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Abstract

Prior research has been unable to explain the phenomenon known as post-earnings announcement drift, raising questions concerning the semi-strong form efficiency of the market typically assumed in capital market research. This study contributes to our understanding of this anomaly by examining drift in the context of theories that consider investors' non-Bayesian behaviors. The empirical evidence reveals that investors' overconfidence about their private information and the reliability of the earnings information are two important factors that explain drift. Finally, this study also provides insight into the puzzling relationship between dispersion and drift discussed in prior research.

Researchers remain puzzled by the way a company's stock price responds after earnings announcements: the price continues to drift up if the earnings surprise is positive and down if negative. This phenomenon is called post-earnings announcement drift (hereafter, drift). Attempts to explain drift as compensation for risk or as a result of flaws in research design have thus far been unsuccessful. Drift appears to represent a form of mispricing, and the accumulated evidence is inconsistent with the traditional view that prices immediately reflect all public information (i.e., capital markets are semi-strong form efficient).

Recent literature attributes pricing anomalies, such as drift, to information processing biases (i.e., deviations from Bayesian behaviors). This study empirically examines two predictions that arise from such biases: (1) overconfidence in private information; and (2) overconfidence in less reliable information and underconfidence in more reliable information. In the first case, the models of Daniel et al. (1998) and Fischer (2001) demonstrate that drift can arise when some investors overreact to their private information, coupled with their self-attribution biases.[1] As a consequence of their overconfidence, these investors overweight their private information and underweight public information such as earnings reports. Under the assumption that these investors can move prices, these models predict that more heterogeneous information across investors should be associated with a higher level of drift.

In the second case, drift arises from investors' underreaction to reliable information. Griffin and Tversky (1992) hypothesize that the pattern of over **[end of page 321]**-confidence and underconfidence observed in human behavior is explained by investors' focus on the strength or extremeness of the available evidence (e.g., favorable or unfavorable earnings information) with insufficient regard for its weight or credence (e.g., the reliability of the earnings information). This hypothesis leads to the prediction that investors tend to underreact to information that is relatively more reliable. Thus, more drift occurs when the earnings information is more reliable.

My empirical tests employ analyst forecasts to construct proxies for the degree of private information and the reliability of the public earnings information. Analyst forecasts likely represent a good proxy for investors' information because financial analysts play an important role in the stock market as information intermediaries (Schipper, 1991; Lang and Lundholm, 1996). I use the correlation in forecast errors across analysts to derive my proxy for investors' private information. Specifically, when the correlation in forecast errors is low, more heterogeneous information is available in the market, implying more private information among investors. When analysts receive more reliable earnings information, the precision (uncertainty) of analyst forecasts increases (decreases). Therefore, I define the level of uncertainty as the expected squared error in individual forecasts averaged across analysts and measure the reduction in uncertainty around earnings announcements as a proxy for the reliability of earnings information.

The empirical tests examining the relationship between these proxies and drift provide evidence consistent with both hypotheses. Specifically, drift has a significantly positive relationship with heterogeneous information and significantly negative relationship with the change in uncertainty around earnings announcements. These results are consistent with the notion that drift can be partially attributed to investors not processing all information in a statistically correct fashion. Restated, the results suggest that the reliability of the earnings information released in the earnings announcement and investors' overconfidence about their private information are two important factors that lead to drift. These results appear robust to a number of sensitivity tests, such as controlling for systematic risk (beta).

This study also provides insight into the puzzling relationship between forecast dispersion and drift discussed in prior research. Both Alford and Berger (1997) and Dische (2001) predict that disagreement among analysts, proxied by dispersion, is positively related to drift. In contrast, the authors in both studies find a negative relationship between dispersion and drift. Consistent with dispersion being a function of both uncertainty and disagreement, my empirical analyses provide evidence that the negative relationship is primarily attributable to the level of uncertainty.

The empirical results are consistent with claims that post-earnings announcement drift represents market inefficiencies arising from investors' non-Bayesian behaviors. In particular, this study's primary contribution is to provide evidence that investors' information processing biases partially explain drift. This paper also builds on a literature focusing on the role of cognitive biases in investors' reactions to analyst forecast revisions (Gleason and Lee, 2002). Understanding such biases may provide insights into methods to deliver or present accounting information in ways to minimize such interpretation issues or biases. However, this study represents only an **[end of page 322]** indirect test, since investors' non-Bayesian behaviors cannot be measured directly. Nevertheless, this paper is a first step empirically linking drift with information processing biases.

The remainder of the paper is organized as follows. Section 1 provides the hypothesis development and research design. Section 2 discusses the data sources and variable measures. Section 3 reviews the empirical results. Section 4 then discusses the supplemental tests, and Section 5 concludes.

1. Hypothesis Development and Research Design

1.1. Literature Review and Hypothesis Development

Many studies document drift over the last three decades. Early work demonstrates that abnormal stock returns are predictable up to two months after annual earnings announcements (e.g., Ball and Brown, 1968) and up to 60 trading days after quarterly earnings announcements (e.g., Jones and Litzenberger, 1970; Foster et al. 1984; Bernard and Thomas, 1989). However, despite repeated attempts, prior research has failed to provide a satisfactory explanation for drift.

Recent studies find that market participants underreact to earnings surprises and do not fully understand the implications of current earnings for future earnings. While these studies claim that drift is due to a market underreaction to the current earnings surprise (e.g., Freeman and Tse, 1989; Bernard and Thomas, 1989, 1990; Abarbanell and Bernard, 1992; Bartov, 1992; Ball and Bartov, 1996; Soffer and Lys, 1998), the cause of this underreaction is unclear. Some researchers argue that the market underreacts to earnings surprises because transaction costs prevent investors from making profits by trading on drift (Bhushan, 1994). However, this explanation begs two difficult questions. First, why would transaction costs cause the initial underreaction to new information, as opposed to simply introducing noise in price or causing overreaction? Second, if a trade ultimately does occur, why shouldn't it occur at a price that fully reflects the public information?

Theoretical studies (e.g., Daniel et al., 1998; Fischer, 2001) demonstrate that market underreaction occurs when investors are overconfident about their private information. Private information in this construct is not necessarily better or insider information, but rather heterogeneous information that could come from either different information sets or different interpretations of the same information. Drift occurs when some investors overweight their heterogeneous information and underweight the public earnings announcements (non-Bayesian investors).[2] For example, in financial markets, market participants generate information for trading through means such as interviewing management, verifying rumors, and analyzing financial statements. If some investors are more confident about signals or assessments with which they have greater personal involvement, they may tend to be overconfident about the information they have generated relative to public signals. Such behavior could induce drift. **[end of page 323]**

Based on psychological biases such as investors' overconfidence about their private information, coupled with self-attribution biases, Daniel et al. (1998) propose a theory of securities market underreactions. Cognitive psychological experiments and surveys provide a large body of evidence about investors' overconfidence. Daniel et al. (1998) define an overconfident investor as one who overestimates the precision of his private information signal, but not of information signals publicly received by all. Consequently, stock prices underreact to public signals such as earnings. Further, they claim that because the model is based on overconfidence about private information, return predictability will be strongest in firms with the most heterogeneous information.

