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The efficiency of earnings forecast pricing

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A B S T R A C T

Prior research has suggested that the information content associated with analysts' forecast revisions is not immediately incorporated into a firm's stock price. We find that the apparent anomaly is concentrated in low-priced firms that receive favorable earnings revisions. Variables (such as analyst coverage and celebrity status) cannot reliably explain variations in price formations. Finally, we find that the magnitude of the post-forecast revision drift has decreased after 2002. Overall, our results suggest that the analysts' forecast revisions anomaly can be explained by a combination of random statistical variations and transaction costs.

1. Introduction

Past research has indicated that the information content associated with revisions of analyst forecasts is not immediately and fully incorporated into a firm's stock price. Givoly and Lakonishok (1980) first report this post-forecast revision drift in a small sample of firms. Stickel (1991) suggest that firms with a recently revised consensus forecast tend to earn abnormal returns for about six months in the direction of the revised forecast. He proposes that the mean cumulative abnormal return three months after the revised consensus forecast is economically significant (approximately 5% for firms with the most positive revisions and −3% for firms with the most negative revisions). Gleason and Lee (2003) estimate abnormal returns of a comparable magnitude and show that analyst coverage and all-star status mitigate the delayed response to analyst forecasts.

The existence of a delayed response to a publicly available signal challenges the efficient market hypothesis and most of known anomalies have attracted extensive research that has scrutinized their

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robustness to alternative econometric techniques and to various conditioning variables. However, much less research has been conducted on post-forecast revisions than on other anomalies such as post-earnings announcement drift or the accrual anomaly. To the extent that the post-forecast revision drift exists, it may be affected by certain types of market friction. In this study, we re-investigate the market pricing of forecast revisions, with an emphasis on the roles of different types of friction in the pricing of forecast revisions. In particular, we consider three main types of friction that have been proposed in literature on other market anomalies: a low price level and liquidity (e.g., Bhushan, 1994; Ball et al., 1995), the riskiness of the investment (e.g., Mendenhall, 2004; Mashruwala et al., 2006), and a low level of investor sophistication (e.g., Bartov et al., 2000; Collins et al., 2003). To assess the stability of cross-sectional differences in the market response to the forecast revisions, we conduct our analyses across different sample periods spanning from 1994 to 2008.

We first calculate the buy-and-hold size-adjusted abnormal return (BHAR) in the months following earnings forecast revisions by financial analysts. We find that different variables (such as volatility, trading volume, or institutional ownership) that have played a role in explaining other anomalies do not consistently affect the delayed response to analyst forecasts across different sample periods. In contrast, price level is key to the existence of a delayed response during the overall sample period and each of its sub-periods. Consistent with Gleason and Lee (2003), we also find that the post-forecast revision drift appears to be mitigated when the coverage is large and when the forecast is issued by a celebrity analyst. However, these findings are affected by the choice of sampling period and control variables. For example, the celebrity analyst effect disappears when we consider the 2003–2008 sub-period. The effect of coverage disappears when we control for variables that have been shown to affect other anomalies.

We then consider an alternative approach to the BHAR specification. Prior studies (e.g., Fama, 1998; Mitchell and Stafford, 2000) suggest that a monthly calendar-time portfolio approach provides more robust statistical inferences for long-term abnormal performance. An additional advantage of this approach is that we can easily consider positive and negative forecast revisions separately (e.g., Huang and Zhang, 2011). We form a hedge portfolio to implement this approach. We go long (short) on firms that received a favorable (unfavorable) earnings revision in the previous months. Consistent with our other findings, we identify an abnormal positive return for the hedge portfolio. However, we find that there is no abnormal return in the short portfolio with unfavorable revisions. This apparent anomaly is concentrated in the sample of firms that receive favorable earnings forecast revisions. The absence of a clear theoretical explanation for this result supports the idea that the apparent anomaly can be explained by the existence of random statistical variation (e.g., Fama, 1998).[1] Importantly, we also find that the abnormal returns exist only in low-priced firms. In contrast, the other partitioning variables (such as volatility, trading volume, institutional ownership, coverage, and celebrity status) do not affect the delayed response to analyst forecasts based on the calendar-time portfolio approach. These results suggest that price level is a key factor in the sub-sample of firms in which the drift is present (i.e., firms that receive favorable earnings revisions). Further, our analyses across different sample periods indicate that the magnitude of the drift has decreased after 2002.

Finally, we conduct additional analyses to explore possible explanations for the presence of the drift identified in the sub-sample. We estimate the transaction costs of the portfolio in which firms with low stock prices receive favorable earnings forecast revisions. We use the methodology proposed by Keim and Madhavan (1997) and Bushee and Raedy (2006) to estimate these costs. On the one hand, we find that this portfolio earns an approximately 8% abnormal return over a six-month horizon. On the other hand, we obtain an estimate of the transaction costs of approximately 6% for a "round trip". We also investigate whether the main source of the drift (i.e., small price stocks with positive forecast revisions) is concentrated around the next four earnings announcements and the next six forecast revisions. We find that much of the incomplete price response to a given revision is corrected when

[1] The lack of significant abnormal returns for unfavorable forecast revisions during our overall sample period can be due to the offsetting of positive and negative random statistical variations in different sub-periods. We find a downward drift for the portfolio of firms with unfavorable forecast revisions in the 1994–1998 period, but this drift essentially disappears when we consider the overall sample (1994–2008) period. In fact, there is a positive upward trend in the 1999–2002 period, followed by a small downward trend in the 2003–2008 period. See Section 4.3 for further details.

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later earnings are realized or forecasts are revised, ruling out risk-based explanations for the post-revision price drift.

This study adds to the literature in several ways. First, we show that prior results concerning the forecast revision anomaly are concentrated in a particular segment of the financial market, that is, in low-priced firms that receive favorable market revisions. Second, Gleason and Lee (2003) indicate that "surprisingly little is known about market factors that either exacerbate or mitigate this empirical regularity." We find that price level is a key factor that explains the existence of post-forecast revision drift, consistent with the prior literature (e.g., Bhushan, 1994; Ball et al., 1995; Mashruwala et al., 2006) that documents the role of price in explaining other anomalies. In addition, we compare our estimated Jensen's alpha in the sub-sample in which the anomaly is present with the trading costs, and find that the abnormal returns are essentially commensurate with the trading costs. Finally, our finding that the magnitude of the drift weakens after 2002 is consistent with the notion that money managers have come to understand the apparent mispricing associated with analyst forecast revisions and have begun to exploit it in the last decade as transaction costs have likely become smaller. Overall, our results suggest that the financial markets are more efficient in the pricing of analyst forecasts than was previously thought.

The remainder of the paper proceeds as follows. Section 2 reviews the literature. Section 3 describes our empirical setting. Section 4 presents our results. Section 5 provides additional analyses. Section 6 concludes the paper.

2. Prior literature

Prior studies have suggested that investors initially under-react to forecast announcements, and that the magnitude of a forecast revision and its level of innovation predict long-term returns in subsequent months. This suggests that the information content associated with analyst forecast revisions is not immediately and fully incorporated into the stock price. Givoly and Lakonishok (1980) first report a post-announcement drift after earnings forecast revisions in a small sample of firms. They find abnormal returns of 2.7% during the two months following the revision month for 584 firms experiencing positive revisions of more than 5% of their forecasted earnings. Hawkins et al. (1984) use a strategy of purchasing the 20 stocks with the largest monthly increase in the I/B/E/S mean consensus forecast and find abnormal returns of 14.2% in the year subsequent to the revisions for the period 1975–1980. Stickel (1991) indicate that firms with a recently revised consensus forecast tend to earn abnormal returns for about six months in the direction of the revision. Chan et al. (1996) show that this anomaly is part of a group of "momentum" strategies that indicate an incomplete market response to information. More recently, Gleason and Lee (2003) report that both the quantity of earnings forecast revisions (i.e., in terms of size and direction) and revision innovation predict the magnitude of the price reaction subsequent to the revision. They define a high-innovation forecast good (bad) news revision as a forecast that is higher (lower) than both the analyst's own prior forecast and the prior consensus. Forecasts that are between the analyst's own prior forecast and the prior consensus are classified as low-innovation revisions.

To the extent that this anomaly exists, it may be affected by different types of market friction. Prior studies have proposed three main types of friction: a low price level and liquidity, the riskiness of the investment, and a low level of investor sophistication. Bhardwaj and Brooks (1992) argue that direct transaction costs such as quoted bid–ask spreads and commission per share are inversely related to share price. Bhushan (1994) use both share price and trading volume as transaction-cost proxies in his study of the relation between transaction costs and post-earnings announcement drift. Ball et al. (1995) use share price as a proxy for such transaction costs and document a strong association between the profitability of the DeBondt and Thaler (1985, 1987) five-year contrarian strategy and low-priced stocks. Mashruwala et al. (2006) report that the accrual anomaly documented by Sloan (1996) is found in low-price, low-volume stocks. In contrast to these findings, Bartov et al. (2000) report that trading volume, stock price, and size do not affect the degree of mispricing associated with post-earnings announcement drift.

The second type of friction is the difficulty of arbitraging anomalies through the use of close substitutes. Mendenhall (2004) finds that the magnitude of post-earnings announcement drift is strongly related to the arbitrage risk measure. Similarly, Mashruwala et al. (2006) consider the effect of idiosyncratic volatility on the accrual anomaly documented by Sloan (1996). They argue that an arbitrageur can reduce the residual variance of returns in a hedge portfolio if he or she can find close substitute stocks with returns that are strongly correlated with the returns of firms subject to mispricing. However, they suggest that identifying such substitutes is a difficult task in practice. Following Pontiff (1996) and Wurgler and Zhuravskaya (2002), they use the idiosyncratic portion of a stock's volatility that cannot be avoided by holding offsetting positions in other stocks and indexes as a proxy for the absence of close substitutes. They find that the accrual anomaly is concentrated in firms with a high idiosyncratic stock return volatility.

