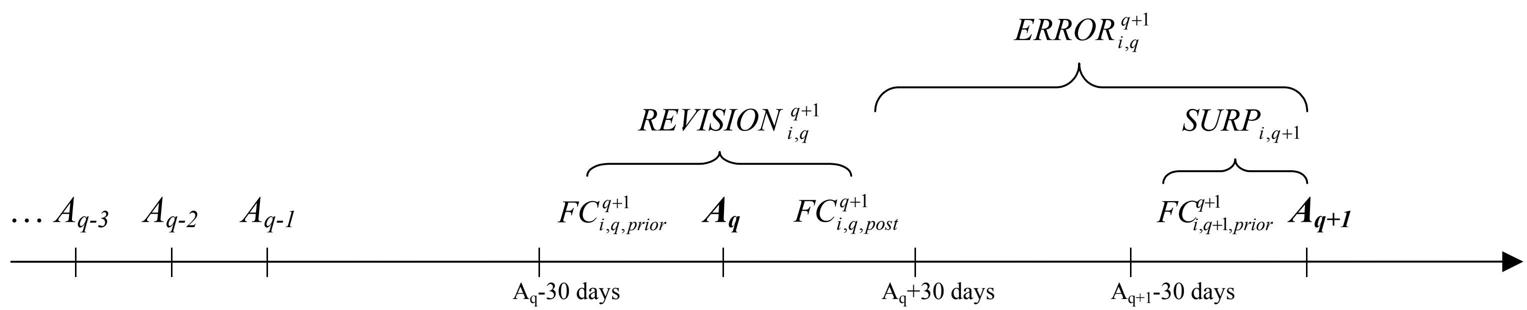
**Figure 1: Time-line Illustration of Measurement of Earnings Surprise Series and Analysts' Forecast Variables**



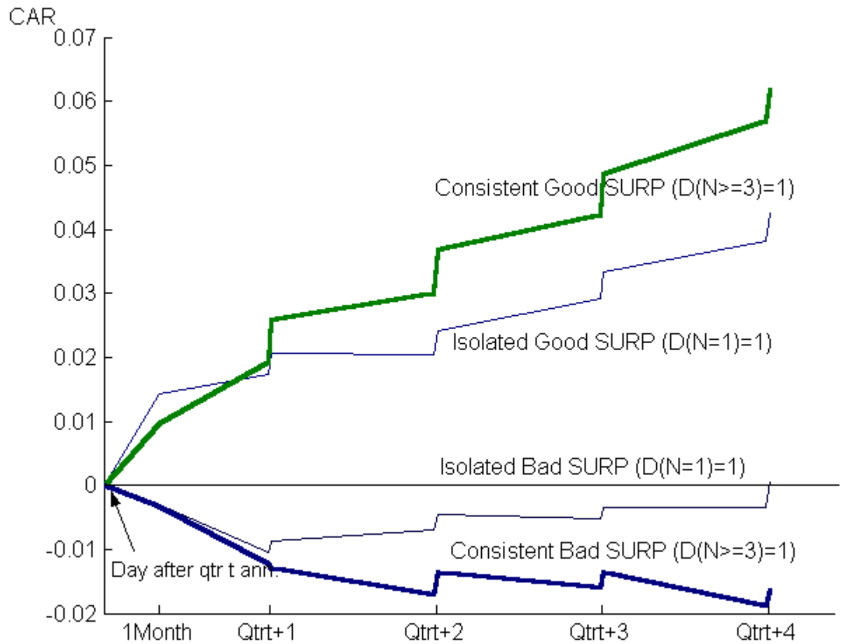

- $A_q$: Announcement dates of quarter q earnings.
- $FC_{i,q,prior}^{q+1}$: Mean of individual analysts' forecasts for quarter q+1 made within 30 days (excluding the most recent week) before quarter q earnings announcements.
- $FC_{i,q,post}^{q+1}$: Mean of individual analysts' forecast for quarter q+1 made within 30 days after quarter q earnings announcements.
- $FC_{i,q+1,prior}^{q+1}$: Mean of individual analysts' forecasts for quarter q+1 made within 30 days (excluding the most recent week) before quarter q+1 earnings announcements.

- $REVISION_{i,q}^{q+1} = \dfrac{FC_{i,q,post}^{q+1} - FC_{i,q,prior}^{q+1}}{P_q}$.
- $ERROR_{i,q}^{q+1} = \dfrac{EPS_{q+1} - FC_{i,q,post}^{q+1}}{P_q}$.
- $SURP_{i,q+1} = \dfrac{EPS_{q+1} - FC_{i,q+1,prior}^{q+1}}{P_q}$.

($P_q$ is share price at the end of fiscal quarter q.)

**Figure 2: Consistent Earnings Surprises and Future Cumulative (Size-adjusted) Abnormal Returns (CARs)**

This figure plots cumulative size-adjusted abnormal daily returns following extreme good or bad earnings surprises over the next four quarters. Bold figure indicates significance level less than 5%. Sample period: 1987-2002. Please refer to text for definition of earnings surprises, indicator of consistency (i.e. D(*N*=i)), and classification of extreme earnings surprises.