To consider Daniel et al. (1998)'s model, one might expect that fully rational investors can profit by trading against the mispricing. If wealth flows from non- Bayesian traders to "smart traders," eventually the "smart traders" may dominate price-setting and the non-Bayesian traders may not survive in equilibrium. Fischer (2001) provides a theoretical link between investors' overconfidence about their private information and the presence of drift, which is consistent with Daniel et al. (1998). Specifically, he models a setting where investors who process information in a non-Bayesian way can survive in the market under the assumption of imperfect security market competition and inelastic security demand. Thus, an overreaction-heuristic trading behavior is economically viable, in the sense that it may perform better than Bayesian trading behavior. Fischer (2001)'s model predicts that drift arises when some investors are non-Bayesian and that more drift is associated with more heterogeneous information among investors.

The studies above provide a theoretical link between drift and investors' non-Bayesian behaviors, specifically their overconfidence about private information.[3] Since more heterogeneous information magnifies the impact of investors' over-reaction to private information, more heterogeneous information leads to more drift. Following these arguments, I hypothesize that when investors have more heterogeneous information about the firms' earnings, more drift appears after earnings announcements:

HI: *Drift is positively associated with the degree of heterogeneous information among investors.*

Drift also can be positively related to the reliability of the earnings information, which is another indication that investors do not process information in a statistically correct fashion. Bloomfield et al. (2000) argue that prices tend to overreact to unreliable information and underreact to highly reliable information because investors' confidence in their information is moderated toward a central level. They refer to this phenomenon as "moderated confidence" because investors' confidence is moderated toward an average level that is insufficiently high or low.

In Bloomfield et al. (2000)'s experiment, securities values are determined by a coin-flipping exercise adapted from Griffin and Tversky (1992). Griffin and Tversky (1992) argue that people update their beliefs based on the strength and weight of new evidence. The strength of evidence is the degree to which it is favorable or **[end of page 324]** unfavorable. The weight of evidence is its statistical reliability or sample size. They measure "weight" as the number of times the coin is flipped and "strength" as the sample proportion of heads. The more flips observed, the more reliable the information contained in the proportion. Unlike equal numbers of heads and tails, they assume that flipping a coin leads to a 50% bias favoring heads or 50% bias favoring tails. A heads-biased coin comes up heads 60% of the times it is flipped and a tails-biased coin comes up tails 60% of the times it is flipped. According to Bayes' rule, a signal strength of 58.8%, from 17 flips (10 heads and 7 tails), has the same probability as a signal strength of 100%, from three flips (3 heads and 0 tails). In both cases, the probability that the bias favored heads is 77%.[4] However, people tend to think the second case has a high probability of heads (100% > 58.8%) because they are not very sensitive to the number of flips. If investors are Bayesian rational, they will respond appropriately to the observed strength of the signal. Otherwise, they will tend to underestimate the probability of highly reliable signals and overestimate the probability of highly unreliable signals.

Using the coin-flipping exercise as an example, Griffin and Tversky (1992) provide a theory capable of predicting both under- and over-confidence in decision-making processes. Consistent with Griffin and Tversky (1992)'s theory, investors tend to be underconfident and underreact to more reliable information such as public earnings announcements. In fact, Bloomfield et al. (2000)'s experimental results show that markets under-react more to more reliable information than they do to less reliable information.[5] Thus, more drift is associated with more reliable information. When investors receive reliable earnings information, their uncertainty about firms' future performance decreases after the earnings announcement. I measure the level of uncertainty right before and after earnings announcements and use the difference in the level of uncertainty around earnings announcements to proxy for the reliability of the earnings information. As more reliable information leads to a greater reduction in investors' uncertainty about firms' future performance, I hypothesize that drift is negatively associated with the change in uncertainty around earnings announcements:

H2: *Drift is negatively associated with the change in uncertainty around earnings announcements.*

1.2. Variable Measures and Research Design

I use analyst forecasts to proxy for the degree of heterogeneous information and the reliability of the earnings information. Analyst forecasts likely represent a good proxy for investors' information, because financial analysts play an important role in the stock market as information intermediaries and their earnings estimates directly assist investors in making trading decisions (Schipper, 1991; Lang and Lundholm, 1996). In fact, recent studies use the mean analyst forecast as a proxy for the market's expectation of earnings and show that drift is related to analyst forecasts **[end of page 325]** (e.g., Mendenhall, 1991; Abarbanell and Bernard, 1992; Alford and Berger, 1997; Liu, 1998; Wu, 1998; Shane and Brous, 2001).

1.2.1. Heterogeneous Information

My measure of heterogeneous information concerns the correlation in forecast errors across analysts. Specifically, I measure the correlation in forecast errors as the average correlation between one analyst's forecast error and other analysts' forecast errors, denoted ρ. The correlation in forecast errors (ρ) estimates the degree to which analysts share the same beliefs or how much the average (mean) belief reflects common versus private information. When all available information is common,[6] all analysts' beliefs are identical and ρ = I. As ρ approaches zero, the amount of private information rises and analysts' beliefs diverge more from the average belief. Thus, I use 1-ρ to proxy for the amount of private information or disagreement among analysts.

My measure of heterogeneous information is different from forecast dispersion, a proxy for disagreement in prior research. First, forecast dispersion represents sample variance of analyst forecasts, while my measure of heterogeneous information is the correlation in forecast errors across analysts. Second, my measure of heterogeneous information is hypothesized to have a positive relationship with drift, while both Alford and Berger (1997) and Dische (2001) find that dispersion, as a proxy for disagreement among analysts, is negatively related to drift.[7] The seemingly contradictory results may be due to dispersion relating to two factors, one of which runs counter to the hypothesized positive relationship between drift and heterogeneous information. Barron et al. (1998) (hereafter BKLS) model forecast dispersion as a function of both uncertainty and disagreement (1-ρ). Thus, if uncertainty is held constant, dispersion could proxy for disagreement (i.e., measured as (1-ρ)), and would be positively associated with drift. However, neither Alford and Berger (1997) nor Dische (2001) are clear about controlling for other factors when they use dispersion as a proxy for disagreement. Thus, the negative relationship between dispersion and drift observed in their studies could result from dispersion being mainly driven by uncertainty in their samples. I examine this possibility and provide further discussion of dispersion in the supplementary tests.

1.2.2. Uncertainty

I measure the level of residual uncertainty as the expected squared error in individual forecasts averaged across analysts. When analysts are uncertain about a firm's future performance, they tend to have larger forecast errors. When analysts are certain about a firm's performance, they make forecasts for that firm with smaller errors. A large decrease in forecast errors after earnings announcements is consistent with a large decrease in analyst uncertainty. The decrease in analyst uncertainty is consistent with analysts receiving very reliable new information. Thus, I measure **[end of page 326]** the change in uncertainty by taking the difference in the level of uncertainty, measured before and after earnings announcements. I use this change in analyst uncertainty to proxy for the reliability of the earnings information released from the earnings announcements.

