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Investor Target Prices*

Shiyang Huang† Xin Liu‡ Chengxi Yin§

This Draft: July 2019

Abstract

We argue that investors have target prices as anchors for the stocks that they own; once a stock exceeds target prices, investors are satisfied and more likely to sell the stock. This increased selling can generate a price drift after good news. Consistent with our argument, using analyst-target-price forecasts as a proxy, we provide evidence that the fraction of satisfied investors generates the post-earnings-announcement drift, and stocks with a high fraction of satisfied investors experience stronger selling around announcements. This pattern is stronger for stocks with low institutional ownership and high uncertainty.

JEL Classification: G11, G12, G14

Keywords: Investor Target Price, Fraction of Satisfied Investors, Price Drift, Forward-looking Anchor, Delayed Adjustment.

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Abstract

We argue that investors have target prices as anchors for the stocks that they own; once a stock exceeds target prices, investors are satisfied and more likely to sell the stock. This increased selling can generate a price drift after good news. Consistent with our argument, using analyst-target-price forecasts as a proxy, we provide evidence that the fraction of satisfied investors generates the post-earnings-announcement drift, and stocks with a high fraction of satisfied investors experience stronger selling around announcements. This pattern is stronger for stocks with low institutional ownership and high uncertainty.

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Keywords: Investor Target Price, Fraction of Satisfied Investors, Price Drift, Forward-looking Anchor, Delayed Adjustment.

1. Introduction

"*You need to consider harvesting gains […] when the investment has reached its target price…*"

- Jay Pestrichelli & Wayne Ferbert. Buy and Hedge: The 5 Iron Rules for Investing Over the Long Term, 2011.

A large body of anecdotal evidence reveals that investors have target prices in mind for the stocks that they hold; a target price is the price at which an investor expects to be the fundamental value of a share in the future.[1] In this paper, we investigate target price as a forward-looking anchor and propose that once a stock exceeds investors' target prices, they are more likely to sell. Such collective selling pressure would have the potential to slow down the price adjustment to positive news. Correspondingly, any reluctance associated with selling a stock whose target price has not yet been met has the potential to restrict the supply of shares and hamper price adjustment to negative news.

Consider the following broad-brush examples, made extreme to highlight the intuition. Stocks A and B are both trading at $10. There are two groups of investors with target prices (sticky beliefs): (1) current investors who hold a positive position before the earnings announcement, and (2) potential investors who do not have any position in the stock before the earnings announcement, probably due to outside options and wealth constraints. Both groups have the same distribution of target prices as their beliefs for future stock prices. In Figure 1a, investors in Stock A have target prices close to the current price, while investors in Stock B have target prices that are more

[1] Other definitions for target price used by practitioners are: "*price set by analysts predicting where the stock will head in the next 52 weeks. Also, price an investor is hoping a stock will go to within a specified period of time.*" (The Street); or "*1. A projected price level as stated by an investment analyst or advisor. 2. A price that, if achieved, would result in a trader recognizing the best possible outcome for his or her investment. This is the price at which the trader would like to exit his or her existing position so that he or she can realize the most reward.*" (Investopedia).

dispersed. Current investors from both stocks believe that the stocks are undervalued. Suppose that, on the next day, both firms announce positive news, and some investors with rational behavior update their beliefs and are willing to pay up to \$12.[2] For Stock A (Figure 1b), a bid price of \$11 exceeds almost all of the current investors' target prices (shown in the shaded area). Because current investors use their target prices as anchors and do not adjust their beliefs based on the new information, they become satisfied with their investment outcome and are likely to sell their shares and realize their gain.[3] For potential investors with the same anchoring bias, they did not buy the stock when it was \$10, therefore they should not buy the stock now as the price is even higher. More importantly, potential investors with target prices below \$11 believe that the stock has been overvalued as the current stock price has exceeded their target prices, and thus may take short positions.[4] This collective selling pressure from current investors and the short selling from potential investors exert a downward pressure and slow down the price adjustment from \$11 to \$12. As a result, Stock A experiences both increased trading activities and a positive price drift as the stock price first appreciates from \$10 to \$11 and then slowly converges to \$12.

Contrast this with Stock B (Figure 1c), a bid price of \$11 satisfies a substantially smaller proportion of current investors. In other words, potential buyers attempting to buy the stock at \$11 will find fewer investors willing to sell, because the price is lower than their target-price anchors. For potential investors, because most of their target prices have not been exceeded yet, there will

[2] These investors could be some current investors or some potential investors. The fundamental difference between these investors and investors with target prices is that the latter group of investors have sticky beliefs and do not adjust their beliefs even when news arrives.

[3] We refer to these investors as satisfied investors hereafter. These investors anchor on their target prices because they do not follow latest news frequently or they overweight their information received from before (e.g., due to behavioral bias).