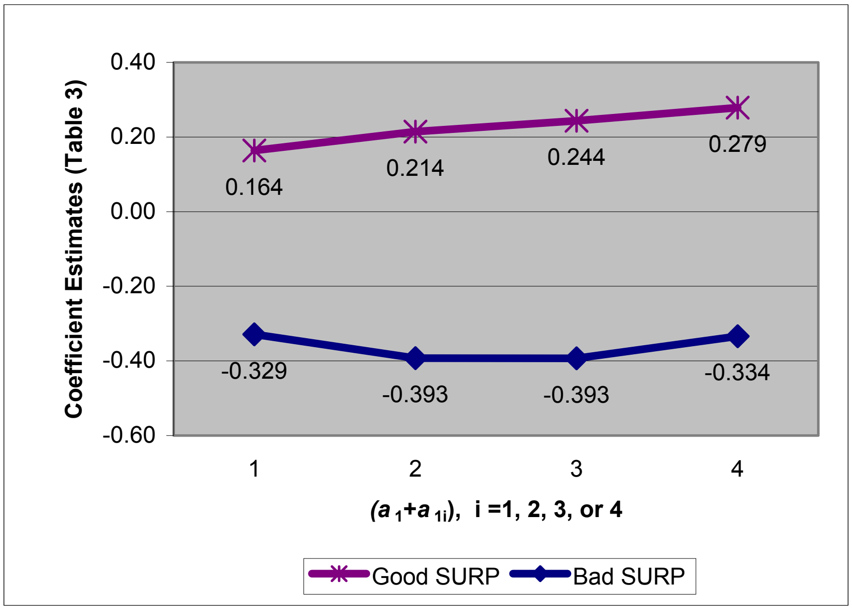



| Earnings Surprise \| Consistent Pattern | CAR over four quarters subsequent to quarter q earnings announcement | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Qtrq+1 | | | Qtrq+2 | | Qtrq+3 | | Qtrq+4 | | |
| | Revision (1-month) | Prior to ann. | 3-day ann. | Prior to ann. | 3-day ann. | Prior to ann. | 3-day ann. | Prior to ann. | 3-day ann. | Total CAR |
| $SURP_q > 0$ : | | | | | | | | | | |
| D(N=1) = 1 | **1.43%** | 0.31% | **0.32%** | -0.01% | **0.36%** | **0.50%** | **0.42%** | **0.48%** | **0.45%** | 4.26% |
| D(N>=3) = 1 | **0.96%** | **0.97%** | **0.66%** | 0.42% | **0.68%** | 0.55% | **0.63%** | **0.82%** | **0.48%** | 6.16% |
| $SURP_q \leq 0$ : | | | | | | | | | | |
| D(N=1) = 1 | **-0.31%** | **-0.74%** | **0.17%** | 0.18% | **0.25%** | -0.08% | **0.19%** | -0.01% | **0.41%** | 0.06% |
| D(N>=3) = 1 | -0.32% | **-0.90%** | -0.06% | -0.42% | **0.35%** | -0.25% | **0.25%** | -0.54% | **0.25%** | -1.63% |

## Figure 3: Coefficient Estimates on Consistent Earnings Surprises

This figure presents results from regressing forecast revisions (Panel A) or forecast errors (Panel B) on an intercept, earnings surprises and interaction terms of earnings surprises with D(*N*=i), where i ranges from 1 to 4 (Please refer to text for definition of D(*N*=i) and specifications of regressions). The figure plots coefficient estimates of $(a_1 + a_{1i})$ and $(b_1 + b_{1i})$, where *i* ranges from 1 to 4.

Panel A: Forecast revision and consistent earnings surprises (Refer to Table 3)




Panel B: Forecast error and consistent earnings surprises (Refer to Table 4)