1.2.3. The Regression Model

I include the level of heterogeneous information after earnings announcements and change in uncertainty before and after earnings announcements in the model to test HI and H2. In addition, I control for firm size, as prior research has documented that drift is inversely related to firm size (Foster et al. 1984; Bernard and Thomas, 1989, 1990; Bhushan, 1994; Ball and Bartov, 1996; Alford and Berger, 1997). I estimate the following model:

$$CAR_{jq} = \gamma_0 + \gamma_1 UE_{jq} + \gamma_2 HI_{jq} * UE_{jq} + \gamma_3 \Delta V_{jq} * UE_{jq} + \gamma_4 SIZE_{jq} * UE_{jq} + \varepsilon_{jq}, \qquad (1)$$

where CAR_{jq} is the cumulative abnormal return after quarterly earnings announcement *q* for firm *j*, and UE_{jq} measures unexpected earnings using analyst forecasts of earnings announcement *q* for firm *j*. HI_{jq} is my proxy for the degree of heterogeneous information after earnings announcement *q* of firm *j* and is measured by 1-ρ, where ρ is the correlation in forecast errors across analysts. ΔV_{jq} is the change in uncertainty, measured as the difference before and after earnings announcement *q* of firm *j*. The coefficients of HI_{iq} and ΔV_{jq} indicate the relationship between drift and measures of heterogeneous information and change in uncertainty among analysts. Based on prior studies, the coefficient γ_1 is predicted to be positive and γ_4 to be negative. The hypotheses tested in the current study predict that the coefficient γ_2 should be positive (i.e., HI) and γ_3 should be negative (i.e., H2).

To minimize problems associated with outliers, as in Bernard and Thomas (1990) and others, UE decile numbers (0, 0.1, 0.2, ... , 1) are used instead of the actual standardized unexpected earnings. Observations for each of the other independent variables are also divided into deciles from 0 to 1. Bernard and Thomas (1990) and Bhushan (1994) argue that the coefficient of the unexpected earnings is the abnormal return on a zero-investment portfolio when *UE* is measured as deciles from 0 to 1. Under this scheme, γ_1 measures the return on a zero-investment portfolio, consisting of firms with the smallest values of $HI_{jq}, \Delta V_{jq}$ and $SIZE_{jq}$. The coefficient γ_2 measures the incremental change in this return if the HI_{jq} decile was the highest instead of the lowest, all else equal. A similar interpretation holds for γ_3 and γ_4.

2. Data

The data come from three sources. This study uses one-quarter-ahead, one-year-ahead and two-year-ahead forecasts of earnings-per-share from the 2001 **[end of page 327]** Institutional Brokerage Estimate System (I/B/E/S) Detail file. Actual quarterly and annual earnings-per-share amounts and adjustment factors for stock splits and stock dividends are also from the I/B/E/S detail data. Earnings announcement dates are obtained from the 2001 Compustat combined quarterly files. Share price, returns and shares outstanding are from the Center for Research in Security Prices (CRSP) tapes. The data are organized by firm-quarters. Firm-quarters missing any of the above data are excluded from the sample. In addition, some firms are excluded from the

Table 1. Sample selection.

Description	Firm-Quarters	Firms
Firm-quarters with earnings announcement dates on Compustat and analyst forecast revisions on IBES from 1989 to 2000[a]	60,797	7,343
Less than two analyst forecast revisions on IBES	(31,345)	(2,691)
No actual annual earnings on IBES	(1,117)	(188)
No quarterly earnings surprises from IBES	(5,002)	(593)
No 60 day returns and price from CRSP[b]	(1,308)	(217)
No beta adjusted returns from CRSP	(1,007)	(310)
Other restrictions[c]	(52)	(9)
Final Sample	20,966	3,335

[a]Firm-quarters are required to have earnings announcement dates recorded on the 2001 Compustat combined quarterly files from 1989 to 2000. Firms releasing their earnings announcements for the fourth-quarter of one year and the first quarter of the following year on the same day or with two earnings announcement dates for the same quarter are excluded from the sample. Firm-quarters also must have analysts, who issue one-year-ahead annual earnings forecasts within 45 days before the quarterly earnings announcement and issue revised one-year-ahead annual earnings forecasts within 30 days after the quarterly earnings announcement. For the fourth quarter, two-year-ahead earnings forecasts within 45 days before the earnings announcement are required.
[b]The closing stock price on the 45th day before the earnings announcements is required. If the 45th day is not a trading day or price is unavailable, I collect the closing stock price within two days around the 45-th day. The adjustment factors for stock splits and stock dividends are also required from IBES.
[c]Observations with no observed transaction price are eliminated. Also, observations with uncertainty (V) equal to zero in the pre- or after-earnings announcement window are excluded.

Sample size by year.

Firm-Quarters	Year
879	1989
1,355	1990
1,432	1991
1,502	1992
1,139	1993
1,710	1994
1,923	1995
2,019	1996
2,190	1997
2,505	1998
2,582	1999
1,730	2000

[end of page 328]

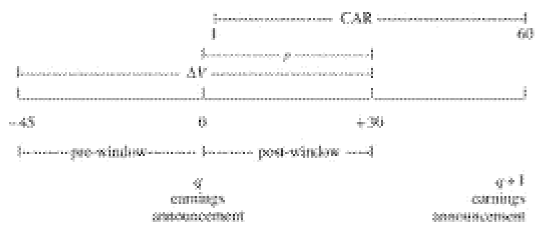

Figure 1. Time line.

sample because they release their earnings announcements for the fourth quarter of one year and the first quarter of the following year on the same day. Finally, I also exclude firms with two earnings announcement dates for the same quarter. The final sample consists of 20,966 firm-quarter observations for 3,335 firms from January of 1989 to December of 2000. Table 1 summarizes the sample selection procedure and the year-by-year sample size.

I examine the sample period from 1989 to 2000 for two reasons. First, the dating of IBES forecasts, which figure prominently in the calculation of my variables, has been shown to become more reliable around 1990 (Barron and Stuerke, 1998). Second, this study focuses on a contemporaneous sample period. The most recent tape available is 2001, so the period covered offers the best extant data.

The forecasts used to measure heterogeneous information and change in uncertainty around earnings announcements have the following characteristics. To be included in my analysis, an analyst must issue a one-year-ahead annual earnings forecast within 45 days before the quarterly earnings announcement *q* (the pre- window), and the same analyst must issue a revised one-year-ahead annual earnings forecast within 30 days after the quarterly earnings announcement *q* (the post- window). For the fourth quarter, I require two-year-ahead earnings forecasts within 45 days before earnings announcement *q* and one-year-ahead earnings forecast revisions within 30 days after earnings announcement *q* for the next fiscal year end. I require forecasts to be the most recent ones relative to the earnings announcement dates (the latest forecasts in the pre-announcement window and the first forecasts in the post-announcement window by the same analysts). I use one-year-ahead annual forecasts of earnings per share reported within 30 days following earnings announcement *q* to calculate HI_{jq} (which is 1-ρ). The forecasts in the pre-announcement and post-announcement windows are used to measure the level of uncertainty before $(V_{j\text{before}})$ and after $(V_{j\text{after}})$ earnings announcement *q* of firm *j* respectively. The change in uncertainty (ΔV_{jq}) is estimated as $V_{j\text{after}} - V_{j\text{before}}$, and ΔV_{jq} is then scaled by the square of the adjusted closing stock price on the 45th day before earnings announcement *q* of firm *j*.[8] Firm-quarters that do not have one-year-ahead annual forecasts made by at least two analysts in the pre- and -post-earnings announcement windows (two-year-ahead forecasts for the fourth quarter in the pre-earnings announcement window) are excluded from the sample. **[end of page 329]**

The forecasts used to measure earnings surprises (UE_{jq}) have the following characteristics. One-quarter-ahead forecasts of quarterly earnings per share reported within 45 days before earnings announcement *q* are used to calculate UE_{jq}, which is then scaled by the adjusted closing stock price on the 45th day before earnings announcement q of firm *j*. Firm-quarters that do not have one-quarter-ahead forecasts made by at least two analysts during that period are excluded from the sample. I measure UE_{jq} as the actual quarter earnings-per-share minus the one-quarter-ahead mean forecast.