[4] In an untabulated test, we examine the daily short interests right after positive earnings announcements and confirm our argument about the potential investors. Specifically, we find that *FracSat* × *RankCAR*(0,1) is significantly positively related to abnormal short interest around the earnings announcement. In other words, when extremely good news arrives and most of the investors' target prices get exceeded, potential investors exhibit shorting behavior. This result is consistent with results on order imbalance.

be little short selling activities as well. As a consequence, trading between \$10 and \$11 will be filled up quickly, and stock price will quickly adjust to \$12.

Finally, consider the case of negative news (Figure 1d). Suppose that bad news arrives and potential buyers are willing to buy both stocks at \$9. Current investors in both stocks will tend to hold onto their shares because this offer price is below their target-price anchors. Potential investors will not short sell the stocks because their target prices are higher than \$9. Consequently, both stocks will exhibit negative price drifts subsequent to the negative news announcements.

Based on this, we hypothesize that stocks with a high fraction of satisfied investors should experience more trading activities and a more sluggish response to positive news than stocks with a low fraction of satisfied investors. This argument is consistent with some recent theories (e.g., Banerjee, Kaniel, and Kremer, 2009; Banerjee and Kremer, 2010; Banerjee, 2011; Eyster, Rabin, and Vayanos, 2018), which argue that investors have sticky beliefs and tend to rely on their anchoring beliefs when new information arrives. This strand of theoretical studies find that investors' sticky beliefs can lead to price drifts/momentum, which provides a theoretical foundation for our empirical results. We use the earnings announcement setting to test this hypothesis. Conceptually, our mechanism should also explain a price drift after negative news. However, given the lack of variation in the fraction of satisfied investors after negative news announcements, we focus on positive earnings surprises.[5] We measure earnings surprise using cumulative DGTW-adjusted abnormal returns in the first two trading days of the announcement, i.e., *CAR*(0,1). Thus, a positive earnings surprise is the one associated with a positive *CAR*(0,1).

[5] In the simplified example, since all target prices are above the current price, the fraction of satisfied investors should always be zero. Empirically, within the subsample of negative earnings announcements (i.e., *CAR*(0,1) < 0 or negative *SUE*), 85% observations have zero fraction of satisfied investors. This is not surprising since prior studies have documented that analysts are usually optimistic on the stocks they cover.

We follow Diether, Malloy and Scherbina (2002) and use information from analysts to proxy for investors' beliefs. Specifically, we use analyst-target-price forecasts to approximate the distribution of investors' target prices. This approximation is appropriate for two reasons. First, investors can easily gain access to analyst target prices from brokers (e.g., Charles Schwab) and financial media (e.g., *Yahoo! Finance*, *TIPRANKS*)[6]. Second, target price forecasts are important elements from analyst reports and investors respond strongly and incrementally to analyst-target-price revisions (Bradshaw 2002; Asquith, Mikhail and Au 2005; Da, Hong, and Lee, 2016).

To implement our empirical tests, we first select the latest analyst target prices announced within a 90-day window prior to earnings announcements. Then, we construct the main variable, *FracSat*, as the fraction of analysts whose target-price forecasts are exceeded by the stock price after the announcement. The calculation of *FracSat* is in the same spirit of Frazzini (2006), which calculates *CGO* (Capital Gain Overhang) after earnings announcement.

We document novel evidence that the post-earnings-announcement drift (PEAD) is present only among observations with a high *FracSat*. When *FracSat* is high, the difference in *CAR*(2,61) between top- and bottom-*CAR*(0,1)-quintile observations equals 2.20% (*t*-statistic = 3.25). That is, the initial earnings surprise (*CAR*(0,1)) positively predicts the subsequent stock market response (*CAR*(2,61)). In sharp contrast, when *FracSat* is low, the difference in *CAR*(2,61) between top- and bottom-*CAR*(0,1)-quintile observations is 0.50% (*t*-statistic = 1.12). That is, price reacts fully and immediately in the first two trading days, and there is no significant subsequent drift in the ensuing three calendar months. Moreover, within the top *CAR*(0,1) quintile, the difference in *CAR*(2,61) between high and low *FracSat* observations is 1.68% (*t*-statistic = 2.42). This suggests that, given the same level of earnings surprise, a high *FracSat* leads to a sluggish market response

[6] An example is provided in Appendix Figure A1 from *TIPRANKS*

to good news. Results from regression analyses, which control for variables that have been suggested to impact the PEAD and the interaction between *CAR*(0,1) and these control variables, are consistent. Based on these findings, we can develop an improved PEAD calendar-trading strategy, which yields a four-factor adjusted alpha of 0.76% per month (*t*-statistic = 2.22).