Finally, the level of investor sophistication can also explain differences in market reactions. Sophisticated investors should incorporate the information contained in analyst reports faster and under-react less to analyst forecasts than unsophisticated or naïve investors. Bartov et al. (2000) find that the post-earnings announcement drift is reduced for firms with greater institutional ownership. Collins et al. (2003) show that sophisticated investors can better price accruals than can naïve investors, and that institutional investors have greater resources for gathering and processing the information contained in financial reports.

Collectively, the literature suggests that firms with a higher price and a higher volume, less idiosyncratic volatility, and more institutional ownership should be less mispriced than firms with the opposite characteristics. However, prior results are somewhat mixed, and the exact role of the various forms of market friction on post-forecast revision drift remains largely unexplored.

3. Empirical setting

We perform two main sets of tests to examine the existence of post-forecast revision drift and the effect of different types of market friction on this potential anomaly. First, we use revision-level BHAR regressions, as in several previous studies (e.g., Stickel, 1991; Gleason and Lee, 2003, among others). Second, we employ the calendar-time portfolio approach suggested by Fama (1998) and Mitchell and Stafford (2000), among others.

3.1. Sample

We obtain analyst forecast data from the I/B/E/S Detail History tapes for the period October 1993 to October 2008. We start our sample period in October 1993 for two reasons. First, forecasts were often delivered to IBES in batches before 1994, and thus the date assigned to a forecast in the database may be inaccurate. Second, as part of our analysis, we replicate the work of Gleason and Lee (2003), whose sample period starts in October 1993. Similar to Gleason and Lee (2003), we use annual forecasts made after the prior year's earnings announcement. Accounting data and stock price are taken from the Compustat annual data files and stock return data are obtained from the CRSP daily and monthly files. We obtain data about institutional ownership from Form 13F, as reported in the Thomson Financial database. We collect the *Institutional Investor* rankings of *All-American Research Team* analysts published each year in the October issue of the magazine.

3.2. BHAR regressions analysis and post analyst revision drift

Our first specification examines market returns in the months following forecast revisions. We first estimate the following regressions, which is very similar to that used by Gleason and Lee (2003).

$$\begin{aligned} BHARxm_{i,j,t} = {} & \alpha_0 + \alpha_1 Sig_{i,j,t} + \alpha_2 Cover_{i,j,t} + \alpha_3 Sig * Cover_{i,j,t} + \alpha_4 All\text{-}star_{i,j,t} \\ & + \alpha_5 Sig * All\text{-}star_{i,j,t} + \alpha_k X^k_{i,j,t} + e_{i,j,t}. \end{aligned} \tag{1}$$

BHARxm is the *x*-month size-adjusted buy-and-hold return starting two days after the forecast revision date. We estimate *BHARxm* for a six-month period (*BHAR6m*) and a twelve-month period (*BHAR12m*).[2] When a security is delisted during the return accumulation period, we include the delisting return if it is available. For the remainder of the accumulation period, we assume that the proceeds are reinvested to earn the average return of the matching size decile portfolio (Gleason and Lee, 2003). We define *Sig* in a similar way to Gleason and Lee (2003) and Clement and Tse (2005). *Sig* is an indicator variable that takes the value of 1 if the forecast is a high-innovation good news forecast (i.e., the forecast exceeds both the prior consensus and the analyst's own prior forecast), −1 if the forecast is below both the prior mean consensus and the analyst's own prior forecast, and 0 otherwise.[3] If the financial markets under-react to revisions in analyst forecasts and the information contained in these forecasts is not immediately incorporated into prices, then α_1 should be significantly positive. Following Gleason and Lee (2003), we include *Cover* and *All-Star*. *Cover* is an indicator variable that takes the value of 1 if the firm's coverage is less than the median coverage, and 0 otherwise. *All-Star* is an indicator variable that takes the value of 1 if the forecast is issued by an All-Star analyst, and 0 otherwise. This classification is based on *Institutional Investor* magazine.

X represents a vector of the control variables. *CAR3d* is the three-day size-adjusted buy–hold return around the forecast revision day. *Rev* is the difference between forecasted earnings and the analyst's prior forecast, scaled by the stock price two days before the analyst forecast date.[4] *Size* is the log of the market value of equity at the beginning of the year. *Mkt-to-Bk* is the market-to-book ratio at the beginning of the year. *Momentum* is the trading momentum, defined as the six-month market-adjusted return before the forecast revision. These variables are also used by Gleason and Lee (2003), and overall our specification is very similar to theirs.[5] The only difference is that we do not include their variable "earnings estimators", which is a measure of whether or not the analyst is highly ranked by the Wall Street Journal. Gleason and Lee (2003) already show that the effect of the interaction between this variable and *Sig* is unstable, *positive* in some of their specifications, and insignificant in others.

However, model (1) does not consider several variables that past research identifies as being related to future stock returns. To examine their potential effect, we estimate the following extended specification.

$$BHARxm_{i,j,t} = \beta_0 + \beta_1 Sig_{i,j,t} + \beta_{2n} Part^n_{i,j,t} + \beta_{3n} Sig * Part^n_{i,j,t} + \beta_{4k} X^k_{i,j,t} + e_{i,j,t} \tag{2}$$

$Part^n$ represents the full set of partitioning variables that can affect the efficiency of earnings forecast pricing. *Price* is an indicator variable that takes a value of 1 if the daily closing price of the firm at the beginning of the calendar month before the issuance of the forecast is less than \$10 and 0 otherwise. This definition is similar to that used by Bartov et al. (2000).[6] *Volume* is an indicator variable that takes the value of 1 if the trading volume is below the median volume, and 0 otherwise. The annual dollar trading volume is calculated as the sum of the daily dollar trading volume (i.e., the product of the daily closing price and the daily number of shares traded) over the fiscal year before the forecast issuance (e.g., Bartov et al., 2000). *IdioVol* is an indicator variable that takes the value of 1 if the idiosyncratic volatility of the firm is less than the median volatility, and 0 otherwise. We follow Mashruwala et al. (2006) in calculating the idiosyncratic volatility.[7] *TInst* is an indicator variable that equals 1 if the percentage of transient institutional investors among the shareholders of the firm at the beginning of the fiscal year is below the median value for all firms by year, and 0 otherwise. We use the population of forecast

2 We use 126 trading days and 252 trading days as the cut-offs for inclusion in our six- and twelve-month portfolios.

3 To be consistent with Gleason and Lee (2003), the consensus is based on all forecasts available before analyst *i*'s revision for firm *j*.

4 Prior studies (e.g., Imhoff and Lobo, 1984; Stickel, 1991) indicate that an analyst's prior forecast is a better benchmark than the consensus forecast for measuring the amount of surprise in an individual forecast revision.

5 Similar to Gleason and Lee (2003), we winsorize *Rev*, *Size*, and *Mkt-to-Bk* at the 1% level and use the untransformed returns, but our results (untabulated) are similar if we use the winsorized firm returns.

6 Our conclusions are not affected when we define *Price* using \$5, \$15, or the cross-sectional median. However, the effect of *Price* becomes weaker when use \$15 or the median to define *Price*.

7 We estimate the market model over a 48-month period ending at the beginning of the fiscal year when the forecast was made. We obtain similar results (untabulated) if we estimate the market model over 253 trading days (i.e., one year) ending one day before the issuance of the forecast revision. We then calculate the variance in the residual for each forecast.

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revisions to calculate the medians by year when we compute our partitioning variables in the BHAR specifications. Using the overall population to calculate the median values gives us similar results (untabulated). *Accr* is an indicator variable that equals 1 if the operating accruals at the beginning of the fiscal year scaled by average total assets are greater than the median, and 0 otherwise.[8] *Mf* is an indicator variable that equals 1 if management issued a forecast of earnings any time during the shorter of two time frames: (1) from the start of the year to when the revised analyst forecast was issued, or (2) from the last forecast issued by the same analyst to the current revised forecast, and 0 otherwise. We include the concurrent issuance of management forecast because Ng et al. (2013) find evidence of under-reaction to management forecast news. Because investors may perceive more optimistically biased forecasts as less credible and may thus take longer to fully understand their information content, we include an indicator variable *Obias*, which is equal to 1 if the individual analyst forecast is optimistic (relative to realized earnings), and 0 otherwise. Finally, we also include *Cover* and *All-Star* (as defined in model (1)) as partitioning variables.[9] $Sig * Part^n$ represents the interaction between *Sig* and our different partitioning variables. If these different variables affect the anomaly, then we expect β_{3n} to be significantly positive except for *Mf* and *All-Star* in regression (2). X^k represents a vector of control variables (*Rev*, *CAR3d*, *Size*, *Mkt-to-Bk*, and *Momentum*) defined in model (1).[10]

3.3. Portfolio-level regressions of post forecast drifts

The literature has raised several issues with the BHAR approach. First, Fama (1998) argues against the BHAR methodology, because the systematic errors that arise with imperfect expected return proxies (the so-called "bad model problem") are compounded with long-horizon returns. Second, our models (1) and (2) are based on observations at the forecast revision level. This implies that we may use some overlapping observations from the same analyst, which means that the error terms are not independent. This may lead to overstated *t*-statistics. Along the same lines, Brav (2000) emphasizes that methods for drawing inferences from BHAR fail to fully correct for the correlation of returns across events not absorbed by the model used to adjust for expected returns. Finally, the calculation of abnormal returns (i.e., a sample firm's return minus the return on a well-diversified portfolio) typically results in a skewed distribution (e.g., Barber and Lyon, 1997; Kothari and Warner, 1997). The results in Section 4.1 suggest the presence of such skewness in our sample. Both deviations from the standard assumptions imply that parametric inferences that rely on independence and normality may be incorrect.