I use one-year-ahead earnings forecasts (two-year-ahead forecasts for the fourth quarter in the pre-earnings announcement windows) to compute heterogeneous beliefs and change in uncertainty. I use one-year-ahead forecasts for two reasons. First, recent research (Liu and Thomas, 1998) documents that long-term forecasts, such as annual earnings forecasts, are more price relevant than short-term forecasts. Liu and Thomas (1998) argue that earnings components that have lower value relevance (e.g., transitory and price irrelevant earnings shocks) are more likely to show up in short-term earnings forecasts, whereas fundamental changes in profitability are more likely to be reflected in long-term forecasts. Second, I require that firms have at least two annual forecast revisions made by the same analysts before and after earnings announcements, which dramatically reduces the sample as shown in Table 1. Since one-year-ahead annual earnings forecasts are the most frequent forecasts that analysts make,[9] I adopt one-year-ahead annual earnings forecasts instead of long-term growth forecasts (two-year-ahead forecasts for the fourth quarter in the pre-earnings announcement windows) to have a reasonable sample size, and to be consistent with prior drift studies.

Following BKLS's model, I measure both heterogeneous information and change in uncertainty by using the properties of analyst forecasts. While we cannot observe the underlying properties of the analysts' information environment, we can observe the properties of their forecasts. I calculate dispersion in analysts' forecasts as the sample variance of forecasts,

$$D = \frac{1}{N-1}\sum_{i=1}^{N} E(f_i - f)^2, \tag{2}$$

where f_i is the most recent annual earnings forecast around the earnings announcement by analyst i, f is the mean forecast, and *N* is the number of forecasts around the earnings announcements. *SE* is defined as the squared error in the mean forecast in BKLS,

$$SE = (y - f)^2, \tag{3}$$

where *y* is the actual annual earnings per share and f is the mean forecast. BKLS define consensus as the correlation in forecast errors across analysts (ρ). Following the BKLS model, I measure consensus (ρ) and uncertainty (*V*) by using properties of **[end of page 330]** the widely available earnings forecast data:

$$\rho = \frac{SE - D/N}{(1 - 1/N)D + SE} \tag{4}$$

$$V = \left(1 - \frac{1}{N}\right)D + SE \tag{5}$$

where *D*, *SE*, and *N* are measures of forecast dispersion, squared error in the mean forecast and the number of forecasts, respectively.

Consistent with prior studies of drift, I calculate the cumulative size-adjusted abnormal return (CAR_{jq}) after earnings announcement *q* for firm *j*. The daily abnormal return for firm *j* on day $t(AR_{jt})$ is computed as the difference between the daily return of firm *j* and the mean return of a firm-size decile that firm *j* is a member of:

$$AR_{jt} = R_{jt} - R_{pt}, \tag{6}$$

where R_{jt} is the daily raw return for firm *j* on day *t* and R_{pt} is the equally weighted mean return on day *t* of the NYSE/AMEX/NASDAQ firm size decile (excluding Unit Investment Trust, Closed-End Funds, Real Estate Investment Trusts, Americus Trusts, Foreign Stocks, and American Depository Receipts).[10] CAR_{jq} is the sum of daily abnormal returns of firm *j* over the sixty-trading day interval (1, 60), where 1 is one day after earnings announcement *q*. Bernard and Thomas (1989) demonstrate that drift behavior is largely unaffected by either risk adjustments or compounding rather than summing returns. Thus, I adopt this cumulative size-adjusted return to be consistent with most drift studies, in addition to controlling for firm size in the multivariate OLS regression model. Nonetheless, I examine the potential effect of risk on my results in the sensitivity analyses discussed later.

I measure size as the market value of common equity on the 45th day before the earnings announcement for quarter *q*. The market value of common equity is the product of the closing stock price and the number of current shares outstanding on that day. Finally, I transform all the independent variables including UE_{jq}, HI_{jq}, ΔV_{jq}, and $SIZE_{jq}$ into deciles, based on their sample distributions within calendar quarters. Zero represents the smallest decile of each variable and nine represents the largest. I then scale deciles by nine to range between zero and one.

3. Empirical Results

3.1. Sample Description

Panel A of Table 2 provides descriptive statistics for the independent variables. The mean of unexpected earnings (*UE*) is slightly negative (- 0.09%), which is consistent with analysts being optimistic in general. *UE* values greater (less) than 5 (- 5) are winsorized to 5 (- 5), consistent with prior research (Bernard and Thomas, 1990; Bhushan, 1994).[11] The median of the correlation in forecast errors across analysts (ρ) is **[end of page 331]**

Table 2.
Panel A: Descriptive statistics ($N = 20{,}966$).

Variable	Mean	Std. Error	Median
UE	− 0.0009	0.0164	0.0003
Correlation (ρ)	0.64	0.38	0.82
Change of Uncertainty (ΔV)	− 0.0024	0.1384	− 0.00002
Firm Size (in millions)	6045.64	18168.08	1436.46
DISP	0.0004	0.0083	0.000006
V_{after}	0.00404	0.14886	0.00005

Panel B: Spearman correlation coefficients ($N = 20{,}966$). (Note: The lower triangle is Pearson correlation coefficients, while the upper is Spearman correlation coefficients.)

Variable	ρ	ΔV	*DISP*	V_{after}	*SIZE*
ρ	—	− 0.139**	− 0.330**	0.366**	− 0.094**
ΔV	− 0.011	—	− 0.319**	− 0.409**	0.232**
DISP	− 0.035**	− 0.537**	—	0.693**	− 0.247**
V_{after}	0.020**	− 0.956**	0.576**	—	− 0.336**
Size	− 0.008	0.005	− 0.013*	− 0.008	—

*Significant at $P < 0.05$.
**Significant at $P < 0.01$.
Description of variables:
UE: Unexpected earnings at *q*; the difference between IBES actual quarterly EPS for quarter *q* and mean forecast of the most recent one-quarter-ahead forecasts of EPS reported within 45 days before earnings announcement *q* scaled by the adjusted closing stock price on the 45th day before earnings announcement *q*. Firm-quarters that do not have forecasts made by at least two analysts during that period are excluded from the sample.
$DISP_{jq}$: The level of forecast dispersion after earnings announcement *q* for firm *j* scaled by the adjusted closing stock price on the 45th day before earnings announcement *q*. I calculate dispersion in analysts' forecasts as the sample variance of one-year-ahead annual earnings forecast revisions reported within 30 days following earnings announcements.

$$D = \frac{1}{N-1}\sum_{i=1}^{N} E(f_i - f)^2,$$

where f_i is the most recent annual earnings forecast revision around the earnings announcement by analyst i, f is the mean forecast, and *N* is the number of forecasts around the earnings announcements. ρ: The correlation of forecast errors across analysts or the BKLS consensus is estimated as follows:

$$\rho = \frac{SE - D/N}{(1 - 1/N)D + SE},$$

where *D* is the forecast dispersion, the sample variance of one-year-ahead annual earnings forecasts reported within 30 days following earnings announcement *q* for each firm; *N* is the number of those forecasts; SE is the squared difference between the IBES actual annual EPS and the mean of those forecasts. Those forecasts are the first revisions made by the same analysts who made one-year-ahead annual earnings forecasts within 45 days before earnings announcement *q*. Firm-quarters that do not have forecasts made by at least two analysts during the pre and post earnings announcement window are excluded from the sample. **[end of page 332]** 0.82, which is consistent with Barron et al. (2002)'s median of ρ, 0.85, after the second quarter earnings announcement. The average firm size in my sample is relatively large ($6,046 million) because I require that firms have at least two one-quarter-ahead quarterly forecasts and at least two one-year-ahead annual forecast revisions.