A concern that arises when sorting stocks using *FracSat* is that it is likely for stocks with extreme earnings surprises to exhibit large *FracSat*. Ideally, we would like the subsamples to contain stocks with similar *CAR*(0,1) but a wide spread in *FracSat*. Our data satisfy this criterion since the correlation coefficient between *CAR*(0,1) and *FracSat* is only 0.21. In addition, we adopt an alternative proxy, *FracSat*1, which is computed as the fraction of analysts whose target price forecasts are exceeded by the stock price one week before the announcement. The correlation between *CAR*(0,1) and *FracSat*1 is −0.01. We find similar results using *FracSat*1 instead of *FracSat*. Thus, our main results are not mechanically driven by any relation between the sorting variables. We also consider other three alternative proxies for *FracSat* (*FracSat*2 - *FracSat*4), and they all produce consistent results.

To further purge out the concern between *CAR*(0,1) and *FracSat*, we replace *CAR*(0,1) with two alternative proxies for earnings surprise, one based on seasonal random walk (*SUE*1), the other based on analyst consensus (*SUE*2). The correlation between *FracSat* and *SUE*1 (*SUE*2) is only 0.02 (0.09), suggesting that *FracSat* and these two *SUE*s are not mechanically correlated. Our main results continue to hold with these two *SUE*s.

To further provide direct evidence for our argument, we examine the interaction effect of *CAR*(0,1) and *FracSat* on buy-sell imbalance around announcements.[7] We have two findings: (1)

[7] Based on Lee and Radhakrishna (2000), we also use the difference in volume between small buy-initiated trades and small sell-initiated trades to measure retail investors' buy-sell imbalance. Within the same *CAR*(0,1) quintile, we find that stocks with a high *FracSat* experience low buy-sell imbalance from retail investors. This is consistent with the finding that our results are stronger for stocks with high retail ownership (see Section 4.1). These results are reported in Appendix A2.

CAR(0,1) itself generates a buying pressure, suggesting that investors buy stocks on good news; (2) *CAR*(0,1)×*FracSat* generates a selling pressure. These not only provide direct evidence for our argument, but also show that our results are not merely driven by the mechanical relation between *CAR*(0,1) and *FracSat.* That is, if *FracSat* only captured extreme *CAR*(0,1), *CAR*(0,1)×*FracSat* would generate stronger buying pressure which is not what we find (see Section 3.3).[8]

We conduct two sets of subsample analysis to further strengthen our argument. First, compared to institutional investors, individual investors are more likely to follow analyst-target-price forecasts due to their limited information sources and insufficient skills. Consistent with this conjecture, we find that our results only exist in the subsample with low institutional ownership. Second, because it is difficult to collect and analyze information related to firms with high uncertainty, current investors may rely more on analyst-target-price forecasts for these stocks. Using idiosyncratic volatility to proxy for uncertainty, we find that our results only exist in the subsample with high idiosyncratic volatility.

Our proposed mechanism should also affect security prices more broadly. Consistent with this notion, we find that a high positive stock return with a high *FracSat* is accompanied by a disproportionately higher subsequent price drift than a stock with the same level of high positive return but a low *FraSat*.

Our study contributes to the literature on the anchoring effect in financial markets. Existing studies in this line of research focus on backward-looking anchors, such as purchase price (Odean, 1998; Grinblatt and Han, 2005; Frazzini, 2006; An, 2015; Wang, Yan, and Yu, 2017; and An, Wang, Wang, Yu, 2017), 52-week high (George and Hwang, 2004; Baker, Pan, and Wurgler, 2012;

[8] Other explanations could be that *FracSat* is correlated with idiosyncratic volatility and analyst responsiveness, which are associated with post-earnings-announcement drifts (Mendenhall, 2004; Zhang, 2008). To rule out these two explanations, we find that the correlation between *FracSat* and idiosyncratic volatility (analyst responsiveness) is −0.04 (0.04). Moreover, the results are unchanged after controlling for idiosyncratic volatility, analyst responsiveness and their interactions with *CAR*(0,1).

George, Hwang, and Li, 2015; Birru, 2015; Hong, Jordan, and Liu, 2015; Huang, Lin, and Xiang, 2018), past returns and historical price patterns (Grinblatt and Keloharju, 2001), the distribution of past returns (Barberis, Mukherjee, and Wang, 2016), round numbers (Donaldson and Kim, 1993; Bhattacharya, Holden and Jacobsen, 2012), and historical high (Li and Yu, 2012). However, work by Kőszegi and Rabin (2006, 2007, 2009), and Meng and Weng (2017) suggest that expectations on future outcomes also play an important role determining investors' trading decisions; nevertheless, all anchoring effects in the existing literature are backward-looking, based on historical price and return records.