Because of these problems with the BHAR approach, Fama (1998) advocates a monthly calendar-time portfolio approach for measuring long-term abnormal performance. Proponents of this approach argue that it has at least three benefits. First, monthly calendar returns are less susceptible than BHAR regressions to the bad model problem, because returns are calculated independently rather than cumulatively. Second, all of the cross-correlations of event-firm abnormal returns are automatically accounted for in the portfolio variance. Finally, the distribution of this estimator is better approximated by a normal distribution, which permits the use of classical statistical inference. We follow the approach suggested by Fama (1998) and Mitchell and Stafford (2000), but we also control for the momentum and liquidity risk factors documented in the literature (e.g., Carhart, 1997; Sadka, 2006). Specifically, we estimate the following regression.

$$Ret_{\mathrm{pt}} = R_{\mathrm{pt}} - R_{\mathrm{ft}} = \varphi_0 + \varphi_1 MktRf_t + \varphi_2 SMB_t + \varphi_3 HML_t + \varphi_4 UMD_t + e_t \tag{3}$$

[8] We consider this variable because Barth and Hutton (2004) report that the post-forecast drift is stronger for firms that also suffer from accrual-based mispricing (as in Sloan, 1996). Similar to Collins and Hribar (2000), we measure accruals as earnings before extraordinary items (Compustat item IB) minus operating cash flows before extraordinary items (Compustat item OANCF – item XIDOC) divided by average total assets. Using a partition based on deciles rather than a binary partition gives similar results (untabulated).

[9] We also control for the listing on the Nasdaq as a robustness check. The interaction of *Sig* and the Nasdaq indicator variable is generally insignificant when we estimate model (2). Our main results are otherwise unaffected.

[10] Given the high correlation between size and our other partitioning variables, such as volume or analyst coverage, we do not interact *Size* with *Sig* or *Rev* in this test to maintain the multicollinearity at a reasonable level. We revisit the issue of the effect of size when we use the calendar-month approach.

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Table 1
Descriptive statistics.

Panel A: Overall sample (Sample size = 930,474)

Variable	Mean	Median	Std. Dev.
CAR3d	−0.0032	−0.0015	0.0829
BHAR12m	0.0288	−0.0301	0.5767
Sig	−0.0243	0.0000	0.8189
Rev	−0.0023	−0.0002	0.0160
Price	0.1789	0.0000	0.3832
Volume	0.4974	0.0000	0.5000
IdioVol	0.4984	0.0000	0.5000
TInst	0.4992	0.0000	0.5000
Cover	0.5130	1.0000	0.4998
All-Star	0.1429	0.0000	0.3499
Accr	0.5004	1.0000	0.5000
Mf	0.3164	0.0000	0.4651
Obias	0.4672	0.0000	0.4989
Size	7.7474	7.6593	1.7050
Mkt-to-Bk	3.7884	2.5893	4.9092
Momentum	0.0116	−0.0188	0.3602

Panel B: Average size-adjusted buy-and-hold return

	Rev > 0	*Rev* < 0	Difference	*Sig* = 1	*Sig* = −1	Difference
1994–1998						
BHAR3m	0.012	−0.023	0.035***	0.017	−0.025	0.042***
BHAR6m	0.016	−0.033	0.049***	0.022	−0.035	0.057***
BHAR12m	0.032	−0.037	0.069***	0.039	−0.039	0.078***
1999–2008						
BHAR3m	0.007	−0.001	0.008***	0.007	−0.000	0.007***
BHAR6m	0.015	0.007	0.008***	0.015	0.006	0.009***
BHAR12m	0.040	0.020	0.020***	0.041	0.016	0.025***
Overall sample (1994–2008)						
BHAR3m	0.008	−0.007	0.015***	0.009	−0.008	0.017***
BHAR6m	0.015	−0.004	0.019***	0.017	−0.006	0.023***
BHAR12m	0.038	0.004	0.034***	0.041	−0.001	0.042***

BHAR3m (*BHAR6m*, *BHAR12m*) represents the three- (six-, twelve-) month size-adjusted buy-and-hold return starting two days after the forecast revision day. *CAR3d* is the firm's size-adjusted return over the three-day event window. *Sig* is an indicator variable that takes the value of 1 if the forecast is a high-innovation good news forecast (i.e., it exceeds both the prior consensus and the analyst's own prior forecast), −1 if the forecast is below both the prior consensus and the previous analyst's own forecast, and 0 otherwise. *Rev* is the forecast revision, which is the forecast minus the analyst's prior forecast, scaled by the stock price two days before the forecast revision date. *Price* is an indicator variable that takes the value of 1 if the daily closing price of the firm at the beginning of the calendar month before the issuance of the forecast is less than $10, and 0 otherwise. *Volume* is an indicator variable that takes the value of 1 if the trading volume is below the median volume, and 0 otherwise. *IdioVol* is an indicator variable that takes the value of 1 if the idiosyncratic volatility is less than the median idiosyncratic volatility, and 0 otherwise. *Tinst* is an indicator variable that takes the value of 1if the percentage of transient institutional investors among the shareholders of the firm is below the median value for all firms, and 0 otherwise. *Cover* is an indicator variable that takes the value of 1 if the firm's coverage is less than the median coverage, and 0 otherwise. *All-Star* is an indicator variable that takes the value of 1 if the forecast is issued by an All-Star analyst, and 0 otherwise. *Accr* is an indicator variable that takes the value of 1 if operating accruals at the beginning of the fiscal year scaled by average total assets are greater than the median value, and 0 otherwise. *Mf* is an indicator variable that takes the value of 1 if firms issue management forecast, and 0 otherwise. *Obias* is an indicator variable that takes the value of 1 if the individual analyst forecast is optimistic (relative to realized earnings), and 0 otherwise. *Size* is the log of the market value of equity at the beginning of the year. *Mkt-to-Bk* is the market-to-book ratio at the beginning of the year. *Momentum* is the trading momentum, defined as the six-month market-adjusted return before the forecast revision date.

*** A two-tailed *t*-test of difference from 0 is significant at the 1% level or less.

The dependent variable, *Ret*, is the event portfolio return, R_p, in excess of the one-month Treasury-bill rate, R_f. To estimate R_p, we form an equally weighted portfolio of all of the forecast revisions that took place within the previous six months (twelve months) before the portfolio formation month. The event portfolio is rebalanced monthly to drop all of the forecast revisions that have reached the end

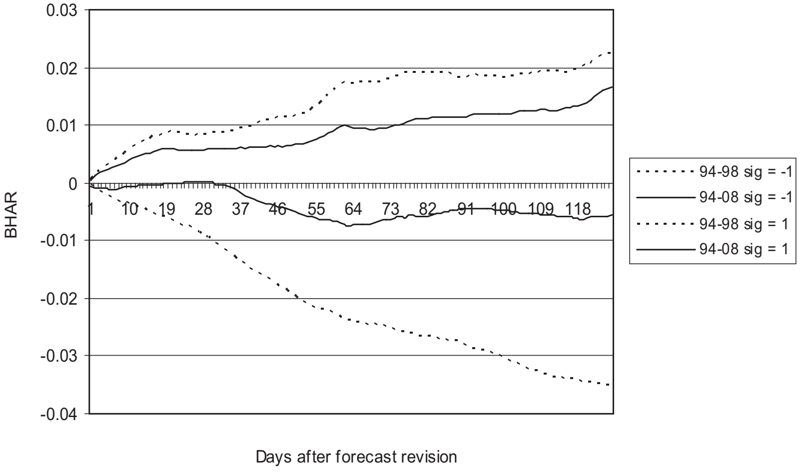

Fig. 1. BHAR for favorable and unfavorable revisions. *Sig* is an indicator variable that takes the value of 1 if the forecast is a high-innovation good news forecast (i.e., it exceeds both the previous consensus and the analyst's own prior forecast, −1 if the forecast is below both the prior consensus and the analyst's own prior forecast, and 0 otherwise.

of their six-month (twelve-month) period and add all of the forecast revisions that have just occurred. For each calendar month, we form a hedge portfolio in which we go long (short) on observations for which *Sig* equals 1 (−1).

We regress the return of the hedge portfolio on four explanatory variables. We use the one-lag Newey–West procedure to correct for heteroskedasticity and serial correlation. *MktRf* is the excess return on the market factor portfolio in calendar month *t*. *SMB* is the difference in returns between portfolios of "small" stocks and "big" stocks. *HML* is the difference between portfolios of "high" book-to-market stocks and "low" book-to-market stocks (see Fama and French, 1993). *UMD* is a momentum factor that is calculated as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.

The intercept, φ_0, measures the average monthly abnormal return, given the model. The difference in intercepts between a *Sig* of 1 and a *Sig* of −1 represents the abnormal return from the zero-investment portfolio that has a long (short) position in the favorable (unfavorable) forecast revisions. If the financial markets under-react to analyst forecasts, then we would expect φ_0 to be significantly positive. We initially estimate these models for our overall sample and subsequently consider various subsamples based on our partitioning variables (described in the foregoing sub-section).