Panel B of Table 2 provides Pearson and Spearman correlation coefficients (the upper triangle is Spearman correlation coefficients). Note that there are high correlations among the variables ρ, ΔV and SIZE. Also, dispersion has highly positive correlations with the level of uncertainty (V_{after}) and highly negative correlations with the correlation in forecast errors across analysts (ρ) in both Spearman and Pearson correlations, which is consistent with dispersion being a function of the level of uncertainty and the correlation in forecast errors across analysts as suggested by BKLS.[12]

Table 3 describes the drift of each decile portfolio formed based on rankings of unexpected earnings (UE_{jq}) within calendar quarters. Drift represents the means of the cumulative size-adjusted return (CAR_{jq}) over the trading days window (1, 60). Prior research reveals that drift is typically negative following negative earnings surprises and positive following positive surprises. The estimates of drift in Table 3 are consistent with past evidence on earnings surprises and drift. Larger earnings surprises are almost monotonically associated with larger drift measures.

$V_{afterjq}$: The level of uncertainty after earnings announcement q for firm j scaled by the adjusted closing stock price on the 45th day before earnings announcement *q*. $V_{afterjq}$ is estimated as:

$$V = \left(1 - \frac{1}{N}\right)D + SE,$$

where I compute *D*, *N* and *SE* using the most recent one-year-ahead annual earnings forecasts revisions reported within 30 days following earnings announcements.
ΔV: The change in uncertainty is estimated as the difference between the uncertainty before and after the earnings announcement (V_{after}-V_{before}) and scaled by the adjusted closing stock price on the 45th day before earnings announcement *q*. Those forecasts are the most recent forecasts (the latest forecasts in the pre window and the first forecasts in the post window by the same analysts). Firm-quarters that do not have forecasts made by at least two analysts during the pre and post earnings announcement window are excluded from the sample.
SIZE: The market value of common equity at the 45th day before earnings announcement *q*. The market value of common equity is the product of the closing stock price and the number of current shares outstanding on that day.

3.2. Regression Results

Panel A of Table 4 replicates the evidence for drift in an OLS regression. As expected, the results show that the coefficient estimate on the unexpected earnings variable (UE_{jq}) is positive and significant. The coefficient (6.3%) represents returns on a zero-investment portfolio with long (short) positions in firms within the highest (lowest) decile of unexpected earnings. The magnitude of 6.3% is higher than the range of 4.2% to 5.3% abnormal returns over the 60 trading days subsequent to the earnings announcement documented by Bernard and Thomas (1989). The adjusted **[end of page 333]**

Table 3. Portfolio descriptive statistics ($N = 20{,}966$).

UE deciles	Drift
1	0.035
2	0.022
3	0.011
4	0.011
5	0.008
6	− 0.008
7	− 0.019
8	− 0.024
9	− 0.027
10	− 0.023

Deciles are formed based on rankings of unexpected earnings (*UE*) within calendar quarters. UE is defined as the difference between IBES actual quarterly EPS for quarter *q* and the mean forecast of the most recent one-quarter-ahead forecasts of EPS reported within 45 days before earnings announcement *q*, scaled by the adjusted closing stock price on the 45th day before earnings announcement *q*. Firm-quarters that do not have forecasts made by at least two analysts during that period are excluded from the sample.
Drift represents the means of the cumulated size-adjusted return (*CAR*) over the trading days window (1, 60).
CAR: The sum of daily abnormal returns; where abnormal returns are measured as the difference between the daily return and the returns for NYSE, AMEX, and the NASDAQ firms (excluding Unit Investment Trust, Closed-End Funds, Real Estate Investment Trusts, Americus Trusts, Foreign Stocks, and American Depository Receipts) of the same size decile over the interval (1, 60), where 1 is the first day after the earnings announcement date *q*. All eligible NYSE firms are ranked by market capitalization on the last trading day of each quarter. Ten equally populated portfolios, or deciles, are then formed.

R^2 is 0.009, which is low but consistent with prior drift studies (e.g., Alford and Berger (1997) document an adjusted R^2 of 0.006). Drift still varies with firm size in a bivariate OLS regression (untabulated), which is consistent with most drift studies (e.g., Bernard and Thomas, 1990; Raedy, 1998).

Panel B of Table 4 reports results for model (1), a multivariate OLS regression, using size-adjusted returns.[13] The coefficients for both the heterogeneous information variable (HI_{jq}) and the change in uncertainty variable (ΔV_{jq}) are statistically significant and have the predicted signs. The coefficient estimate on the unexpected earnings variable (UE_{jq}) is 0.087 and significant at the 1% level. The parameter estimates of $UE_{jq} * HI_{jq}$ and $UE_{jq} * \Delta V_{jq}$ are 0.022 and - 0.064, both significant at the 1% level. These results imply that the return to a zero-investment portfolio, consisting of firms in the lowest *HI* decile, Δ*V* decile and *SIZE* decile, with a long position in *UE* decile 10 and a short position in *UE* decile 1, is 8.7%. The incremental change in the above return is 2.2% if positions are taken in the highest as opposed to **[end of page 334]**

Table 4.

Panel A: Test of market underreaction to quarterly earnings in a univariate OLS regression ($N = 20{,}966$).

$$CAR_{jq} = \alpha + \beta\, UE_{jq} + \varepsilon_{jq}$$

Coefficient	Expected Sign	Parameter Estimate	Adjusted R^2
α intercept	–	– 0.033*	
β UE_{jq}	+	0.063*	0.009

Panel B: Test of market underreaction to quarterly earnings in a multivariate OLS regression ($N = 20{,}966$).

$$CAR_{jq} = \gamma_0 + \gamma_1 UE_{jq} + \gamma_2 HI_{jq} * UE_{jq} + \gamma_3 \Delta V_{jq} * UE_{jq} + \gamma_4 SIZE_{jq} * UE_{jq} + \varepsilon_{jq}.$$

Coefficient	Expected Sign	Parameter Estimate	Adjusted R^2
γ_0 Intercept	?	– 0.031*	
γ_1 UE_{jq}	+	0.087*	
γ_2 Hetero-information	+	0.022*	
γ_3 Chg Uncertainty	–	– 0.064*	
γ_4 Size	–	– 0.011	0.012

*Significant at $p < 0.01$.

CAR_{jq}: The sum of daily abnormal returns; where abnormal returns are measured as the difference between the daily return and the returns for NYSE, AMEX, and the NASDAQ firms (excluding Unit Investment Trust, Closed-End Funds, Real Estate Investment Trusts, Americus Trusts, Foreign Stocks, and American Depository Receipts) of the same size decile over the interval (1, 60), where 1 is the first day after the earnings announcement date q. All eligible NYSE firms are ranked by market capitalization on the last trading day of each quarter. Ten equally populated portfolios, or deciles, are then formed.

HI_{jq}: Heterogeneous information; it is estimated as 1-ρ, where ρ is the correlation in forecast errors across analysts.