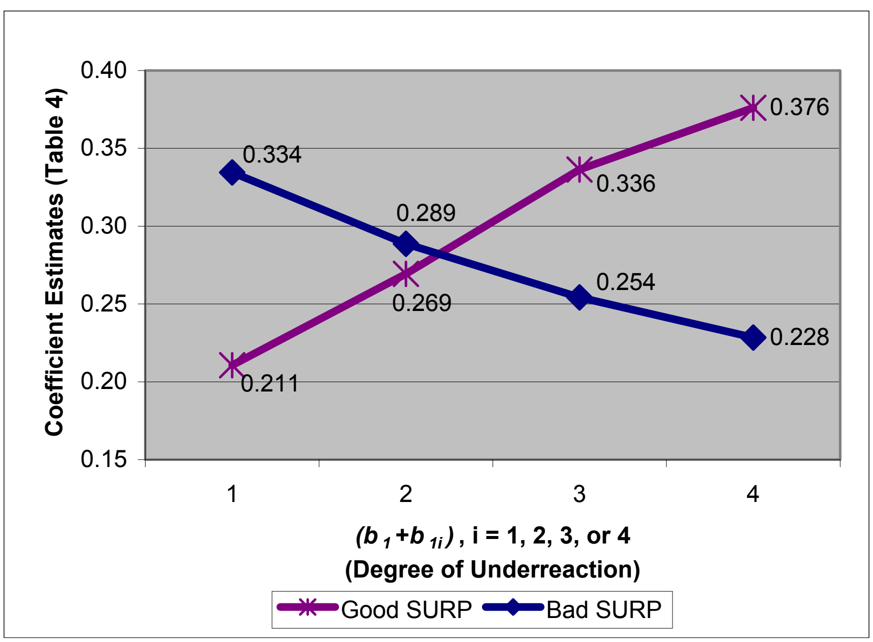
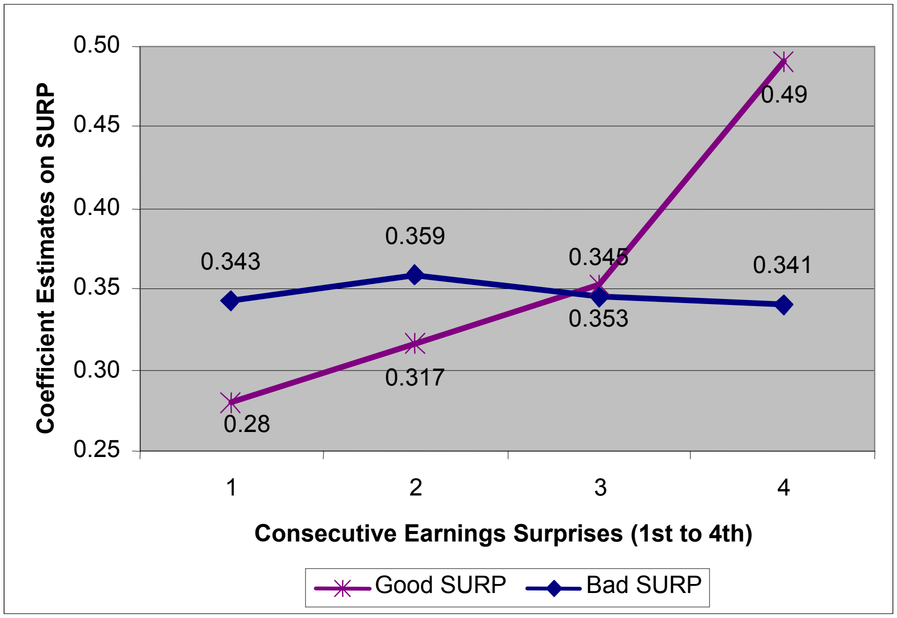


**Figure 4: Coefficient Estimates on Consistent Earnings Surprises (associated with Forecast Errors). All Sample Firms have Four Consecutive Good/Bad Earnings Surprises**

This figure presents results from separate regressions of forecast errors on an intercept and earnings surprises across four consecutive good or bad earnings surprises. The separate regressions are estimated based on a constant subsample of firms (i.e. firms having four consecutive good or bad earnings surprises). The figure plots coefficient estimates on earnings surprises across each individual consistent earnings surprise.



## Table 1: Descriptive Statistics for Selected Variables

This table reports summary statistics for the sample firms (Panel A) and Pearson (above diagonal) and Spearman (below diagonal) correlations between selected variables (Panel B). Primary sample period covers from 1987 to 2002. All variables are winsorized at ± 1%.

| | |
|---|---|
| $SURP_q$: | Reported earnings (in IBES) minus mean of individual analysts' forecasts made within 30 days (excluding the most recent week) before quarter q earnings announcements, scaled by share price at the end of quarter q-1. |
| $REVISION_q^{q+1}$ | Mean of individual analysts' forecast for quarter q+1 made within 30 days after quarter q earnings announcements minus mean of individual analysts' forecasts made within 30 days (excluding the most recent week) before quarter q earnings announcements, scaled by share price at the end of quarter q. |
| $ERROR_q^{q+1}$: | Reported earnings (in IBES) minus mean of individual analysts' forecasts for quarter q+1 within 30 days after quarter q earnings announcements, scaled by share price at the end of quarter q. |
| *ROA*: | Return on assets (earnings before extraordinary items/lagged total assets). |
| *MVE:* | Market value of common equity (in millions). |
| *BM*: | Book-to-market ratio (common equity/*MVE*). |
| Δ*XFIN*: | Net external financing, measured as the sum of net equity financing (Δ*EQUITY*) and net debt financing (Δ*DEBT*), scaled by lagged total assets. |
| Δ*EQUITY*: | Equity issuance minus equity repurchase minus dividends, scaled by lagged total assets. |
| Δ*DEBT*: | Long-term debt issuance minus long-term debt retirements plus the net change in notes payable, scaled by lagged total assets. |
| $DISP_q$: | Standard deviation of individual analysts' forecasts for quarter q+1 made within 30 days after quarter q earnings announcements. |
| $ACCURATE_q$: | Absolute value of $ERROR_q^{q+1}$. |