To our knowledge, this paper is the first to provide empirical evidence that investors' target prices can affect their trading decisions. Target prices capture investors' expectations on future stock prices. This forward-looking nature is fundamentally different from historical anchors documented in existing studies, such as *Capital Gain Overhang* and *Nearness to 52-week High*, both of which are based on historical information (purchase price and 52-week high, respectively). Target prices affect not only current investors but also potential investors. This feature clearly distinguishes our proxy from existing anchoring proxies based on historical prices and returns, which only affect current investors (e.g., *Capital Gain Overhang*). Moreover, we find that our target-price-based measure still has explanatory power to the price drift after controlling for *Capital Gain Overhang* and *Nearness to 52-week High*, and their interaction with *CAR*(0,1). Our results suggest that target price may be an example of the expectation-based reference point modeled in Kőszegi and Rabin (2006, 2007, 2009), Meng and Weng (2017), Banerjee, Kaniel, and Kremer (2009), Banerjee and Kremer (2010), Banerjee (2011), and Eyster, Rabin, and Vayanos (2018).

Moreover, our study is more comprehensive in terms of empirical designs. For example, earlier studies (e.g., Frazzini, 2006; Birru,2015; and George, Hwang, and Li, 2015) focus on the earnings announcement setting whereas ours shows that target prices not only play an important role in generating PEAD, but also has a broader asset pricing implication on general price drifts. Empirical results regarding trading volumes and selling pressures further strengthen our argument. In proposing target price as a behavioral bias which results in market underreaction to positive news and general price drift, our study adds to the empirical literature on market underreaction, such as Hou and Moskowitz (2005), Hou (2007), Cohen and Lou (2012), Lou (2012), and Lou (2014).

Since investors' expectations on future stock prices are unobservable, we use the distribution of analyst-target-price forecasts as a proxy for the distribution of investors' target prices. Relative to analysts' earnings forecasts and recommendations, the data on analyst-target-price forecasts have been under-studied. We contribute to the literature by providing a novel application of analyst-target-price forecasts.

2. Data

2.1. Sample Description

We take analyst-target-price forecasts from the Institutional Brokers' Estimate System (I/B/E/S), quarterly financial statements from COMPUSTAT and financial market data from the Center for Research in Security Prices (CRSP). The sample period spans from 1999 to 2015 and is determined by the availability of analyst-target-price forecasts.

We focus on quarterly earnings announcements that are available in both COMPUSTAT and I/B/E/S[9]. Following Livnat and Mendell (2006) and standard literature, we impose these restrictions:

(1) Ordinary common shares listed on the NYSE, AMEX, or NASDAQ;
(2) The earnings announcement date is reported in both COMPUSTAT and I/B/E/S, and the earnings report dates in COMPUSTAT and in I/B/E/S differ by no more than one calendar day;
(3) The price-per-share at the end of the fiscal quarter is available from COMPUSTAT and is greater than \$5;
(4) The market value of equity at the fiscal quarter-end is available and is larger than \$5 million;
(5) Daily stock returns are available in CRSP for the dates around the earnings announcement. Moreover, we should be able to assign a stock to one of the 125 DGTW portfolios based on size, book-to-market ratio and momentum (Daniel, Grinblatt, Titman, and Wermers 1997);
(6) Earnings surprise (*CAR*(0,1)), which is defined as the cumulative abnormal return from the announcement day and the day following the announcement, should be positive;
(7) Data available to compute our main variable of interest, *FracSat*.

2.2. Measurement of Earnings Surprise and the PEAD

We compute daily abnormal returns as raw daily returns minus daily value-weighted returns on a portfolio of firms with similar size, book-to-market ratio and momentum. We follow the categorization outlined in Daniel, Grinblatt, Titman, and Wermers (1997). For robustness, we also

[9] We use the link table provided by Prof. Byoung-Hyoun Hwang from Cornell University. This link table provides a mapping from I/B/E/S ticker to CRSP permno and can be downloaded from his personal webpage: http://www.bhwang.com/code.html.

consider abnormal returns adjusted by the six Fama-French benchmark portfolios formed on size and book-to-market ratio. We compute Fama-French benchmark adjusted returns as the raw daily returns minus daily value-weighted returns on a portfolio of firms with similar size and book-to-market ratio.

Our main proxy for earnings surprise is *CAR*(0,1), which is the sum of the DGTW-adjusted returns from day 0 to day 1, where day 0 is the announcement day. If news is announced on a non-trading day, or on a trading day but after stock markets are closed, we use the ensuing trading day as the announcement day. We define a positive earnings surprise as an announcement with a positive *CAR*(0,1).

We compute *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) as the cumulative DGTW-adjusted abnormal returns after the announcement. *CAR*(2,30) is the sum of daily abnormal returns from day 2 to day 30; *CAR*(2,45) is the sum of daily abnormal returns from day 2 to day 45; *CAR*(2,61) is the sum of daily abnormal returns from day 2 to day 61. We winsorize *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) at the 1^{st} and 99^{th} percentiles to mitigate the effect of extreme observations.