Other variable definitions are in Table 2.

the lowest *HI* decile. If the positions are taken in the highest ΔV decile, the incremental change is - 6.4%. The regression results fail to provide evidence that drift still varies with firm size after controlling for heterogeneous information and change in uncertainty effects.[14] The adjusted R^2 is 0.012, which is improved about 33% compared to Panel A of Table 4. Even though this adjusted R^2 is relatively low, it is consistent with the drift literature. For example, Bartov et al. (2000) examine drift using multivariate OLS regression models similar to model (1), and their R^2s range from 0.011 to 0.015.

The regression results are consistent with both hypotheses and show that drift is positively related to the degree of heterogeneous information and negatively related to the change in uncertainty around earnings announcements. The results are consistent with drift being attributable to investors not processing all information in a statistically correct fashion. Specifically, the results are consistent with a common implication of two models that drift arises when some investors overreact to heterogeneous information. The results also suggest that drift arises when investors underreact to highly reliable earnings information. **[end of 335]**

4. Supplementary Tests

4.1. Using Risk-Adjusted Returns

To evaluate the possibility that failure to adjust for risk drives my results, I use the risk-adjusted return ($CARB_{jq}$) in a sensitivity test. I measure daily risk-adjusted abnormal return for firm *j* on day *t* (ARB_{jt}) as the difference between the daily return of firm *j* and the expected return of firm *j*. To estimate the expected return for firm *j* over the 60-trading day interval, I adopt the market model to estimate α and β by using the raw return for firm *j* and the equally-weighted mean return on day *t* of the NYSE/AMEX/NASDAQ firm size decile that firm *j* is a member of. I estimate α and β over a 300-trading day interval (- 345, - 45) with a minimum requirement of 250 trading days, where - 45 denotes 45 days before earnings announcement *q*:

$$R_{jt} = \alpha + \beta R_{pt}, \tag{7}$$

$$ARB_{jt} = R_{jt} - (\alpha + \beta R_{pt}), \tag{8}$$

where *Rjt* and *Rpt* are as defined in equation (6); α and β are the intercept and the risk factor estimated over the 300-trading day interval. $CARB_{jq}$ represents the sum of daily risk-adjusted abnormal returns of firm j on day t(ARB_{jt}) over the 60-trading day interval (1, 60), where 1 is one day after earnings announcement *q*.

Panel A of Table 5 displays evidence for drift in an OLS regression using risk-adjusted returns. As expected, the coefficient estimate on the unexpected earnings variable (*UEjq*) is positive and significant. The coefficient (1.3%) represents returns on a zero-investment portfolio with long (short) positions in firms within the highest (lowest) decile of unexpected earnings. The magnitude of 1.3% is smaller than the range of 4.2% to 5.3% abnormal returns over the 60 trading days subsequent to earnings announcements documented by Bernard and Thomas (1989), and the adjusted R^2 (0.0003) is lower as well. However, the reported statistics are consistent with the argument by Ball et al. (1993) that drift relates to the risk factor (Beta) but is not eliminated by controlling for risk. Drift still varies with firm size in a bivariate OLS regression (untabulated), which is consistent with most drift studies (e.g., Bernard and Thomas, 1990; Raedy, 1998).

Panel B of Table 5 reports results for model (1), a multivariate OLS regression using risk-adjusted returns. Consistent with the results in Panel B of Table 4, the coefficients for both heterogeneous information (HI_{jq}) and change in uncertainty (ΔV_{jq}) are statistically significant, having the predicted sign. The coefficient estimate on unexpected earnings (UE_{jq}) is 0.034 and significant at the 1% level. The parameter estimates of the interaction terms, $UE_{jq} * HI_{jq}$ and $UE_{jq} * \Delta V_{jq}$, are 0.064 and -0.096, both significant at the 1% level. These results imply that the return to a zero-investment portfolio is 3.4%. The zero-investment portfolio consists of firms in the lowest *HI*, ΔV and *SIZE* deciles, with a long position in *UE* decile 10 and a short position in *UE* decile 1. The incremental change in the above return is 6.4% if positions are taken in the highest as opposed to the lowest *HI* decile. If positions are **[end of page 336]**

Table 5.

Panel A: Test of market underreaction to quarterly earnings in a univariate OLS regression using risk-adjusted returns ($N = 20{,}966$).

$$CARB_{jq} = \alpha + \beta UE_{jq} + \varepsilon_{jq}.$$

Coefficient	Expected Sign	Parameter Estimate	Adjusted R^2
α Intercept	−	− 0.024**	
β UE_{jq}	+	0.013**	0.0003

Panel B: Test of market underreaction to quarterly earnings in a multivariate OLS regression using risk-adjusted returns ($N = 20{,}966$).

$$CARB_{jq} = \gamma_0 + \gamma_1 UE_{jq} + \gamma_2 HI_{jq} * UE_{jq} + \gamma_3 \Delta V_{jq} * UE_{jq} + \gamma_4 SIZE_{jq} * UE_{jq} + \varepsilon_{jq}.$$

Coefficient	Expected Sign	Parameter Estimate	Adjusted R^2
γ_0 Intercept	?	− 0.021**	
γ_1 UE_{jq}	+	0.034**	
γ_2 Hetero-information	+	0.064**	
γ_3 Chg Uncertainty	−	− 0.096**	
γ_4 Size	−	− 0.018*	0.009

*Significant at $p < 0.05$.

**Significant at $p < 0.01$.

$CARB_{jq}$: The sum of daily risk-adjusted abnormal returns over the interval (1, 60), where 1 is the first day after the earnings announcement date *q*; where abnormal returns are measured as the difference between the daily return and the expected return for firm *j*. To estimate the expected return for firm *j*, I adopt the market model to estimate α and β by using the raw return for firm *j* and the equally-weighted mean return of NYSE, AMEX, and the NASDAQ firm-size decile that firm *j* is a member of (excluding Unit Investment Trust, Closed-End funds, Real Estate Investment Trusts, Americus Trusts, Foreign Stocks, and American Depository Receipts). All eligible NYSE firms are ranked by market capitalization on the last trading day of each quarter. Ten equally populated portfolios, or deciles, are then formed. I estimate α and β over a 300-trading day interval (− 345, − 45) with a minimum requirement of 250 trading days, where −45 is 45 days before earnings announcement *q*.

Other variable definitions are in Table 2.

taken in the highest ΔV decile, the incremental change is - 9.6%. The regression results provide evidence that drift still varies with firm size after controlling for heterogeneous information and change in uncertainty effects at the 5% significance level.[15] Finally, the adjusted R^2 is 0.009.

4.2. Issues Related to Forecast Dispersion

Prior studies conjecture that forecast dispersion can proxy for disagreement and is related to drift. Dische (2001) relies on Hong and Stein (1999) and Daniel et al. (1998)'s theory and predicts that return profitability from the momentum trading strategy is higher with higher information asymmetries. Using dispersion as a proxy for information asymmetry, he actually finds the opposite from what he had predicted and what one might expect based on the evidence I present in Table 4.[16] Similarly, Alford and Berger (1997) also find a negative relationship between dispersion and drift. **[end of page 337]**

The seemingly contradictory results about how dispersion relates to drift may be a result of dispersion being comprised of two factors, one of which countervails the positive association between drift and dispersion. BKLS specifically model forecast dispersion as follows:

$$D = V(1 - \rho),$$

where *D* is forecast dispersion, *V* is the level of uncertainty and ρ is the correlation in forecast errors across analysts or consensus. As revealed in equation (9), dispersion is determined by both *V* and (1 - ρ). Thus, if *V* is held constant, dispersion could proxy for disagreement, which is (1- ρ), and would be positively associated with drift. However, neither Alford and Berger (1997) nor Dische (2001) are clear about controlling for other factors when they use dispersion as a proxy for disagreement. The negative relationship between dispersion and drift observed in their studies could result from dispersion being mainly driven by uncertainty in their samples. Thus, dispersion is related to two countervailing factors and likely not a good proxy for disagreement.