4. Empirical results

4.1. Descriptive statistics

Table 1 reports the descriptive statistics for the main variables. Panel A provides the statistics for the overall sample. The mean and median values are materially different for *BHR12m*, suggesting the presence of skewness in the data. About 18% of our overall observations have a stock price below $10 and about 32% have a concurrent management forecasts. Panel B provides the statistics for the three-month, six-month, and twelve-month BHAR distribution (*BHAR3m*, *BHAR6m*, and *BHAR12m*) conditional on *Sig* being equal to either 1 or −1, and on *Rev* being greater than 0 or less than 0. Panel B also shows the statistics for the BHAR distribution for the 1994–1998 period (i.e., that used by Gleason and Lee, 2003), the 1999–2008 period, and the overall sample period (1994–2008). For the 1994–1998 period, untabulated *t*-tests indicate that the mean returns are significantly different from 0 in all cases (a *p*-value of less than 0.001 in all cases). The returns for the "good news" portfolios (*Sig* = 1 or *Rev* > 0) are positive, whereas those for the "bad news" portfolios (*Sig* = −1 or *Rev* < 0) are

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Table 2
Correlation table.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16
1. *BHAR12m*	**1.00**															
2. *Car3d*	**−0.01**	**1.00**														
3. *Sig*	**0.02**	**0.25**	**1.00**													
4. *Rev*	−0.00	**0.16**	**0.40**	**1.00**												
5. *Price*	**0.13**	**−0.01**	**−0.05**	**−0.11**	**1.00**											
6. *Volume*	**−0.02**	−0.00	**−0.02**	**−0.03**	**0.21**	**1.00**										
7. *IdioVol*	**−0.03**	**0.02**	**−0.01**	**0.04**	**−0.26**	**−0.17**	**1.00**									
8. *TInst*	**0.01**	**0.00**	**−0.06**	**−0.02**	**0.05**	**−0.00**	**0.23**	**1.00**								
9. *Cover*	**−0.03**	**−0.01**	**−0.04**	**−0.05**	**0.16**	**0.62**	**−0.14**	**−0.03**	**1.00**							
10. *All-Star*	0.00	**0.00**	**−0.01**	**0.01**	**−0.05**	**−0.10**	**0.11**	**0.02**	**−0.06**	**1.00**						
11. *Accr*	**−0.04**	**−0.01**	**−0.04**	**−0.02**	**−0.04**	**0.02**	**0.10**	**0.07**	**0.10**	**0.00**	**1.00**					
12. *Mf*	**0.00**	**−0.02**	**0.02**	**0.01**	**−0.12**	**−0.12**	**0.04**	**−0.04**	**−0.07**	**0.02**	**0.03**	**1.00**				
13. *Obias*	**−0.15**	**−0.09**	**−0.06**	**−0.07**	**0.03**	**0.04**	0.00	**0.06**	**0.04**	**−0.01**	**0.05**	**−0.06**	**1.00**			
14. *Size*	**−0.00**	**0.02**	**0.04**	**0.07**	**−0.37**	**−0.70**	**0.42**	**0.17**	**−0.62**	**0.12**	0.00	**0.16**	**−0.05**	**1.00**		
15. *Mkt-to-Bk*	**−0.02**	**−0.01**	**0.03**	**0.03**	**−0.07**	**−0.14**	**−0.07**	**−0.03**	**−0.11**	**−0.01**	**−0.05**	**0.03**	**−0.03**	**0.17**	**1.00**	
16. *Momentum*	**0.03**	**0.04**	**0.22**	**0.19**	**−0.14**	**0.02**	**−0.03**	**−0.10**	**−0.01**	0.00	**−0.05**	**−0.02**	**−0.16**	**−0.02**	**0.01**	**1.00**

All of the correlations in bold are significant at the 5% level or less. *BHAR12m* represents the twelve-month size-adjusted buy-and-hold return starting two days after the forecast revision day. *CAR3d* is the firm's size-adjusted return over the three-day event window. *Sig* is an indicator variable that takes the value of 1 if the forecast is a high-innovation good news forecast (i.e., it exceeds both the prior consensus and the analyst's prior forecast), −1 if the forecast is below both the prior consensus and the analyst's prior forecast, and 0 otherwise. *Rev* is the forecast revision, which is the forecast minus the analyst's own prior forecast, scaled by the stock price two days before the forecast revision date. *Price* is an indicator variable that takes a value of 1 if the daily closing price of the firm at the beginning of the calendar month before the issuance of the forecast is less than $10, and 0 otherwise. *Volume* is an indicator variable that takes the value of 1 if the trading volume is below the median volume, and 0 otherwise. *IdioVol* is an indicator variable that takes the value of 1 if the idiosyncratic volatility is less than the median idiosyncratic volatility, and 0 otherwise. *Tinst* is an indicator variable that takes the value of 1 if the percentage of transient institutional investors among the shareholders of the firm is below the median value for all firms, and 0 otherwise. *Cover* is an indicator variable that takes the value of 1 if the firm's coverage is less than the median coverage, and 0 otherwise. *All-Star* is an indicator variable that takes the value of 1 if the forecast is issued by an All-Star analyst, and 0 otherwise. *Accr* is an indicator variable that takes the value of 1 if operating accruals at the beginning of the fiscal year scaled by average total assets are greater than the median value, and 0 otherwise. *Mf* is an indicator variable that takes the value of 1 if firms issue management forecast, and 0 otherwise. *Obias* is an indicator variable that takes the value of 1 if the individual analyst forecast is optimistic (relative to realized earnings), and 0 otherwise. *Size* is the log of the market value of equity at the beginning of the year. *Mkt-to-Bk* is the market-to-book ratio at the beginning of the year. *Momentum* is the trading momentum, defined as the six-month market-adjusted return before the forecast revision date.

negative. These results are similar to Gleason and Lee (2003). For the 1999–2008 period, the results for the "good news" portfolios are comparable to those based on the 1994–1998 period. This suggests the presence of an apparent post-forecast revision drift following good news revisions. However, the returns are close to or even positive for the "bad news" portfolios in the 1999–2008 period. The presence of a trend for bad news that is upward in some periods and downward in others is consistent with the presence of random sampling variation that creates the appearance of mispricing in certain periods. For the overall sample period, we naturally observe the average of the two periods. The mean BHAR following bad news revisions is less than 1% in the three-, six-, and twelve-month periods. These results suggest that post-forecast revision drift following bad news revisions is sensitive to the sample period.

Fig. 1 gives a graphical presentation of the performance of two buy-and-hold portfolios. The first portfolio is formed with firms that received a favorable forecast revision (i.e., *Sig* = 1). The second portfolio is formed using firms that received an unfavorable revision (i.e., *Sig* = −1). We estimate the returns for the 1994–1998 period and the 1994–2008 period. We observe an apparent upward drift for the portfolio of firms with favorable forecast revisions in both periods. This drift is approximately linear over the horizon that we consider. In contrast, we observe a downward drift for the portfolio of firms with unfavorable forecast revisions in the 1994–1998 period, but this drift essentially disappears when we consider the overall sample (1994–2008) period (aside from a period of small negative

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returns between the 30th and the 60th trading day). This suggests that the under-reaction to unfavorable revisions, if any, may be concentrated in the 1994–1998 period. This finding is consistent with the results in Panel B of Table 1.

Table 2 presents a correlation table. Consistent with the prior literature, the correlation between *Sig* and *BHAR12m* is significantly positive. *Coverage* (*All Star*) is positively (negatively) and significantly correlated with a stock price below $10. Given the high correlation between *Cover* and *Volume* (0.62) reported in Table 2, we orthogonalize *Volume* with respect to *Cover* in the specifications in which we use both variables at the same time.[11]

4.2. BHAR regression

Before using our main specifications, we first consider the magnitude of the post-forecast drift by regressing *BHAR6m* and *BHAR12m* on *Sig*. The untabulated results indicate that the coefficients associated with *Sig* are approximately 0.028 (0.037) for the 1994–1998 period, 0.004 (0.013) for the 1999–2008 period, and 0.011 (0.020) for the overall period for six-month (twelve-month) returns. This suggests that a strategy of shorting firms with negative forecast revisions and buying firms with positive forecast revisions yields an abnormal return of 5.6% (7.4%) over a six-month (twelve-month) period for the 1994–1998 period but only 2.2% (4.0%) for the 1994–2008 period. The estimate for the 1994–1998 period is consistent with the estimate in Gleason and Lee (2003).

Note that there were significant changes in analyst regulations during our sample period. In October 2000, the Securities and Exchange Commission (SEC) implemented Regulation Fair Disclosure (Reg FD). Reg FD mandates that all publicly traded companies must disclose material information to all investors at the same time.[12] To comply with the Sarbanes–Oxley Act of 2002 (SOX), the National Association of Securities Dealers (NASD) promulgated Rule 2711 (Research Analysts and Research Report) and the New York Stock Exchange (NYSE) amended its Rule 351 (Reporting Requirement) and Rule 472 (Communication with the Public). These rules, together with the enforcement action known as the Global Settlement (GS), aim to mitigate analysts' conflicts of interest by separating research analysts from the influence of investment banking and brokerage businesses.[13] To the extent that these regulations affect the information environment in the capital markets, they may affect the pricing efficiency with respect to analyst forecasts. To examine whether our results are stable across the different periods, we divide our overall sample period into the following four sub-periods: (1) the Gleason and Lee (GL) period (November 1993–October 1998); (2) the post-GL and pre-Reg-FD period (November 1998–October 2000); (3) the post-Reg-FD and pre-NASD2711/GS period (November 2000–August 2002); and (4) the Post-NASD2711/GS period (September 2002–October 2008).[14]

We then estimate model (1) for the four sub-periods and the overall sample period and present the results in columns 1–5 of Table 3.[15] To be consistent with Gleason and Lee (2003), we initially correct

[11] We only orthogonalize the partitioning variables that are strongly correlated with each other. We do not orthogonalize the control variables to be consistent with Gleason and Lee (2003).