2.3. Measurement of the Fraction of Satisfied Investors

The main variable of interest is the fraction of investors whose target prices are exceeded. Since investors' expectations are unobservable, we follow the spirit of Diether, Malloy and Scherbina (2002) by using analyst-target-price forecasts to approximate the distribution of investors' target prices, and then construct the fraction of satisfied investors. This approximation is appropriate for two reasons. First, investors can easily gain access to analyst target prices in various ways. For example, online brokers, such as Charles Schwab, offer access to analysts' reports. In addition, several websites, such as *Yahoo! Finance* and *TIPRANKS*, provide detailed information on each individual analyst's target price forecast (see Appendix Figure A1 for detailed analyst-target-price forecasts on Alphabet Inc. (Ticker: GOOGL) provided by *TIPRANKS*). Second, target price forecasts are important elements from analyst reports (Bradshaw 2002) and prior empirical studies provide evidence that analysts' target prices subsume information contained in analysts' earnings and earnings growth forecasts (Asquith, Mikhail and Au 2005; Da, Hong, and Lee, 2016). Therefore, we expect investors to respond strongly and incrementally to analyst-target-price revisions.

To implement our empirical test, we construct the fraction of satisfied investors as follows. First, we select 12-month analyst-target-price forecasts that are announced within the 90-day window preceding the earnings announcement. Further, we require an analyst-target-price forecast to be greater than the month-end stock price right before the target price forecast is announced (both prices are adjusted to take into account of distribution events such as stock splits and stock dividends). This requirement is based on the proposition that only optimistic investors hold a long position in a stock. Practically, few target price forecasts are below the market price at the time the forecast is announced and untabulated results show that this requirement does not materially alter our findings.

We compute the main variable, *FracSat*, as the fraction of analysts whose target price forecasts are exceeded by the price at the end of day 1, where day 0 is the earnings announcement day or the ensuing trading day if news is announced on a non-trading day or after markets are closed. Both prices are adjusted to take into account of distribution events such as stock splits and stock dividends. The calculation of *FracSat* is in the spirit of Frazzini (2006), who calculates *CGO* (*Capital Gain Overhang*) after earnings announcement. We consider four alternative ways to construct this proxy in the Section 3.2.

2.4. Control Variables

Our control variables are constructed as follows: (1) *Capital Gain Overhang* is the percentage deviation of the stock price from the aggregate purchase price of mutual funds; (2) *Market Capitalization* (in million $) is the market value of common stocks measured at the end of the most recent June; (3) *Book-to-Market* is the firm's book-to-market ratio, where book value of equity is measured as of the fiscal year end in calendar year t-1, and market value of equity is measured as of the end of December of calendar year t-1; the book-to-market ratio so computed is matched with earnings announcements from July of year t to June of year t+1; (4) *Past Return*(t−7,t−1) is the cumulative raw return over the six-month period ending one month prior to the month of the earnings announcement; (5) *Institutional Ownership* is the fraction of total shares outstanding held by institutional investors as of the end of the quarter prior to the earnings announcement; (6) *Nearness to 52-week High* is the ratio of closing price on day −11 to the highest closing price from the prior 52 weeks; (7) *Turnover* is measured as the average of the daily ratios of the number of shares traded to the total number of shares outstanding from day −40 to day −11;[10] (8) *Amihud Ratio* is the average of the daily ratios of absolute stock return to its dollar volume from day −40 to day −11; (9) *SUE* is the standardized unexpected earnings, defined as the difference between the actual earnings per share and the median of analyst forecasts in the 90 days prior to the earnings announcement, scaled by price; (10) *Earnings Volatility* is measured as the standard deviation of quarterly earnings surprises from a seasonal random walk model over the preceding four years; (11) *Earnings Persistence* is the first-order auto-regressive coefficient of quarterly earnings-per-share over the preceding four years; (12) *Reporting Lag* is the number of days between the fiscal

[10] For NASDAQ stocks, the trading volume is adjusted based on Gao and Ritter (2010).

quarter-end date and the earnings announcement date; (13) *# of Analysts* is the number of analysts reporting earnings-per-share forecasts for the firm; (14) *# of Announcements is* the number of firms announcing quarterly earnings on the same earnings announcement day (or the ensuring announcement day); (15) *Friday* is a dummy variable which equals one if the announcement day is a Friday, and zero otherwise; (16) Fama-French 10 industry fixed effects; (17) Time fixed effects. We winsorize all control variables at the 1st and 99th percentiles to mitigate the effects of extreme observations.