Panel A: Descriptive statistics for the full Sample

| | Mean | Stddev | Q1 | Median | Q3 | Obs. |
|---|---|---|---|---|---|---|
| *Earnings surprises and Analysts' Forecasting variables* | | | | | | |
| $SURP_q$ | -0.04% | 0.68% | -0.08% | 0.02% | 0.14% | 53,599 |
| $REVISION_q^{q+1}$ | -0.09% | 0.36% | -0.12% | -0.01% | 0.03% | 53,599 |
| $ERROR_q^{q+1}$ | -0.19% | 1.05% | -0.23% | 0.00% | 0.12% | 53,599 |
| *Firm performance and Information environment* | | | | | | |
| $ROA_q$ | 0.79% | 4.91% | 0.30% | 1.37% | 2.57% | 38,050 |
| $BM_q$ | 41.78% | 37.60% | 15.41% | 32.22% | 57.34% | 53,104 |
| $MVE_q$ | 6,957 | 22,160 | 259 | 906 | 3,606 | 38,099 |
| $\Delta FIN_q$ | 3.74% | 14.75% | -1.90% | 0.43% | 4.37% | 38,087 |
| $\Delta EQUITY_q$ | 1.52% | 12.09% | -1.33% | 0.00% | 0.64% | 38,082 |
| $\Delta DEBT_q$ | 2.25% | 9.54% | -0.73% | 0.00% | 3.34% | 38,039 |
| $DISP_q$ | 5.15% | 98.89% | 0.82% | 1.87% | 4.24% | 50,261 |
| $ACCURATE_q$ | 0.49% | 0.94% | 0.05% | 0.16% | 0.48% | 53,599 |

**Table 1 (Cond.)**

Panel B: Pearson (above diagonal) and Spearman correlations of selected variables

| | $SURP_q$ | $REVISION_q^{q+1}$ | $ERROR_q^{q+1}$ | $ROA_q$ | $BM_q$ | $MVE_q$ | $\Delta FIN_q$ | $\Delta EQUITY_q$ | $\Delta DEBT_q$ |
|---|---|---|---|---|---|---|---|---|---|
| $SURP_q$ | | 0.43 | 0.35 | 0.23 | -0.13 | 0.02 | -0.01 | 0.02 | -0.02 |
| $REVISION_q^{q+1}$ | 0.39 | | 0.33 | 0.21 | -0.22 | 0.05 | -0.01 | 0.01 | -0.02 |
| $ERROR_q^{q+1}$ | 0.37 | 0.34 | | 0.13 | -0.18 | 0.04 | -0.02 | 0.00 | -0.03 |
| $ROA_q$ | 0.21 | 0.25 | 0.14 | | -0.17 | 0.09 | -0.19 | -0.21 | -0.05 |
| $BM_q$ | -0.10 | -0.21 | -0.16 | -0.37 | | -0.15 | -0.04 | -0.05 | -0.01 |
| $MVE_q$ | 0.06 | 0.16 | 0.12 | 0.27 | -0.51 | | -0.05 | -0.06 | -0.01 |
| $\Delta FINq$ | -0.04 | -0.03 | -0.05 | -0.16 | -0.01 | -0.13 | | 0.72 | 0.62 |
| $\Delta EQUITYq$ | 0.04 | 0.02 | 0.02 | -0.13 | -0.07 | -0.26 | 0.50 | | -0.07 |
| $\Delta DEBTq$ | -0.07 | -0.06 | -0.07 | -0.06 | 0.02 | 0.03 | 0.66 | -0.13 | |

## Table 2: Analysts' Forecasts, Selected Firm Characteristics and Consistent Earnings Surprises

This table summarizes the mean values of selected variables for various subsamples. D(*N* = i) is dummy variables equal 1 when the current earnings surprise is good (or bad) and preceded by (i-1) consecutive good (or bad) earnings surprises; and 0 otherwise (Refer to text for details on the classification of good and bad earnings surprises). Please refer to Table 1 for variable definitions. Primary sample period covers from 1987 to 2002. All variables are winsorized at ± 1%.

| | $SURP_q > 0$ (N = 30,957) | | | | | $SURP_q \leq 0$ (N = 22,642) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | D(*N*=1)=0 | D(*N*=1)=1 | D(*N*=2)=1 | D(*N*=3)=1 | D(*N*>=4)=1 | D(*N*=1)=0 | D(*N*=1)=1 | D(*N*=2)=1 | D(*N*=3)=1 | D(*N*>=4)=1 |
| **Panel A: Firm performance and Information environment** | | | | | | | | | | |
| $ROA_{q+1}$ | 1.78% | 0.73% | 0.73% | 1.32% | 1.68% | 1.41% | -0.13% | -0.71% | -1.29% | -1.16% |
| $ROA_q$ | 1.94% | 0.78% | 1.10% | 1.43% | 1.80% | 1.64% | 0.15% | -0.74% | -1.04% | -1.31% |
| $BM_q$ | 0.295 | 0.472 | 0.451 | 0.412 | 0.383 | 0.345 | 0.483 | 0.570 | 0.613 | 0.598 |
| $MVE_q$ | 12,504 | 4,278 | 4,177 | 4,110 | 2,856 | 9,936 | 4,371 | 3,187 | 2,154 | 2,682 |
| $\Delta FIN_q$ | 3.79% | 3.75% | 3.71% | 3.76% | 5.43% | 2.70% | 3.83% | 4.00% | 3.61% | 3.70% |
| $\Delta EQUITY_q$ | 1.56% | 1.69% | 2.22% | 2.63% | 3.93% | 0.42% | 1.32% | 1.07% | 0.76% | 0.95% |
| $\Delta DEBT_q$ | 2.24% | 2.13% | 1.59% | 1.18% | 1.55% | 2.30% | 2.54% | 2.90% | 2.92% | 2.76% |
| $DISP_q$ | 2.16% | 8.41% | 8.82% | 4.90% | 5.22% | 2.38% | 5.51% | 6.51% | 7.05% | 12.04% |
| $ACCURATE_q$ | 0.18% | 0.53% | 0.53% | 0.51% | 0.53% | 0.29% | 0.66% | 0.90% | 1.03% | 1.25% |
| **Panel B: Earnings surprises and Analysts' forecasting variables** | | | | | | | | | | |
| $SURP_{q+1}$ | 0.01% | 0.04% | 0.11% | 0.19% | 0.25% | -0.06% | -0.18% | -0.30% | -0.33% | -0.56% |
| $SURP_q$ | 0.04% | 0.41% | 0.48% | 0.46% | 0.49% | -0.03% | -0.44% | -0.64% | -0.77% | -0.94% |
| $REVISION^q_{q+1}$ | -0.02% | -0.01% | 0.03% | 0.04% | 0.06% | -0.06% | -0.21% | -0.30% | -0.35% | -0.34% |
| $ERROR^q_{q+1}$ | -0.05% | -0.04% | 0.07% | 0.18% | 0.25% | -0.17% | -0.44% | -0.64% | -0.75% | -0.95% |
| *Obs.* | 14,885 | 8,031 | 3,509 | 1,814 | 2,718 | 6,618 | 8,273 | 3,646 | 1,777 | 2,328 |