I conduct a sensitivity analysis to investigate how drift relates to dispersion. The results in Table 6 show that the negative relationship between dispersion and drift is primarily attributable to the level of uncertainty. First, I estimate the following regression to examine how dispersion is related to drift beyond the firm-size effect:

$$CAR_{jq} = \theta_0 + \theta_1 UE_{jq} + \theta_2 DISP_{jq} * UE_{jq} + \theta_3 SIZE_{jq} * UE_{jq} + \varepsilon. \quad (10)$$

Consistent with both Alford and Berger (1997) and Dische (2001), dispersion is negatively related to drift (- 0.03) and highly significant at the 1% level. Second, I add uncertainty (VanerJq) into the regression and examine how dispersion is related to drift after controlling for the level of uncertainty:

$$CAR_{jq} = \varphi_0 + \varphi_1 UE_{jq} + \varphi_2 DISP_{jq} * UE_{jq} + \varphi_3 V_{\text{after}jq} * UE_{jq} + \varphi_4 SIZE_{jq} * UE_{jq} + \varepsilon_{jq}. \quad (11)$$

The results from the multivariate regression fail to provide evidence that dispersion is negatively related to drift after controlling for the level of uncertainty. Further, the coefficient of the uncertainty variable is- 0.068 and highly significant at the 1% level. The size variable is negatively related to drift and highly significant. The condition index of 8.13 fails to indicate severe multicollinearity, suggesting that the insignificant coefficient of dispersion is not attributable to collinearity. The overall results are consistent with dispersion relating to multiple factors.

4.3. Other Tests

I also conduct several diagnostic tests, adding the following additional control variables to my primary regression. First, I control for the number of analysts (*N*) around each earnings announcement in the sample. I use *N* to proxy for the **[end of page 338]**

Table 6.

Panel A: Test of market underreaction and dispersion ($N = 20{,}966$).

$$CAR_{jq} = \theta_0 + \theta_1 UE_{jq} + \theta_2 DISP_{jq} * UE_{jq} + \theta_3 SIZE_{jq} * UE_{jq} + \varepsilon_{jq}.$$

Coefficient	Expected Sign	Parameter Estimate	Adjusted R^2
θ_0 intercept	?	−0.034*	
θ_1 UE_{jq}	+	0.090*	
θ_2 Dispersion	−	−0.030*	
θ_3 Size	−	−0.022	0.010

Panel B: Test of market underreaction, dispersion and uncertainty ($N = 20{,}966$).

$$CAR_{jq} = \varphi_0 + \varphi_1 UE_{jq} + \varphi_2 DISP_{jq} * UE_{jq} + \varphi_3 V_{\text{after}jq} * UE_{jq} + \varphi_4 SIZE_{jq} * UE_{jq} + \varepsilon_{jq}.$$

Variable	Expected Sign	Parameter Estimate	Adjusted R^2
φ_0 intercept	?	−0.034*	
φ_1 UE_{jq}	+	0.110*	
φ_2 Dispersion	+	0.011	
φ_3 Uncertainty	−	−0.068*	
φ_4 Size	−	−0.033*	0.011

*Significant at $p < 0.01$.

$DISP_{jq}$: The level of forecast dispersion after earnings announcement q for firm j scaled by the adjusted closing stock price on the 45th day before earnings announcement q. I calculate dispersion in analysts' forecasts as the sample variance of one-year-ahead annual earnings forecast revisions reported within 30 days following earnings announcements.

$$D = \frac{1}{N-1} \sum_{i=1}^{N} E(f_i - \bar{f})^2,$$

where f_i is the most recent annual earnings forecast revision around the earnings announcement by analyst i, $\bar{f}$ is the mean forecast, and N is the number of forecasts around the earnings announcements.

$V_{\text{after}jq}$: The level of uncertainty after earnings announcement q for firm j scaled by the adjusted closing stock price on the 45th day before earnings announcement q. $V_{\text{after}jq}$ is estimated as:

$$V = \left(1 - \frac{1}{N}\right) D + SE,$$

where I compute D, N and SE using the most recent one-year-ahead annual earnings forecasts revisions reported within 30 days following earnings announcements.

information flow around earnings announcements that is incremental to the size variable.

Second, Lee and Swaminathan (2000) show that high trading volume (turnover) magnifies price-based momentum in the intermediate-term. High volume is also associated with high dispersion (Barron, 1995). Since price momentum and earnings momentum are related (Chan et al., 1996), I add both volume and price momentum in the model to control for the spurious relationship among volume, price momentum and drift, which is correlated with the heterogeneous information variable (HI_{jq}) I measure volume as the average daily turnover in percent during the **[end of page 339]**

Table 7. Sensitivity tests of market underreaction to quarterly earnings in a multivariate OLS regression ($N = 20{,}966$).

$$\mathrm{CAR}_{jq} = \gamma_0 + \gamma_1 UE_{jq} + \gamma_2 HI_{jq} * UE_{jq} + \gamma_3 \Delta V_{jq} * UE_{jq} + \gamma_4 SIZE_{jq} * UE_{jq} + \gamma_5 N_{jq} * UE_{jq} + \gamma_6 Vol_{jq} * UE_{jq} + \gamma_7 Comp_{jq} * UE_{jq} + \gamma_8 Sign_{jq} * UE_{jq} + \gamma_9 PE_{jq} * UE_{jq} + \varepsilon_{jq}.$$

Coefficient	Expected Sign	Parameter Estimate	Adjusted R^2
γ_0 Intercept	?	−0.026**	
γ_1 UE_{jq}	+	−0.003	
γ_2 Hetero-information	+	0.026**	
γ_3 Chg uncertainty	−	−0.064**	
γ_4 Size	−	−0.003	
γ_5 Num of analysts	−	−0.004	
γ_6 Volume	+	0.047**	
γ_7 Compound return	+	0.029**	
γ_8 Sign of UE	?	0.033**	
γ_9 PE ratio	+	0.012*	0.015

*Significant at $p < 0.05$.
**Significant at $p < 0.01$.
N_{jq}: The number of analysts around each firm quarter in the sample; also represents the number of forecasts in the pre- and post-earnings announcement window.
Vol_{jq}: The average daily turnover in percent during the 45 days before earnings announcement q, where daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day.
$Comp_{jq}$: The compound return over the six months prior to earnings announcement q.
$Sign_{jq}$: A dummy variable equal to 1 when earnings surprises are positive; 0 when earnings surprises are negative.
PE_{jq}: Mean annual earnings forecast within 45 days before earnings announcement q scaled by the closing stock price on the 45th day before earnings announcement q. I divide all firm-quarters with positive earnings into nine groups (1, 2, . . . , 9) with an approximately equal number of firm-quarters per group. All firm-quarters with negative earnings are in group 0. I classify firm-quarters in the middle six groups as 1 and firm-quarters in the bottom and top two groups as 0.
Other variable definitions are in Table 2.