2.5. Summary Statistics

Table 1 presents descriptive statistics for all variables in our sample, which contains 52,071 firm-quarter observations with a positive *CAR*(0,1) and non-missing control variables. The mean *FracSat* is 17.8%. The distribution of *FracSat* is such that it equals zero until the 65th percentile. In our later tests, we categorize an observation as having a "High Fraction Satisfied" if *FracSat* is above the 80th percentile and as having a "Low Fraction Satisfied" otherwise. In untabulated results, we show that the findings are robust for the cutoffs from the 70th percentile to the 85th percentile. We use the 80th percentile for a conservative reason. In the panel regressions, we use a continuous variable of *FracSat*. To further address this concern, we construct several alternative measures of *FracSat*, including a continuous measure and dummy measures. Section 3.2 will introduce these alternative measures in detail.

[Table 1 Here]

In Panel C of Table 1, we examine the determinants of *FracSat*. Our analysis shows that *FracSat* is negatively related to *Capital Gain Overhang*, size, book-to-market ratio and institutional ownership, while positively related to Nearness-to-52-Week-High, analyst dispersion, momentum, and idiosyncratic volatility.

2.6. Informativeness of Analyst-Target-Price Forecasts

In this section, we study market reactions to analyst-target-price revisions. Our aim is to justify the proposition that analyst-target-price forecasts can approximate investors' target prices in mind. For each target price revision, we compute the cumulative abnormal return from the target price revision day to the ensuing trading day. We use the subsequent trading day as the revision day if the revision occurs on a non-trading day or after market-hours. Abnormal returns are DGTW-adjusted returns.

We conduct quarterly Fama-MacBeth regressions of this cumulative abnormal return on the percentage change in the target price forecast, *Target Price Revision*. Sometimes, target price revisions are associated with concurrent revisions in quarterly earnings forecasts and stock recommendation levels. Thus, our analysis controls earnings forecast revisions and stock recommendation changes, which are defined as follows. *Earnings Forecast Revision* is the percentage change in quarterly earnings forecasts.[11] *Recommendation Revision* is the change in recommendation levels.[12] If no earnings forecast or recommendation revision is made on the day of the target price revision, we check for revisions in the 90-day period prior to the target price revision announcement. If a revision was made within that window, we include the most recent earnings forecast revision or recommendation revision as a control. Otherwise, *Earnings Forecast Revision* or *Recommendation Revision* is set to zero. In our regression analysis, we include

[11] We obtain similar results when constructing *Earnings Forecast Revision* based on annual earnings forecasts

[12] We obtain information regarding analyst stock recommendations from the I/B/E/S detailed recommendation file. The I/B/E/S recommendation file tracks all recommendations made by each analyst. Recommendations (ITEXT) include: "Strong Buy," "Buy," "Hold," "Underperform," and "Sell." We assign the following numerical scores: 5 (strong buy), 4 (buy), 3 (hold), 2 (underperform), and 1 (sell). A high value indicates a more bullish view.

Earnings Forecast Revision and *Recommendation Revision*, as well as dummy variables, *I*(*Earnings Forecast Revision*) and *I*(*Recommendation Revision*), denoting whether any revisions were made prior to the target price revision announcement. In separate regressions, we also experiment with a *Recommendation Upgrade* dummy and a *Recommendation Downgrade* dummy. We report the time-series average of coefficient estimates in Table 2. Newey-West (1987) standard errors are reported in the parentheses. *, **, *** indicates significance at 10%, 5%, or 1%, respectively.

[Table 2 Here]

Results reported in Table 2 reveal that analyst-target-price forecast revisions are strongly positively associated with two-day abnormal returns around revision announcements. The estimate of 0.110 (*t*-statistic = 10.89) implies that a 10% increase in the target price forecast (e.g., from $10 to $11) is associated with 1.10% more positive two-day cumulative abnormal returns around the price revision.

Although both revisions in earnings forecasts and recommendations also have significant market reaction, the positive association between target price revision and market reaction remains substantial, both economically and statistically, when controlling for revisions in earnings forecasts and recommendations. These findings suggest that the general population of investors does react to information contained in analyst-target-price forecasts. Thus, it is appropriate to use analyst-target-price forecasts to approximate target prices from the general population of investors.

3. Main Results

3.1. FracSat and the Post-Earning-Announcement Drift

We hypothesize that the post-earning-announcement drift is generated by a large fraction of current investors who anchor on their target prices and become satisfied once the market price exceeds their anchoring prices. In order to test this hypothesis, in each calendar quarter, we first assign stocks with a positive earnings surprise into quintiles based on *CAR*(0,1). Within each quintile, we divide stocks into two groups based on *FracSat.* Because the distribution of *FracSat* is such that it equals zero until the 65th percentile, we categorize an observation as having a "High Satisfied Fraction" if *FracSat* is above the 80th percentile and as having a "Low Satisfied Fraction" otherwise. In untabulated analysis, we find that our results are robust for different cutoffs from the 70th percentile to the 85th percentile. In the panel regressions, we use a continuous variable of *FracSat* to mitigate the concern for using different cutoffs. To further address this concern, we construct alternative measures of *FracSat*, including a continuous measure and dummy measures. Section 3.2 introduces these alternative measures in detail. After sorting stocks into 10 (5×2) portfolios, we compute the time-series means of *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) for these portfolios. Results are reported in Table 3.