## Table 3: Consistent Earnings Surprises and Analysts' Forecast Revisions

This table summarizes coefficient estimates and associated t-statistics (in parentheses) of estimating the following equation using GMM estimation (assuming fourth-order serial correlations in residuals). Primary sample period covers from 1987 to 2002. *REVISION* and |*SURP*| are measured as percentile rankings. Please refer to Table 1 for variable definitions. P-values are based on two-tailed t-tests of differences in coefficient estimates. */**/*** indicates significance level at less than 10% / 5% / 1%. All variables are winsorized at ± 1%.

$$REVISION_q^{q+1} = a_0 + a_1 |SURP_q| + a_{11} |SURP_q| * D(N=1) + a_{12} |SURP_q| * D(N=2) + a_{13} |SURP_q| * D(N=3) + a_{14} |SURP_q| * D(N \geq 4) + a_2 DISP_q + a_3 MVE_q + a_4 BM_q + a_5 ROA_q + \delta_{q+1} \quad (1)$$

| | $SURP_q > 0$ | | | | $SURP_q \leq 0$ | | | |
|---|---|---|---|---|---|---|---|---|
| | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat |
| $a_0$ | 0.394 | (118.06)*** | 0.328 | (29.33)*** | 0.671 | (179.57)*** | 0.656 | (56.6)*** |
| $a_1$ | 0.234 | (18.29)*** | 0.325 | (20.92)*** | -0.257 | (-13.21)*** | -0.187 | (-8.21)*** |
| $a_{11}$ | -0.070 | (-6.61)*** | -0.038 | (-2.95)*** | -0.072 | (-4.35)*** | -0.014 | (-0.7) |
| $a_{12}$ | -0.020 | (-1.63) | 0.004 | (0.28) | -0.136 | (-7.69)*** | -0.056 | (-2.72)*** |
| $a_{13}$ | 0.009 | (0.65) | 0.042 | (2.38)** | -0.136 | (-7.06)*** | -0.060 | (-2.63)*** |
| $a_{14}$ | 0.044 | (3.45)*** | 0.056 | (3.67)*** | -0.077 | (-4.12)*** | -0.015 | (-0.7) |
| $a_2$ | | | -0.091 | (-10.9)*** | | | -0.259 | (-27.18)*** |
| $a_3$ | | | 0.091 | (10.15)*** | | | 0.090 | (9.79)*** |
| $a_4$ | | | -0.081 | (-7.82)*** | | | -0.043 | (-4.34)*** |
| $a_5$ | | | 0.089 | (11.33)*** | | | 0.053 | (6)*** |
| | | *P*-value | | *P*-value | | *P*-value | | *P*-value |
| $a_1 + a_{11}$ | 0.164 | <.0001 | 0.287 | <.0001 | -0.329 | <.0001 | -0.201 | <.0001 |
| $a_1 + a_{12}$ | 0.214 | <.0001 | 0.329 | <.0001 | -0.393 | <.0001 | -0.243 | <.0001 |
| $a_1 + a_{13}$ | 0.244 | <.0001 | 0.366 | <.0001 | -0.393 | <.0001 | -0.247 | <.0001 |
| $a_1 + a_{14}$ | 0.279 | <.0001 | 0.381 | <.0001 | -0.334 | <.0001 | -0.202 | <.0001 |
| $a_{11} - a_{12}$ | -0.050 | <.0001 | -0.042 | 0.000 | 0.064 | <.0001 | 0.042 | <.0001 |
| $a_{12} - a_{13}$ | -0.030 | 0.030 | -0.037 | 0.025 | 0.000 | 0.161 | 0.004 | 0.821 |
| $a_{13} - a_{14}$ | -0.035 | 0.012 | -0.015 | 0.395 | -0.059 | 0.035 | -0.045 | 0.005 |
| *Adj.* $R^2$ | 0.047 | | 0.105 | | 0.140 | | 0.247 | |
| *Obs.* | 30,957 | | 20,729 | | 22,642 | | 14,960 | |