[12] There is ongoing debate as to whether Reg FD has improved or worsened analysts' information environment. Heflin et al. (2003) find no reliable evidence that analyst forecast dispersion or accuracy has changed, but Bailey et al. (2003) show that the dispersion of analyst forecasts has significantly increased, suggesting that Reg FD may have impaired the market's ability to reach a consensus. More recently, Kross and Suk (2012) suggest that the information environment has improved following the enactment of Reg FD.

[13] Consistent with this objective, Hovakimian and Saenyasiri (2010) report that forecast error has declined in the period following the GS and Kadan et al. (2009) report that the fraction of buy recommendations has fallen whereas the fractions of neutral and sell recommendations have increased in the post-GS period. However, there is some concern as to whether the GS has actually led to an improvement in the quality of the information environment in the capital markets. Kadan et al. (2009) report that the informativeness of analysts' recommendations has declined following the implementation of GS and Begley et al. (2009) find that the average information quality has not improved in the post-GS period.

[14] September 2002 was the month immediately after both the NYSE (amended rule 472) and NASD (rule 2711) rules designed to limit communications between investment bankers and security analysts were enacted. Following Kadan et al. (2009), we use September 2002 as the beginning period of the NASD/GS period.

[15] For brevity, we report our results in Table 3 and Table 4 based on *BHAR12m*. Our results are largely unaffected when we use *BHAR6m*.

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Table 3
"Buy-and-hold abnormal returns" regressions.

Variable	Dependent variable = *BHAR12m*				
	1 GL period	2 Post-GL & pre-Reg-FD	3 Post-Reg-FD & pre-NASD2711/GS	4 Post-NASD2711/GS	5 Full sample period
Intercept	0.042	0.333***	0.036	0.036	0.074***
	(1.25)	(4.84)	(0.84)	(1.38)	(4.13)
Rev	0.389*	0.466	0.578***	−0.614*	0.117
	(1.95)	(1.55)	(4.56)	(−1.83)	(0.96)
CAR3d	0.090*	0.110	−0.120**	−0.127**	−0.059*
	(1.93)	(1.53)	(−2.45)	(−2.28)	(−1.78)
Sig	0.014**	−0.008	−0.016**	0.020***	0.010***
	(2.25)	(−0.58)	(−2.42)	(4.48)	(3.30)
Cover	−0.007	−0.160***	−0.022	−0.040***	−0.040***
	(−0.46)	(−4.71)	(−1.24)	(−3.94)	(−5.07)
Sig ∗ *Cover*	0.021**	0.037*	0.014	0.026***	0.022***
	(2.36)	(1.85)	(1.32)	(4.19)	(4.73)
All-star	−0.001	−0.048***	0.027***	0.006	−0.002
	(−0.26)	(−3.50)	(3.91)	(1.29)	(−0.52)
Sig ∗ *All-star*	−0.007*	0.019	−0.017***	0.003	−0.001
	(−1.73)	(1.52)	(−2.92)	(0.76)	(−0.46)
Momentum	0.103***	0.069***	0.091***	−0.044***	0.051***
	(3.49)	(3.44)	(5.35)	(−2.59)	(4.57)
Size	−0.010**	−0.021***	0.003	−0.001	−0.004*
	(−2.17)	(−2.70)	(0.59)	(−0.22)	(−1.80)
Mkt-to-Bk	0.010**	−0.006***	−0.011***	−0.001	−0.004***
	(2.32)	(−5.10)	(−12.55)	(−0.50)	(−4.51)
N	296,552	123,564	141,784	582,674	1,144,574
R^2	0.010	0.009	0.038	0.003	0.004

BHAR12m represents the twelve-month size-adjusted buy-and-hold return starting two days after the forecast revision date. *CAR3d* is the firm's size-adjusted return over the three-day event window. *Sig* is an indicator variable that takes the value of 1 if the forecast is a high-innovation good news forecast (i.e., it exceeds both the prior consensus and the analyst's prior forecast), −1 if the forecast is below both the prior consensus and the analyst's prior forecast, and 0 otherwise. *Rev* is the forecast revision, which is the forecast minus the analyst's own prior forecast, scaled by the stock price two days before the forecast revision date. *Cover* is an indicator variable that takes the value of 1 if the firm's coverage is less than the median coverage, and 0 otherwise. *All-Star* is an indicator variable that takes the value of 1 if the forecast is issued by an All-Star analyst, and 0 otherwise. *Size* is the log of the market value of equity at the beginning of the year. *Mkt-to-Bk* is the market-to-book ratio at the beginning of the year. *Momentum* is the trading momentum, defined as the six-month market-adjusted return before the forecast revision date. The standard errors in the *t*-statistics are corrected to allow for the clustering of observations by firm. Column 1 shows the results for the Gleason and Lee (GL) period (November 1993–October 1998). Column 2 shows the results for the post-GL and pre-Reg-FD period (November 1998–October 2000). Column 3 shows the results for the post-Reg-FD and pre-NASD2711/GS (November 2000–August 2002). Column 4 shows the results for the post- NASD2711/GS period (September 2002–October 2008).

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

the *t*-statistics for heteroskedasticity and the clustering of observations by firm. The results reported in column 1 of Table 3 are qualitatively similar to those in Gleason and Lee (2003). For the period 1994–1998, *Sig* is significantly positive, the interaction between *Sig* and *Cover* is significantly positive, and the interaction between *Sig* and *All-Star* is significantly negative. However, when we consider other periods, we find different results. In particular, the interaction between *Sig* and *All-Star* becomes insignificant in the second and fourth periods, and insignificant in the overall period.

We next report the results of an estimation based on the extended model (2) for the four sub-periods and the overall sample period, and present the results in columns 1–5 of Table 4. The interaction between *Sig* and *Price* is significantly positive in the overall sample period and each sub-periods. Specifically, the *t*-statistics equal 3.58, 2.22, 2.47, 3.14, and 4.95, respectively for period 1 to period 4 and

Table 4
"Buy-and-hold abnormal returns" regressions – full model.

Variable	Dependent variable = *BHAR12m*				
	1 GL period	2 Post-GL & pre-Reg-FD	3 Post-Reg-FD & pre-NASD2711/GS	4 Post-NASD2711/GS	5 Full sample period
Intercept	−0.100	0.493***	−0.078	0.086*	0.026
	(−1.56)	(3.81)	(−1.16)	(1.91)	(0.79)
Rev	0.107	0.864	−0.341	−0.902	−0.577
	(0.30)	(1.50)	(−0.74)	(−1.45)	(−1.61)
Sig	−0.013	−0.025	−0.006	−0.006	−0.006
	(−1.27)	(−0.96)	(−0.46)	(−0.80)	(−1.13)
Price	0.276***	0.372***	0.194***	0.156***	0.224***
	(14.86)	(7.13)	(8.04)	(8.56)	(17.66)
Sig ∗ Price	0.045***	0.073**	0.040**	0.031***	0.039***
	(3.58)	(2.22)	(2.47)	(3.14)	(4.95)
IdioVol	−0.015	−0.118***	0.122***	−0.003	−0.006
	(−0.92)	(−3.79)	(7.89)	(−0.38)	(−0.82)
Sig ∗ IdioVol	0.014*	0.021	0.005	0.016***	0.011***
	(1.69)	(1.04)	(0.47)	(3.58)	(2.78)
Volume	−0.005	−0.061***	0.028***	−0.008	−0.004
	(−0.54)	(−3.49)	(3.35)	(−1.37)	(−1.01)
Sig ∗ Volume	0.014***	0.016	0.000	0.006***	0.007***
	(3.09)	(1.52)	(0.06)	(2.74)	(3.74)
TInst	0.029**	0.033	−0.002	0.004	0.009
	(2.39)	(1.27)	(−0.16)	(0.43)	(1.21)
Sig ∗ TInst	0.026***	−0.006	0.000	−0.004	0.004
	(3.35)	(−0.34)	(0.01)	(−0.98)	(1.18)
Cover	−0.003	−0.228***	−0.006	−0.030**	−0.031***
	(−0.14)	(−4.90)	(−0.28)	(−1.96)	(−2.66)
Sig ∗ Cover	0.007	−0.033	−0.007	0.015***	0.004
	(0.77)	(−1.46)	(−0.66)	(2.84)	(0.85)
All-star	0.004	−0.028**	0.022***	0.005	0.000
	(0.60)	(−2.26)	(3.20)	(1.37)	(0.07)
Sig ∗ All-star	−0.008*	0.008	−0.011*	0.004	−0.002
	(−1.71)	(0.73)	(−1.89)	(1.49)	(−0.77)
Accr	0.011	−0.034	0.004	−0.039***	−0.021***
	(0.95)	(−1.10)	(0.27)	(−4.82)	(−3.40)
Sig ∗ Accr	0.010	0.030	0.002	0.014***	0.012***
	(1.36)	(1.48)	(0.21)	(3.52)	(3.00)
Mf	0.046**	0.013	0.024**	−0.012	0.009
	(2.41)	(0.57)	(2.15)	(−1.51)	(1.42)
Sig ∗ Mf	−0.012	−0.014	−0.001	−0.009**	−0.012***
	(−0.76)	(−0.71)	(−0.12)	(−2.12)	(−3.62)
Obias	−0.092***	−0.122***	−0.071***	−0.079***	−0.081***
	(−9.24)	(−4.74)	(−6.08)	(−12.59)	(−16.96)
Sig ∗ Obias	−0.010	0.012	−0.000	0.012***	0.006
	(−1.50)	(0.68)	(−0.03)	(2.77)	(1.48)
Car3d	−0.129**	−0.075	−0.255***	−0.264***	−0.205***
	(−2.30)	(−0.95)	(−4.36)	(−4.56)	(−5.43)
Size	0.011	−0.019	0.013*	0.004	0.010***
	(1.31)	(−1.34)	(1.77)	(0.76)	(2.60)
Mkt-to-Bk	0.007*	−0.008***	−0.008***	−0.001	−0.003***
	(1.93)	(−5.32)	(−6.93)	(−0.84)	(−4.33)
Momentum	0.030	0.077***	0.049***	−0.055***	0.037***
	(0.94)	(2.85)	(2.73)	(−3.31)	(3.00)
N	201,755	98,731	107,730	522,258	930,474
R^2	0.055	0.045	0.056	0.017	0.024