[Table 3 Here]

We find that PEAD is present only among observations with a high *FracSat*. For example, when *FracSat* is high, the difference in *CAR*(2,61) between top- and bottom-quintile-*CAR*(0,1) observations is 2.20% (*t*-statistic = 3.25). That is, the initial earnings surprise (*CAR*(0,1)) positively predicts the subsequent stock market response (*CAR*(2,61)). In sharp contrast, when *FracSat* is low, the difference in *CAR*(2,61) between top- and bottom-*CAR*(0,1)-quintile observations is 0.50% (*t*-statistic = 1.12). That is, price reacts fully and immediately in the first two trading days, and there is no significant subsequent drift in the ensuing three calendar months. Moreover, within the top *CAR*(0,1) quintile, stocks with a high satisfied fraction have an average *CAR*(2,61) of 2.30%, while stocks with a low satisfied fraction only have an average *CAR*(2,61) of 0.62%. The difference is 1.68% with a *t*-statistic of 2.42. This suggests that, given the same level of earnings surprise, a high *FracSat* leads to a sluggish market response to good news. This difference is not statistically significant for the rest of the *CAR*(0,1) quintiles. Similar patterns are obtained for *CAR*(2,30) and *CAR*(2,45) as well. Overall, this evidence is consistent with our conjecture that high *FracSat* generates under-reaction to good news and positive PEAD.

We next test our prediction using panel regressions. There are two advantages of this approach. First, it allows us to control for variables that have been found to affect the PEAD. Second, it allows us to examine the robustness of our results for a continuous measure of *FracSat*, to mitigate the concern that different cutoffs might affect our sorting results.

We follow the previous literature (e.g., Hirshleifer, Lim, and Teoh 2009) in estimating the following panel regressions with time and industry fixed effects:

$$CAR(2,\tau)_{i,t} = \alpha + \beta_1 \times RankCAR(0,1)_{i,t} + \beta_2 \times FracSat_{i,t} \times RankCAR(0,1)_{i,t} + \beta_3 \times FracSat_{i,t} + \gamma_1 \times \boldsymbol{X}_{i,t} + \gamma_2 \times RankCAR(0,1)_{i,t} \times \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where *i* indexes firms and *t* indexes time. $CAR(2,\tau)$ denotes *CAR*(2,30), *CAR*(2,45), or *CAR*(2,61).

In each calendar quarter *t*, we assign stocks (with a positive *CAR*(0,1)) into quintile portfolios based on *CAR*(0,1). *RankCAR*(0,1) equals one for stocks from the bottom *CAR*(0,1) quintile, and five for stocks from the top *CAR*(0,1) quintile. ***X*** represents a set of lagged control variables, including: (1) *Capital Gain Overhang*; (2) log(*Market Capitalization*); (3) log(*Book-to-Market*); (4) *Past Return*(*t*−7,*t*−1); (5) *Institutional Ownership*; (6) *Nearness to 52-week High*; (7) *Turnover*; (8) *Amihud Ratio*; (9) *SUE*; (10) *Earnings Volatility*; (11) *Earnings Persistence*; (12) *Reporting Lag*; (13) log(*# of Analysts*); (14) *# of Announcements*; (15) *Friday*; (16) Fama-French 10-industry fixed effects; (17) Time fixed effects. We have also included the interaction between

RankCAR(0,1) and all control variables, such as *Capital Gain Overhang* and *Nearness to 52-week High*. Results are reported in Table 4.[13]

[Table 4 Here]

These regressions confirm our results from double sorts. For example, in column 1, we use *CAR*(2,30) as the dependent variable, and find a coefficient of 0.003 (*t*-statistic = 2.46) on *FracSat* × *RankCAR*(0,1) and a coefficient of 0.002 (*t*-statistic = 0.29) on *RankCAR*(0,1). These estimates suggest that when no target price gets exceeded (i.e., *FracSat* = 0%), there is no significant difference in *CAR*(2,30) between top- and bottom-quintile-*CAR*(0,1) observations; but when all target prices get exceeded (i.e., *FracSat* = 100%), the difference in *CAR*(2,30) between top- and bottom-quintile-*CAR*(0,1) observations increases by 2.00% (*t*-statistic = 2.46).[14] This result is both statistically significant and economically large. Moreover, it matches the double sorting results reported in Table 3. Regressions on *CAR*(2,45) and *CAR*(2,61) produce similar results.