## Table 4: Consistent Earnings Surprises and Analysts' Forecast Errors

This table summarizes coefficient estimates and associated t-statistics (in parentheses) of estimating the following equation using GMM estimation (assuming fourth-order serial correlations in residuals). Primary sample period covers from 1987 to 2002. *ERROR* and *SURP* are measured as percentile rankings. Please refer to Table 1 for variable definitions. P-value are based on two-tailed t-tests of differences in coefficient estimates. */**/*** indicates significance level at less than 10% / 5% / 1%. All variables are winsorized at ± 1%.

$$ERROR_q^{q+1} = b_0 + b_1 SURP_q + b_{11} SURP_q * D(N=1) + b_{12} SURP_q * D(N=2) + b_{13} SURP_q * D(N=3) + b_{14} SURP_q * D(N \geq 4) + b_2 DISP_q + b_3 MVE_q + b_4 BM_q + b_5 ROA_q + \varepsilon_{q+1} \quad (2)$$

| | $SURP_q > 0$ | | | | $SURP_q \leq 0$ | | | |
|---|---|---|---|---|---|---|---|---|
| | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat |
| $b_0$ | 0.366 | (110.49)*** | 0.392 | (36.27)*** | 0.355 | (71.5)*** | 0.482 | (39.75)*** |
| $b_1$ | 0.274 | (21.53)*** | 0.335 | (21.82)*** | 0.272 | (40.03)*** | 0.162 | (15.87)*** |
| $b_{11}$ | -0.063 | (-5.96)*** | -0.049 | (-3.9)*** | 0.062 | (8.52) | 0.052 | (5.96)*** |
| $b_{12}$ | -0.004 | (-0.37) | 0.009 | (0.61) | 0.017 | (1.43) | 0.023 | (1.63) |
| $b_{13}$ | 0.063 | (4.5)*** | 0.088 | (5.26)*** | -0.017 | (-0.97) | 0.001 | (0.04) |
| $b_{14}$ | 0.102 | (8.5)*** | 0.104 | (7.25)*** | -0.044 | (-2.53)** | -0.054 | (-2.53)** |
| $b_2$ | | | -0.073 | (-8.92)*** | | | -0.191 | (-19.26)*** |
| $b_3$ | | | 0.031 | (3.56)*** | | | 0.128 | (12.78)*** |
| $b_4$ | | | -0.097 | (-9.61)*** | | | -0.046 | (-4.31)*** |
| $b_5$ | | | 0.006 | (0.81) | | | -0.061 | (-6.58)*** |
| | | *P*-value | | *P*-value | | *P*-value | | *P*-value |
| $b_1 + b_{11}$ | 0.211 | <.0001 | 0.285 | <.0001 | 0.334 | <.0001 | 0.214 | <.0001 |
| $b_1 + b_{12}$ | 0.270 | <.0001 | 0.344 | <.0001 | 0.289 | <.0001 | 0.185 | <.0001 |
| $b_1 + b_{13}$ | 0.337 | <.0001 | 0.423 | <.0001 | 0.255 | <.0001 | 0.163 | <.0001 |
| $b_1 + b_{14}$ | 0.376 | <.0001 | 0.439 | <.0001 | 0.228 | <.0001 | 0.108 | <.0001 |
| $b_{11} - b_{12}$ | -0.059 | <.0001 | -0.059 | <.0001 | 0.045 | 0.000 | 0.029 | 0.048 |
| $b_{12} - b_{13}$ | -0.067 | 0.030 | -0.079 | 0.025 | 0.034 | 0.091 | 0.022 | 0.361 |
| $b_{13} - b_{14}$ | -0.039 | 0.012 | -0.016 | 0.395 | 0.027 | 0.276 | 0.055 | 0.057 |
| *Adj.* $R^2$ | 0.088 | | 0.119 | | 0.080 | | 0.131 | |
| *Obs.* | 30,957 | | 20,729 | | 22,642 | | 14,960 | |

## Table 5: Equity Financing Activities, Consistent Earnings Surprises and Analysts' Forecast Errors

This table summarizes coefficient estimates and associated t-statistics (in parentheses) of estimating the following equation using GMM estimation (assuming fourth-order serial correlations in residuals). Primary sample period covers from 1987 to 2002. *ERROR* and *SURP* are measured as percentile rankings. *ISSUE* is a dummy variable, which equals 1 when $\Delta EQUITY_q > 0$, and 0 if $\Delta EQUITY_q \leq 0$. Coefficients on control variables are omitted for ease of exposition. Please refer to Table 1 for variable definitions. P-values are based on two-tailed t-tests of differences in coefficient estimates. */**/*** indicates significance level at less than 10% / 5% / 1%. All variables are winsorized at ± 1%.