BHAR12m represents the twelve-month size-adjusted buy-and-hold return starting two days after the forecast revision date. *CAR3d* is the firm's size-adjusted return over the three-day event window. *Sig* is an indicator variable that takes the value of 1 if the forecast is a high-innovation good news forecast (i.e., it exceeds both the prior consensus and the analyst's own prior forecast), −1 if the forecast is below both the prior consensus and the analyst's own prior forecast, and 0 otherwise. *Rev* is the forecast revision, which is the forecast minus the analyst's own prior forecast, scaled by the stock price two days before the

forecast revision date. *Price* is an indicator variable that takes the value of 1 if the daily closing price of the firm at the beginning of the calendar month before the issuance of the forecast is less than $10, and 0 otherwise. *Volume* is an indicator variable that takes the value of 1 if the trading volume is below the median volume, and 0 otherwise. *IdioVol* is an indicator variable that takes the value of 1 if the idiosyncratic volatility is less than the median idiosyncratic volatility, and 0 otherwise. *TInst* is an indicator variable that takes the value of 1 if the percentage of institutional investors among the shareholders of the firm is below the median value for all firms, and 0 otherwise. *Cover* is an indicator variable that takes the value of 1 if the firm's coverage is less than the median coverage, and 0 otherwise. *All-Star* is an indicator variable that takes the value of 1 if the forecast is issued by an All-Star analyst, and 0 otherwise. *Accr* is an indicator variable that takes the value of 1 if the operating accruals at the beginning of the fiscal year scaled by average total assets are greater than the median value, and 0 otherwise. *Mf* is an indicator variable that takes the value of 1 if firms issue management forecast, and 0 otherwise. *Obias* is an indicator variable that takes the value of 1 if the individual analyst forecast is optimistic (relative to realized earnings), and 0 otherwise. *Size* is the log of the market value of equity at the beginning of the year. *Mkt-to-Bk* is the market-to-book ratio at the beginning of the year. *Momentum* is the trading momentum, defined as the six-month market-adjusted return before the forecast revision date. The standard errors in the *t*-statistics are corrected to allow for the simultaneous clustering of observations by firm. Column 1 shows the results for the Gleason and Lee (GL) period (November 1993–October 1998). Column 2 shows the results for the post-GL and pre-Reg-FD period (November 1998–October 2000). Column 3 shows the results for the post-Reg-FD and pre-NASD2711/GS (November 2000–August 2002). Column 4 shows the results for the post-NASD2711/GS period (September 2002–October 2008).

* Significance at the 10% level.

** Significance at the 5% level.

*** Significance at the 1% level.

the overall period (columns 1–5).[16] We also notice that the coefficient on *Sig* ∗ *Price* is smallest in the fourth period. In contrast to the results for model (1) reported in Table 3, the interaction between *Sig* and *Cover* becomes insignificantly different from 0 in the 1994–1998 period (with *t*-statistic in column 1 equal to 0.77). The interaction between *Sig* and *All Star* becomes insignificant in the second and fourth sub-periods (columns 2 and 4) and the overall period (column 5). The interaction between *Sig* and *Cover* is only significant in the fourth period (column 4). The interaction between *Sig* and the other partitioning variables (*IdioVol*, *TInst*, *Volume*, *Accr*, *Mf*, *Obias*) is significant in some periods but, contrary to the effect of *Price*, this significance is unstable and often disappears.[17]

4.3. Calendar month regressions – overall effect

We then conduct an analysis using the calendar-month portfolio approach outlined in model (3). We report the results of the six-month portfolios based on *Sig* in Panel A and the twelve-month portfolios in Panel B of Table 5. They are very similar. We first consider a two-factor model with a six-month horizon. Consistent with the results in Tables 3, the intercept is significantly positive, with a *t*-statistic of 2.83 in Panel A and 2.72 in Panel B. The economic magnitude is between 0.2% and 0.3% per month for the six- and twelve-month horizons. This yields a six-month cumulative abnormal return of approximately 2%, an estimate similar to that obtained using the BHAR specification for the same period. In the next column, we control for *HML* and *UMD* in addition to *MktRf* and *SMB*. Both the statistical significance of the intercept and its magnitude are reduced (the *t*-statistic equals 1.88 rather than 2.83 in the first column, and the magnitude is reduced to 0.2%).[18] Overall, we conclude that the post-forecast anomaly is robust to the calendar approach.

Next, we consider the long and short portfolios separately, because the literature suggests results between positive and negative revisions are asymmetric. Stickel (1991), for example, indicates that the mean cumulative abnormal return three months after a revised consensus forecast is

[16] When we consider the six-month horizon (*BHAR6m*), untabulated results show that the interaction between *Sig* and *Price* is significantly positive in the overall sample period and three of the four sub-periods (first, second, and fourth). We also partition our overall sample period into three five-year periods (1994–1998, 1999–2003, and 2004–2008). The interaction between *Sig* and *Price* is significantly positive in each of these five-year periods. Specifically, the t-statistics equal 3.95, 3.44, and 2.92 when we consider a six-month horizon 3.58, 3.62, and 2.47 when we consider a twelve-month horizon.

[17] The results presented in Table 4 are qualitatively similar when we re-estimate the specifications allowing for clustering by analyst, firm and year (Petersen, 2009; Gow et al., 2010).

[18] As a robustness test, we also control for the two liquidity factors proposed by Sadka (2006) (*LIQ-Fixed* and *LIQ-Variables*). Untabulated results indicate that *LIQ-Fixed* or *LIQ-variable* is insignificant, but the point estimate of the intercept is not affected. Given that the two last liquidity factors have only a marginal effect on the intercept, we do not include them in our further tests, and focus instead on the four-factor model, which is more commonly used in the literature.

approximately 5% for firms with the most positive revisions and -3% for firms with the most negative revisions. In Panels A and B, we observe that the economic magnitude and statistical significance of the intercept increase in the long portfolios compared with the hedge portfolios. In contrast, the intercept becomes insignificant in the short portfolios. These results hold when we consider a six-month horizon (columns 3 and 4) and a twelve-month horizon. These findings are consistent with the analysis presented in Fig. 1. We thus conclude that the anomaly, if any, comes from investors under-reacting to favorable revisions.

We further estimate the intercepts for the positive revisions separately for each of the four subperiods described in the BHAR analysis. Our results (untabulated) indicate a declining trend in the magnitude of the drift over time. The intercepts are smallest in the fourth period (the intercepts are 0.002 and 0.001 and the *t*-stats are 1.89 and 1.51 for the six-month and twelve-month horizons, respectively).[19] Our results are consistent with the possibility that money managers came to understand the apparent mispricing associated with analyst forecast revisions and began to exploit it in later periods. Recent work by Green et al. (2011) suggests that this is the case for the widely documented accrual pricing anomaly. Their paper suggests that the accrual anomaly no longer exists because it has been arbitraged away. Because transactions costs have probably become smaller over time,[20] it may well be the case that exploiting the analyst forecast revision anomaly has become easier and less costly, particularly for simple buy-and-hold strategies like that which would be needed to exploit the anomaly documented in our study.

The under-reaction to unfavorable revisions, however, is concentrated in the first period (i.e., the GL period). Indeed, there is a positive upward trend in the second and third periods, followed by a small downward trend (which is statistically insignificant) in the last period (i.e., the Post-NASD2711/GS period). This finding for unfavorable revisions can be explained by the existence of random statistical variation in the samples considered in the literature (e.g., Fama, 1998).[21]

The calendar-month portfolio approach suggests that our model (1) suffers from misspecification because we regress *BHARxm* on *Sig* and the interaction of *Sig* with the various partitioning variables. By so doing, we implicitly assume a symmetric effect when *Sig* is equal to -1 or 1. However, the results for the short and long portfolios indicate that this assumption is incorrect. Addressing this misspecification in the context of our model (1) is not straightforward, but the calendar-month portfolio approach enables us to distinguish easily between the two values.[22]

4.4. Calendar month regressions – partitioning variables

Given the results in Table 5 indicating that the anomaly is limited to the sample of firms that receive favorable revisions, we focus on the long portfolio. We further partition our sample of firms receiving favorable revisions (i.e., *Sig* = 1) into those with a high and low value for the partitioning variables. We form new hedge portfolios in which we go long on firms with a high level of friction (low price, small size, high volatility, low volume, low institutional ownership, low coverage, small analysts profile, and low accrual) and go short on firms with a low friction (the opposite characteristics to the high friction set). We use the population of firm-year observations to compute the median on a yearly basis when computing the partitioning variables in the calendar month specification. The results (untabulated) are similar if we use the overall median. We also estimate the regressions for

[19] We also compare the mean bias and mean accuracy for favorable forecasts in each of the four periods. However, we do not find an improvement in forecast quality in the fourth period. The mean bias (mean accuracy) is 0.004 (0.008), 0.003 (0.010), 0.006 (0.012), and 0.004 (0.011) for periods 1 to 4, respectively.

[20] It is reasonable to believe that many of the structural changes in the equity markets, including trading in decimals rather than eighths and the rapid growth of online trading, have resulted in a significant reduction in transaction costs over the past ten years.