45 days before earnings announcement q, where daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day. I use the compound return over the six months prior to earnings announcement q to capture the price momentum.

Third, to examine whether the results vary across positive versus negative earnings surprises, I also add a dummy variable (Sign) in the model. Sign equals one when earnings surprises are positive, and zero otherwise.

Lastly, to control for differential persistence in the earnings signal across my sample, I add the P/E ratio as a proxy for persistence. As prior studies (Ali and Zarowin, 1992; Baber et al., 1999) show, extremely high (low) earnings-price ratios indicate that earnings are transitorily high (low), while nonextreme ratios indicate that earnings are predominantly permanent. I adopt the mean annual earnings forecast within 45 days before earnings announcement q scaled by the adjusted closing stock price on the 45th day before earnings announcement q as the earnings- **[end of page 340]** price ratio.[17] I then divide all firm-quarters with positive earnings into nine groups (1, 2, ... , 9) with an approximately equal number of firm-quarters per group. All firm-quarters with negative earnings are in group 0. I classify firm-quarters in the middle six groups as I and firm-quarters in the bottom and top two groups as 0.

Results are robust to adding the above variables. The coefficients for both the heterogeneous information variable (HI_{jq}) and the change in uncertainty variable (ΔV_{jq}) are statistically significant and have the predicted signs after controlling for the number of analysts, volume, price momentum, the sign of earnings surprises and earnings-price ratios.[18] In particular, the coefficients of HI_{jq} and ΔV_{jq} are 0.026 and -0.064, both significant at the 1% level. Consistent with prior studies (Barron, 1995; Chan et al., 1996; Lee and Swaminathan, 2000), the coefficients of volume and price momentum are both positive (0.047 and 0.029) and significant at the 1% level. The evidence suggests that drift varies across positive and negative earnings surprises and more drift is associated with positive earnings surprises. The coefficient estimate of Sign is 0.033 with a 1% significance level. The regression results fail to provide evidence that drift varies with firm size and the number of analysts after controlling for other variables. The coefficient estimate of the earnings-price ratio (PE) is 0.012 with a 5% significance level, consistent with the argument that greater drift is associated with more persistent earnings.

5. Conclusion and Future Research

The empirical evidence in this study lends credence to claims that anomalies, such as post-earnings announcement drift, represent market inefficiencies arising from imperfect information-processing behavior by investors. The results indicate that post-earnings announcement drift can be partially attributed to investors' information processing biases: (I) overconfidence in private information and (2) over-confidence in less reliable information and underconfidence in more reliable information. Specifically, the empirical evidence reveals that drift has a positive relationship with heterogeneous information and negative relationship with the change in uncertainty around earnings announcements. These results are consistent with the notion that investors' non-Bayesian behaviors can lead to drift. Finally, this study also provides insight into the puzzling negative relationship between dispersion and drift discussed in prior research (Alford and Berger, 1997; Dische, 2001). While the latter studies predict a positive relationship between dispersion and drift, my paper provides evidence that the observed negative relationship is likely driven by the level of uncertainty, suggesting dispersion is a function of both uncertainty and disagreement.

This study is of interest for several reasons. First, I view this paper as a first step in empirically linking drift with information processing biases. An anomaly is not an anomaly once people understand the factors that cause it. An important contribution of this study is to identify factors that may partially explain drift. Second, this study should help people develop some decision aids to mitigate investors' information processing biases after realizing that drift is related to those **[end of page 341]** biases. In particular, analysts may change the way they make decisions after taking into account these non-Bayesian behaviors. Similar to a language, accounting information communicates key signals regarding a firm's financial health. Likewise, financial disclosure is a key process in accounting; therefore, presenting information in certain formats may help investors infer information correctly and avoid those biases. Future research may examine whether other anomalies documented in finance and accounting research, such as the accrual anomaly documented by Sloan (1996), can be explained by investors' non-Bayesian behaviors. Future research may also consider investors' information processing biases in other contexts, such as the effect of a new accounting standard or disclosure policy.

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Notes

1. In this setting, private information is not necessarily better or insider information, but rather heterogeneous information that could come from either different information sets or different interpretations of the same information.
2. Non-Bayesian investors are investors who cannot process all information in a statistically correct fashion. This kind of behavior could be due to investors' psychological biases, such as overconfidence about their private information.
3. Hong and Stein (1999) examine a setting where the market underreaction occurs among newswatchers. They define newswatchers as investors who rationally use fundamental news but ignore prices. To some extent, their setting can be interpreted as assuming that newswatchers overreact to fundamental news and drift occurs because of newswatchers' overreaction.
4. Refer to footnote 2 in Bloomfield et al. (2000) to calculate 77%.
5. Gleason and Lee (2002) show that investors' cognitive limitations help explain a significant portion of the delayed price response to individual analyst forecast revisions.
6. Common information refers to information that is shared by all analysts.
7. Diether et al. (2002) also document a negative relationship between dispersion and future returns, although they do not examine drift.

8. If the 45th day is not a trading day or price is not available, I collect the adjusted closing stock price within two days around the 45th day. Consistent with prior research (Christie, 1987), I choose price as the deflator. The results are qualitatively the same if I use the mean earnings forecast as the deflator. **[end of page 342]**
9. One-year-ahead annual forecasts are about twice as frequent as one-quarter-ahead quarterly earnings forecasts, and are about seven times as frequent as long-term growth forecasts.
10. All eligible NYSE firms are ranked by market capitalization on the last trading day of each quarter. Ten equally populated portfolios, or deciles, are then formed. Stocks that are traded on the AMEX and NASDAQ are placed into these deciles according to their respective market capitalization using the NYSE breakpoints (1996 CRSP Access97 Indices File Guide, WRDS).
II. The regression results are insensitive to this winsorization.
12. Refer to equation (9) in the supplementary test.
13. I employ two alternative measures for the size-adjusted return (CAR): (I) starting 3 days after the announcement *q* through 60 trading days after the announcement *q*, and (2) starting 30 trading days after the announcement *q* through 60 trading days after the announcement *q*. Results are qualitatively the same to those presented.
14. Since most variables on the right-hand side of the regression are measured using analyst forecasts and Panel B of Table 2 shows high correlation among variables ρ, ΔV and *HI*, I conduct a diagnostic test for multicollinearity. The estimated condition index (7.04) recommended by Belsley et al. (1980) fails to provide evidence of significant multicollinearity in the regression model.
15. As in Table 4, I conduct a diagnostic test for multicollinearity, with the condition index of 7.04 failing to provide evidence of significant multicollinearity in the regression model.
16. His study differs from mine because he examines the German market, whereas I focus on the US market. In addition, he examines the returns after revisions in analysts' forecasts, whereas post-earnings announcement drift relates to returns after earnings surprises.
17. I also use actual EPS scaled by the closing stock price from the previous quarter (*q* - I) as a measure of the earnings-price ratio. In addition, I add the book-to-market (B/M) of previous quarter (q -I) as a proxy for growth and the monthly number of analyst estimates from the IBES summary data in the model. Adding new variables reduces the sample size, although the results still hold.
18. As done previously, I also employ two alternative measures of size-adjusted returns (CAR): (I) starting 3 days after the announcement *q* through 60 trading days after the announcement *q* and (2) starting 30 trading days after the announcement *q* through 60 trading days after the announcement *q*. In addition, I also examine beta-adjusted returns (CARB) for this analysis. Results are qualitatively the same across all specifications.

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