$$\begin{aligned} ERROR_q^{q+1} &= c_0 + c_1 SURP_q + c_{11} SURP_q * D(N=1) + c_{11F} SURP_q * D(N=1) * ISSUE + c_{12} SURP_q * D(N=2) \\ &+ c_{12F} SURP_q * D(N=2) * ISSUE + c_{13} SURP_q * D(N=3) + c_{13F} SURP_q * D(N=3) * ISSUE \\ &+ c_{14} SURP_q * D(N \geq 4) + c_{14F} SURP_q * D(N \geq 4) * ISSUE + b_2 DISP_q + b_3 MVE_q + b_4 BM_q + b_5 ROA_q + \gamma_{q+1} \end{aligned} \quad (3)$$

| | $SURP_q > 0$ | | $SURP_q \leq 0$ | |
|---|---|---|---|---|
| | Coeff. | t-stat | Coeff. | t-stat |
| $c_0$ | 0.386 | (34.58)*** | 0.492 | (39.4)*** |
| $c_1$ | 0.335 | (21.83)*** | 0.164 | (16.01)*** |
| **Equity Repurchasing Firms** | | | | |
| | | *P*-value | | *P*-value |
| $c_1 + c_{11}$ | 0.269 | <.0001 | 0.228 | <.0001 |
| $c_1 + c_{12}$ | 0.347 | <.0001 | 0.215 | <.0001 |
| $c_1 + c_{13}$ | 0.418 | <.0001 | 0.211 | <.0001 |
| $c_1 + c_{14}$ | 0.442 | <.0001 | 0.125 | <.0001 |
| $c_{11} - c_{12}$ | -0.078 | <.0001 | 0.013 | 0.501 |
| $c_{12} - c_{13}$ | -0.071 | <.0001 | 0.004 | <.0001 |
| $c_{13} - c_{14}$ | -0.024 | <.0001 | 0.086 | <.0001 |
| **Equity Issuing Firms** | | | | |
| | | *P*-value | | *P*-value |
| $c_1 + c_{11} + c_{11F}$ | 0.306 | <.0001 | 0.200 | <.0001 |
| $c_1 + c_{12} + c_{12F}$ | 0.341 | <.0001 | 0.146 | <.0001 |
| $c_1 + c_{13} + c_{13F}$ | 0.429 | <.0001 | 0.096 | 0.001 |
| $c_1 + c_{14} + c_{14F}$ | 0.436 | 0.286 | 0.084 | 0.286 |
| $(c_{11} + c_{11F}) - (c_{12} + c_{12F})$ | -0.035 | 0.037 | 0.054 | 0.018 |
| $(c_{12} + c_{12F}) - (c_{13} + c_{13F})$ | -0.088 | <.0001 | 0.050 | 0.176 |
| $(c_{13} + c_{13F}) - (c_{14} + c_{14F})$ | -0.007 | 0.708 | 0.012 | 0.786 |
| *Adj.* $R^2$ | 0.119 | | 0.131 | |
| *Obs.* | 20,721 | | 14,956 | |

## Table 6: Mean value of selected variables for Subsample Firms with Consistent "Neutral" Earnings Surprises

This table summarizes mean values of selected variables for various subsamples of firms. ND($N$ = i) is dummy variables equal 1 when the current earnings surprise is neutral and preceded by (i-1) consecutive neutral earnings surprises; and 0 otherwise (Please refer to text for details on the classification of neutral earnings surprises). Please refer to Table 1 for variable definitions. Primary sample period covers from 1987 to 2002. All variables are winsorized at ± 1%.

| | $SURP_q > 0$ | | | | | $SURP_q \leq 0$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ND($N$=1)=0 | ND($N$=1)=1 | ND($N$=2)=1 | ND($N$=3)=1 | ND($N$>=4)=1 | ND($N$=1)=0 | ND($N$=1)=1 | ND($N$=2)=1 | ND($N$=3)=1 | ND($N$>=4)=1 |
| **Panel A: Firm performance and Information environment** | | | | | | | | | | |
| $ROA_{q+1}$ | 0.96% | 1.65% | 1.66% | 1.79% | 1.86% | -0.54% | 0.89% | 0.93% | 1.08% | 1.84% |
| $ROA_q$ | 1.10% | 1.97% | 1.86% | 1.72% | 1.99% | -0.40% | 1.00% | 1.29% | 1.41% | 2.06% |
| $BM_q$ | 0.446 | 0.324 | 0.325 | 0.320 | 0.270 | 0.534 | 0.440 | 0.406 | 0.365 | 0.280 |
| $MVE_q$ | 3,984 | 6,208 | 7,608 | 7,884 | 17,108 | 3,604 | 5,164 | 6,734 | 7,212 | 13,423 |
| $\Delta FIN_q$ | 4.04% | 4.56% | 4.91% | 5.59% | 2.87% | 3.83% | 2.76% | 2.74% | 2.31% | 2.73% |
| $\Delta EQUITY_q$ | 2.31% | 2.81% | 2.74% | 2.62% | 0.58% | 1.15% | 0.15% | 0.60% | 0.33% | 0.51% |
| $\Delta DEBT_q$ | 1.80% | 1.77% | 2.20% | 2.98% | 2.30% | 2.70% | 2.62% | 2.15% | 1.98% | 2.25% |
| $DISP_q$ | 7.55% | 2.82% | 2.57% | 2.41% | 1.75% | 6.83% | 3.26% | 2.58% | 2.39% | 1.94% |
| $ACCURATE_q$ | 0.52% | 0.24% | 0.22% | 0.25% | 0.14% | 0.84% | 0.44% | 0.37% | 0.27% | 0.20% |
| **Panel B: Earnings surprises and Analysts' forecasting variables** | | | | | | | | | | |
| $SURP_{q+1}$ | 0.11% | 0.04% | 0.01% | 0.00% | 0.00% | -0.28% | -0.11% | -0.07% | -0.06% | -0.03% |
| $SURP_q$ | 0.44% | 0.05% | 0.05% | 0.05% | 0.04% | -0.59% | -0.03% | -0.03% | -0.03% | -0.02% |
| $REVISION^q_{q+1}$ | 0.01% | -0.03% | -0.03% | -0.04% | -0.02% | -0.26% | -0.09% | -0.08% | -0.07% | -0.05% |
| $ERROR^q_{q+1}$ | 0.06% | -0.02% | -0.06% | -0.08% | -0.05% | -0.59% | -0.27% | -0.22% | -0.14% | -0.11% |
| *Obs.* | 16,072 | 3,295 | 1,993 | 1,464 | 8,133 | 16,024 | 1,585 | 928 | 669 | 3,436 |