[21] It could be argued that changes in analyst regulations (especially NASD Rule 2711/Global Settlement) may have improved the pricing efficiency in the fourth period. However, investigation of the exact causes of this improvement is beyond the scope of this study.

[22] One option is to use two indicator variables, the first of which takes the value of 1 when *Sig* is equal to 1, and 0 otherwise, and the second of which takes the value of 1 when *Sig* equals -1, and 0 otherwise. We would then interact these two variables with our six different partitioning variables. However, this approach would lead to a high degree of multicollinearity in our regressions, and would probably yield unreliable coefficient estimates.

Table 5
Calendar month portfolio regressions.

	Hedge	Hedge	*Sig* = 1	*Sig* = −1
Panel A: Six-month portfolios based on Sig				
Intercept	0.003***	0.002*	0.003***	0.002
	(2.83)	(1.88)	(3.17)	(1.33)
MktRf	−0.009	0.031*	1.137***	1.106***
	(−0.24)	(1.67)	(42.69)	(43.40)
SMB	−0.052	−0.142***	0.484***	0.626***
	(−1.30)	(−4.55)	(8.87)	(12.22)
HML		−0.084*	0.113***	0.197***
		(−1.88)	(2.99)	(3.59)
UMD		0.220***	−0.155***	−0.375***
		(8.35)	(−6.00)	(−10.43)
N	180	180	180	180
Panel B: Twelve-month portfolios based on Sig				
Intercept	0.002***	0.002**	0.003***	0.001
	(2.72)	(2.51)	(2.90)	(1.25)
MktRf	0.016	0.022*	1.112***	1.090***
	(0.63)	(1.68)	(41.61)	(46.54)
SMB	−0.038	−0.111***	0.541***	0.652***
	(−1.49)	(−4.45)	(10.09)	(14.44)
HML		−0.106***	0.133***	0.239***
		(−3.08)	(3.87)	(5.48)
UMD		0.128***	−0.207***	−0.335***
		(7.38)	(−6.81)	(−9.75)
N	180	180	180	180

Ret is the event portfolio return, R_p, in excess of the one-month Treasury-bill rate, R_f. To estimate R_p, we form equally weighted portfolios of all of the forecast revisions that took place within the six months (twelve months) before the portfolio formation month. The event portfolio is rebalanced monthly to drop all of the forecast revisions that have reached the end of their six-month (twelve-month) period and add all of the forecast revisions that have just occurred. For each calendar month, we form a hedge portfolio where we go long on observations for which *Sig* equals 1 and short on observations for which *Sig* equals −1. We then estimate the following model for each of the nine portfolios.
$Ret_{pt} = R_{pt} - R_{ft} = \varphi_0 + \varphi_1 MktRf_t + \varphi_2 SMB_t + \varphi_3 HML_t + \varphi_4 UMD_t + e_t$,
where *MktRf* is the excess return on the market factor portfolio in calendar month *t*, *SMB* is the difference in returns between the portfolios of "small" stocks and "large" stocks, *HML* is the difference between the portfolios of "high" book-to-market stocks and "low" book-to-market stocks, and *UMD* is a momentum factor calculated as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. We use the one-lag Newey–West procedure to correct for heteroskedasticity and serial correlation in estimating the regressions.
* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

forecast revisions with concurrent management forecasts and those without concurrent management forecasts.[23] We use the calendar-month portfolio approach outlined in model (3) to estimate the intercepts. We tabulate the intercepts from the six-month portfolio regressions in Panel A of Table 6 and of the twelve-month regressions in Panel B. A significant intercept for these new hedge portfolios indicates that the partitioning variable explains differences in the abnormal returns. We include the four risk factors used in Table 5 (*MktRf*, *SMB*, *HML* and *UMD*) in these specifications, but do not tabulate their estimated coefficients associated with these four factors.

The results indicate that, although the intercept is usually larger in portfolios in which friction is expected to be more present, the difference is statistically significant at the one percent level only for the partition based on price (with *t*-statistics of 5.42 and 5.48 when we consider a six- or twelve-month horizon). Removing observations in which there was an earnings announcement or analyst forecast for the same firm the day before, the same day, or the day after does not affect our conclusions. Our results also hold when we remove observations where a management earnings

[23] For the calendar-month regressions, we do not partition the sample based on the sign of forecast bias because the optimistic (pessimistic) bias naturally leads to negative (positive) future earnings surprise, which is mechanically related to stock return.

Table 6
Calendar month portfolio approach – univariate partitions.

Panel A: Six-month portfolios

	Low Price	High Price	Low Volume	High Volume	Low Volatility	High Volatility
Intercept	0.013 (5.05)	−0.000 (−0.47)	0.003 (2.55)	0.003 (2.77)	0.002 (2.13)	0.005 (2.81)
Hedge portfolio	*t*-statistic = 5.42		*t*-statistic = 0.27		*t*-statistic = 1.56	
N	180	180	180	180	180	180
	Low TInst	High TInst	Low Cover	High Cover	All Star	Not All Star
Intercept	0.005 (3.33)	0.003 (2.67)	0.003 (2.12)	0.003 (2.94)	0.003 (3.04)	0.003 (3.11)
Hedge portfolio	*t*-statistic = 0.80		*t*-statistic = 0.14		*t*-statistic = 0.04	
N	180	180	180	180	180	180
	Low Size	High Size	Low Accruals	High Accruals	No Mgmt Forecast	Mgmt Forecast
Intercept	0.004 (2.83)	0.003 (2.76)	0.005 (3.33)	0.003 (2.49)	0.003 (3.03)	0.004 (2.75)
Hedge Portfolio	*t*-statistic = 0.88		*t*-statistic = 1.42		*t*-statistic = 0.51	
N	180	180	180	180	180	180

Panel B: Twelve-month portfolios

	Low Price	High Price	Low Volume	High Volume	Low Volatility	High Volatility
Intercept	0.011 (4.98)	−0.001 (−0.72)	0.003 (2.50)	0.003 (2.71)	0.001 (1.62)	0.004 (2.74)
Hedge portfolio	*t*-statistic = 5.48		*t*-statistic = 0.32		*t*-statistic = 1.79	
N	180	180	180	180	180	180
	Low TInst	High TInst	Low Cover	High Cover	All Star	Not All Star
Intercept	0.004 (3.54)	0.003 (2.47)	0.003 (2.38)	0.003 (2.56)	0.002 (2.17)	0.003 (2.95)
Hedge portfolio	*t*-statistic = 1.33		*t*-statistic = 0.50		*t*-statistic = 1.33	
N	180	180	180	180	180	180
	Low Size	High Size	Low Accruals	High Accruals	No Mgmt Forecast	Mgmt Forecast
Intercept	0.004 (2.66)	0.003 (2.72)	0.005 (3.32)	0.004 (2.66)	0.003 (2.72)	0.003 (2.24)
Hedge Portfolio	*t*-statistic = 0.80		*t*-statistic = 1.95		*t*-statistic = 0.11	
N	180	180	180	180	180	180

For each of the partitioning variables (except for management forecast issuance), we partition the sample based on the median. We then estimate the following model for each of the nine portfolios.
$Ret_{pt} = R_{pt} - R_{ft} = \varphi_0 + \varphi_1 MktRf_t + \varphi_2 SMB_t + \varphi_3 HML_t + \varphi_4 UMD_t + e_t$,
where *Ret* is the event portfolio return, R_p, in excess of the one-month Treasury-bill rate, R_f. To estimate R_p, we form equally weighted portfolios of all of the forecast revisions that took place within the previous six months (twelve months) before the portfolio formation month. The event portfolio is rebalanced monthly to drop all of the forecast revisions that have reached the end of their six-month (twelve-month) period and add all of the revisions that have just occurred. For each monthly event portfolio, we form a hedge portfolio where we go long on observations for which friction is high and short on observations for which friction is low. *MktRf* is the excess return on the market factor portfolio in calendar month *t*. *SMB* is the difference in returns between portfolios of "small" stocks and "large" stocks. *HML* is the difference between portfolios of "high" book-to-market stocks and "low" book-to-market stocks. *UMD* is a momentum factor calculated as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. We use the one-lag Newey–West procedure to correct for heteroskedasticity and serial correlation in estimating the regressions. We tabulate the value of the intercepts and the corresponding *t*-statistics for each sub-sample.

forecast was issued any time during the shorter of the two time frames: (1) from the start of the year to when the revised analyst forecast was issued, or (2) from the last forecast issued by this same analyst to the current revised forecast. These results are broadly consistent with our results in Table 4. In addition, the intercepts are significant in all of the sub-samples except that composed of firms with a stock price above $10 (with *t*-statistics of −0.47 and −0.72 when we consider six- and twelve-month horizons), suggesting that the anomaly is concentrated in firms with a low nominal price. We conclude that post analyst forecast revision drift, where it exists, appears to be concentrated in a specific segment of the financial markets (i.e., low-price firms receiving a favorable forecast revision).

To graphically illustrate the effect of the partition based on price, we calculate the performance of two buy-and-hold portfolios and present the results in Fig. 2. The first portfolio is formed with firms that receive a favorable forecast revision (i.e., *Sig* = 1) and are priced at or below $10. We form the second portfolio using firms that received a favorable revision but have a stock price above $10. The difference is striking. The abnormal return for low-priced firms linearly increases at nearly a 45 degree angle, whereas the line for the portfolio of high-priced firms is essentially flat.[24]

Collectively, the literature (reviewed in Section 2) shows that several apparent anomalies are caused by trading friction, and do not represent a departure from the prediction of the efficient market theory. This is also what we find when we consider post analyst forecast drift, an anomaly that has received less scrutiny. The exact nature of the friction that prevents a departure from the expected return varies across studies. If markets are efficient, then the estimated intercept in a return regression should be 0 on average. However, random variation across samples is to be expected (e.g., Fama, 1998). This is not a problem for the theory if these departures are within the magnitude of the various types of trading friction. However, if these sub-samples are not identified by researchers, then they may generate significant intercepts in larger samples and create apparent anomalies. Given the multiplicity of sources of market friction, different types of friction may explain different apparent anomalies, and the efficient market theory does not predict which particular friction should drive apparent abnormal returns. Our empirical results suggest that price level is the key issue in a sub-sample of firms subject to post analyst forecast drift for the period that we consider.

4.5. Daily abnormal returns following forecast revisions

To better understand the temporal patterns of price movements, we examine the daily abnormal returns around forecast revisions. We consider the period from the day on which a forecast was issued to 20 trading days afterward. We calculate the expected return for each firm by estimating a four-factor model using the 200 trading days ending 30 trading days before the forecast issuance. The untabulated results indicate that the cumulative abnormal return following a positive revision (i.e., *Sig* equals 1) in the overall sample is 0.3% from $t+2$ to $t+10$ and 0.5% from $t+2$ to $t+20$. For negative revisions (i.e., *Sig* equals -1), the abnormal return is 0.1% from $t+2$ to $t+20$.[25] The returns are even smaller for the sub-sample of firms priced above $10, at least when the news is positive. For these firms, the cumulated abnormal return is 0.2% from day $t+2$ to $t+10$ and 0.3% from $t+2$ to $t+20$ when there is a positive revision. When there is a negative revision, the cumulated abnormal return is -0.2% from day $t+2$ to $t+10$ and -0.1% from $t+2$ to $t+20$. For firms priced at or below $10 that receive a positive revision, the cumulated abnormal return is 0.9% from day $t+2$ to $t+10$ and 1.7% from $t+2$ to $t+20$. For firms priced at or below $10 that receive a negative revision, there is a small *positive* return in the days following the revision (0.3% from $t+2$ to $t+10$ and 0.9% from $t+2$ to $t+20$).

5. Further investigations

5.1. Transaction costs

In this section, we first consider the effect of transaction costs for the sub-sample in which the drift is present (i.e., favorable earnings forecast revisions for low-price firms). Bushee and Raedy (2006) indicate that price impact adjustments and block holding constraints have a large negative effect on portfolio returns with most strategies. Such constraints eliminate significant abnormal returns for the size and return reversal strategies, whereas the cash-flow-to-price, return momentum, and post-earnings-announcement drift strategies continue to perform well, as do the book-to-market and operating accrual strategies in some scenarios. Bushee and Raedy (2006) do not consider the effects of transaction costs on post-forecast drift. We focus on the effect of price impacts on the profitability of a strategy in the presence of post forecast revision drift. Keim and Madhavan (1997) explain that there are two major components to trading costs: explicit costs consisting primarily of commission costs, and implicit costs consisting primarily of the price impact of a trade. We use their estimate

[24] The figures exhibit similar patterns when we use $5 or $15 as the price cutoff.

[25] The daily returns are statistically different from 0 for the first 19 days after a positive revision and the first 4 days for negative revisions. However, this significance is difficult to interpret, because the huge sample size (between 440,000 and 520,000 observations) means that there is a high likelihood of finding significant results.

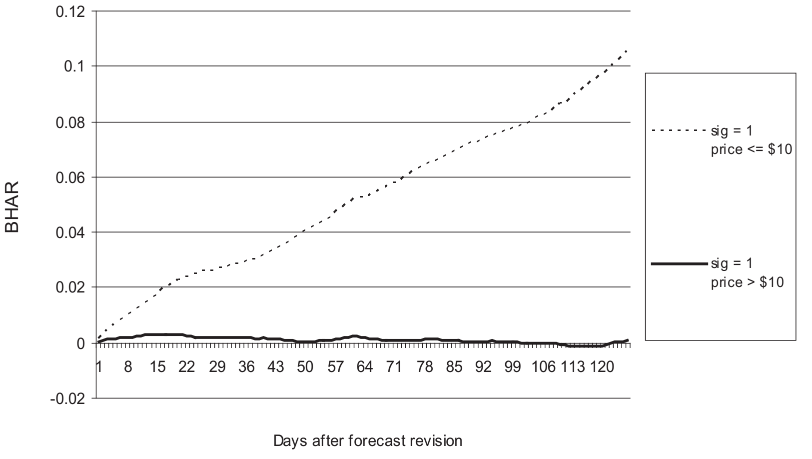

Fig. 2. BHAR for favorable revisions – price above and below \$10. *Sig* is an indicator variable that takes the value of 1 if the forecast is a high-innovation good news forecast (i.e., it exceeds both the prior consensus and the analyst's own prior forecast, −1 if the forecast is below both the prior consensus and the analyst's own prior forecast, and 0 otherwise.

of trading costs, which was also used by Barber et al. (2001) and Bushee and Raedy (2006). Specifically, we estimate the price impact for buyer-initiated trades as

$$\begin{aligned} \mathit{Price\ Impact}\ (\%) = {} & 1.259 + 0.336 * \mathit{NASDAQ} + 0.092 * \mathit{TRSIZE} - 0.084 * \mathit{MKTCAP} \\ & + 13.807 * \mathit{InvPrice}. \end{aligned} \tag{4}$$

For seller-initiated trades, we estimate the price impact as

$$\begin{aligned} \mathit{Price\ Impact}\ (\%) = {} & 1.223 + 0.058 * \mathit{NASDAQ} + 0.214 * \mathit{TRSIZE} - 0.059 * \mathit{MKTCAP} \\ & + 6.537 * \mathit{InvPrice}. \end{aligned} \tag{5}$$

NASDAQ is an indicator variable that equals 1 if the stock being traded is listed on the *NASDAQ*, and 0 otherwise. *TRSIZE* is the ratio of the order value of the market capitalization of the traded stock. *MKTCAP* is the log of the market capitalization of the stock being traded at $t + 1$, and *InvPrice* is defined as 1 over the price per share of the stock being traded at $t + 1$. The constant term in both models includes both the intercept, which represents explicit transaction costs, and the coefficient on a technical manager indicator variable that reflects the extra transaction costs of active portfolio management.

These models give us an estimate of the round trip cost of approximately 6%. This estimate appears reasonable compared with the figures in the prior literature. For example, Stoll and Whaley (1983) report that transaction costs account for 2% of the market value for the largest NYSE decile and 9% for the smallest decile. According to Bhardwaj and Brooks (1992), transaction costs account for 2% of the market value for securities priced over \$20.00 and 12.5% for securities priced below \$5.00. Barber et al. (2001) report a 4% transaction cost for small stocks. Nonetheless, we acknowledge that our estimate of transaction costs may not be representative. On the one hand, there are reasons to suggest that our estimate is conservative. First, Keim and Madhavan (1997) explicitly note that they ignore some transaction costs, such as taxes or clearance and settlement fees, in their calculation. Second, we ignore the other types of trading friction described in Bushee and Raedy (2006), such as the maximum stake size that a fund can hold or the maximum portfolio weight constraints that some funds face for tax reasons. We also ignore short selling restrictions. These restrictions will not play a role if investors simply want to buy a long portfolio, but may become an issue if investors want to hedge the risk associated with the portfolio. This could cause further problems in implementing a strategy based on post forecast revision drift. On the other hand, it could be argued that at least two factors may cause transaction costs to be overestimated with these models. First, the coefficient estimates obtained from Keim and Madhavan (1997) are based on a data sample from 1991 to 1993, and it is possible that the rapid growth of online trading in recent years has in fact reduced transactions costs. Second, the exchanges reduced the tick size during this period, resulting in a reduction in transactions costs.

5.2. Abnormal returns around subsequent earnings announcements and analyst forecast revisions

Gleason and Lee (2003) find that a disproportionate amount of the post-revision price drift occurs within the short windows around the next four earnings announcements and the next six forecast revisions of other analysts, ruling out risk-based explanations for the post-revision price drift. To verify whether the drift documented in our study exhibits the same characteristic, we calculate the abnormal returns for three-day windows around the subsequent four earnings announcements and subsequent six analyst forecast revisions for the observations where analysts issued favorable revisions (i.e. $Sig = 1$). We find that the abnormal return over 12 days around the subsequent four earnings announcements is 1.5%, which is 37% of the one-year abnormal return. The abnormal return over 18 days around the subsequent six analyst forecast revisions is 0.4%, which is 10% of the one-year abnormal return. These results are comparable to those reported in Gleason and Lee (2003), that is, much of the incomplete price response to a given revision is corrected when later earnings are realized or forecasts are revised. This finding increases our confidence that the drift that we document can be explained by the transaction cost.

6. Conclusion

Prior research has indicated that the information content associated with forecast revisions by analysts is not immediately and fully incorporated into the stock price. We find that it is concentrated in low-priced firms that receive favorable earnings forecast revisions. Different variables (such as volatility, trading volume, institutional ownership, or managerial guidance) that have played a role in explaining other anomalies do not consistently affect the delayed response to analyst forecasts across different sample periods. Although the literature suggests that the degree of mispricing is affected by analyst coverage and celebrity status, we also find that these results are sensitive to the choice of sampling period and control variables. Our results suggest that the analyst forecast revision anomaly can be explained by a combination of random statistical variation and high transaction costs. Additionally, we find that the magnitude of the drift associated with favorable forecast revisions declines in the post-2002 period, which is consist with the notion that money managers have come to understand the apparent mispricing associated with analyst forecast revisions and have begun to exploit it in the past decade as transaction costs have decreased. We conclude that the financial markets are more efficient in the pricing of analyst forecasts than was previously thought.

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