## Table 7: Consecutive "Neutral" Earnings Surprises and Analysts' Forecast Errors

This table summarizes coefficient estimates and associated t-statistics (in parentheses) of estimating the following equation using GMM estimation (assuming fourth-order serial correlations in residuals). Primary sample period covers from 1987 to 2002. *ND(N = i)* is dummy variables equal 1 when the current earnings surprise is neutral and preceded by (i-1) consecutive neutral earnings surprises; and 0 otherwise (Please refer to text for details on the classification of neutral earnings surprises). *REVISON, |SURP|, ERROR* and *SURP* are measured as percentile rankings. Coefficients on control variables are omitted for ease of exposition. Please refer to Table 1 for variable definitions. P-value are based on two-tailed t-tests of differences in coefficient estimates. */**/*** indicates significance level at less than 10% / 5% / 1%. All variables are winsorized at ± 1%.

$$REVISION_q^{q+1} = a'_0 + a'_1 |SURP_q| + a'_{11} |SURP_q| * ND(N=1) + a'_{12} |SURP_q| * ND(N=2) + a'_{13} |SURP_q| * ND(N=3) + a'_{14} |SURP_q| * ND(N \geq 4) + a'_2 DISP_q + a'_3 MVE_q + a'_4 BM_q + a'_5 ROA_q + \delta'_{q+1} \quad (5)$$

$$ERROR_q^{q+1} = b'_0 + b'_1 SURP_q + b'_{11} SURP_q * ND(N=1) + b'_{12} SURP_q * ND(N=2) + b'_{13} SURP_q * ND(N=3) + b'_{14} SURP_q * ND(N \geq 4) + b'_2 DISP_q + b'_3 MVE_q + b'_4 BM_q + b'_5 ROA_q + \varepsilon'_{q+1} \quad (6)$$

| | Dependent Variable: $REVISION_q^{q+1}$ | | | | | Dependent Variable: $ERROR_q^{q+1}$ | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $SURP_q > 0$ | | $SURP_q \leq 0$ | | | $SURP_q > 0$ | | $SURP_q \leq 0$ | |
| | Coeff. | t-stat | Coeff. | t-stat | | Coeff. | t-stat | Coeff. | t-stat |
| $a'_0$ | 0.323 | (29.26)*** | 0.656 | (56.22)*** | $b'_0$ | 0.384 | (34.98)*** | 0.479 | (39.35)*** |
| $a'_1$ | 0.326 | (41.07)*** | -0.217 | (-22.24)*** | $b'_1$ | 0.348 | (43.57)*** | 0.200 | (14.59)*** |
| | | *P*-value | | *P*-value | | | *P*-value | | *P*-value |
| $a'_1 + a'_{11}$ | 0.375 | <.0001 | -0.197 | <.0001 | $b'_1 + b'_{11}$ | 0.407 | <.0001 | 0.156 | <.0001 |
| $a'_1 + a'_{12}$ | 0.309 | <.0001 | -0.187 | <.0001 | $b'_1 + b'_{12}$ | 0.363 | <.0001 | 0.157 | <.0001 |
| $a'_1 + a'_{13}$ | 0.260 | <.0001 | -0.241 | <.0001 | $b'_1 + b'_{13}$ | 0.375 | <.0001 | 0.174 | <.0001 |
| $a'_1 + a'_{14}$ | 0.322 | <.0001 | -0.180 | <.0001 | $b'_1 + b'_{14}$ | 0.277 | <.0001 | 0.170 | <.0001 |
| $a'_{11} - a'_{12}$ | 0.066 | 0.016 | -0.010 | 0.846 | $b'_{11} - b'_{12}$ | 0.044 | 0.112 | -0.001 | 0.907 |
| $a'_{12} - a'_{13}$ | 0.049 | 0.162 | 0.054 | 0.363 | $b'_{12} - b'_{13}$ | -0.012 | 0.729 | -0.017 | 0.357 |
| $a'_{13} - a'_{14}$ | -0.062 | 0.039 | -0.061 | 0.218 | $b'_{13} - b'_{14}$ | 0.098 | 0.001 | 0.004 | 0.751 |
| Obs. | 20,729 | | 14,960 | | | 20,729 | | 14,960 | |
| Adj. R2 | 0.101 | | 0.246 | | | 0.106 | | 0.129 | |