Results in Table 4 also help us interpret the spread in PEAD between all satisfied investors (*FracSat* = 100%) and no satisfied investors (*FracSat* = 0%), given the same level of earnings surprise. For example, column 3 shows that, within the top *CAR*(0,1) quintile observations, the *CAR*(2,61) when all investors are satisfied is 1.50% higher than the *CAR*(2,61) when no investor is satisfied.[15] This is consistent with the double sorting results reported in Table 3. Similar results are obtained with *CAR*(2,30) and *CAR*(2,45) as well.

[13] In order to save space, we do not report the coefficient estimates for interaction terms between *RankCAR*(0,1) and all control variables in Table 4, we report the full results of Table 4 in Appendix Table A.5.

[14] When *FracSat* equals 0%, the difference in *CAR*(2,30) between top- and bottom-quintile-*CAR*(0,1) observations equals to $0.002\times(5-1) + 0.003\times0\%\times(5-1) = 0.80\%$. When *FracSat* equals 100%, the difference equals $0.002\times(5-1) + 0.003\times100\%\times(5-1) = 2.00\%$.

[15] Within the top *CAR*(0,1) quintile, the difference in *CAR*(2,61) between *FracSat* = 100% (all investors get satisfied) and *FracSat* = 0% (no investors get satisfied) is calculated as $0.006 \times 5 \times (100\% - 0\%) - 0.015 \times (100\% - 0\%) = 1.50\%$.

These results suggest that, investors are more likely to sell their stocks when the market price is above their target-price anchors. This increased willingness to sell has the potential to generate market underreaction after positive news and positive PEAD.

3.2. Alternative Measures for FracSat and Earnings Surprise

A potential concern is that the results documented here may be mechanical. Because *FracSat* is likely driven by an extremely positive earnings surprise, it is possible that even within the top *CAR*(0,1) quintile, sorting by *FracSat* is a further sort on the earnings surprise. We address this concern in four ways.

First, we examine the correlation between *FracSat* and *CAR*(0,1) . As shown in Panel B of Table 1, the correlation coefficient between *FracSat* and *CAR*(0,1) is low (0.21). Thus, the results are not likely to be purely mechanical. Moreover, in the panel regressions reported in Table 4, the interaction term of *FracSat* and *RankCAR*(0,1) effectively controls for the level of positive earnings surprise when testing the effect of *FracSat* on the PEAD.

Second, we construct four alternative measures of *FracSat* and re-conduct our regression analyses. For the first alternative measure, we change the timing of *FracSat*. We define *FracSat*1 as the fraction of analysts whose target price forecasts are exceeded by the stock price one week before the earnings announcement. By construction, this alternative measure, *FracSat*1, should not be mechanically correlated with *CAR*(0,1). As shown in Panel A of Table 5, the correlation between *FracSat*1 and *CAR*(0,1) is only −0.01. Yet, as shown in Panel B1, we still find consistent results with this alternative measure in the panel regressions.

[Table 5 Here]

To address the concern that our main proxy for *FracSat* only captures a ratio and is zero up to the 65th percentile, we construct a second alternative proxy, *FracSat*2, as the relative difference between the stock price and the target prices:

$$FracSat2 = (Prc - Min[\text{TP}])/(Max[\text{TP}] - Min[\text{TP}]), \tag{2}$$

where *Prc* is the closing price in day 1, *Min*[TP] is the minimum target price, and *Max*[TP] is the maximum target price. If the maximum equals to the minimum target price, *FracSat*2 is set to 1 if *Prc* exceeds the target price, and zero otherwise.

We also construct two dummy variables as alternative proxies for *FracSat*, *FracSat*3 and *FracSat*4, by comparing *Prc* to the mean and median target price, respectively. If *Prc* is greater than or equal to the mean (median) target price, *FracSat*3 (*FracSat*4) is set to 1, and zero otherwise.

As shown in Panels B2-B4 of Table 5, all these alternative measures of *FracSat* have reasonably low correlations with *CAR*(0,1), and our results are robust using these alternative proxies for *FracSat*.

Thirdly, we consider two alternative proxies of earnings surprise, one based on seasonal earnings growth model (*SUE*1), and the other based on analyst forecast consensus (*SUE*2). Specifically, *SUE*1 is defined as the difference in earnings per share before extraordinary items between quarter *t* and quarter *t*−4, scaled by the price at quarter *t*. *SUE*2 is defined as the difference between the actual earnings per share and the median of analyst forecasts announced within the 90-day window prior to the earnings announcement, scale by price. By construction, *SUE*1 and *SUE*2 should not be mechanically correlated with *FracSat*. Indeed, as shown in Panel A of Table 6, the correlation coefficient between *FracSat* and *SUE*1 (*SUE*2) is 0.02 (0.09). We re-conduct the analysis in Table 4 using these two measures and reports results in Panels B1 and B2 of Table 6. We find similar results based on these two alternative proxies for the earnings surprise as well.

[Table 6 Here]

As our final way to purge out the concern on the relation between *FracSat* and *CAR*(0,1), we examine the effect of *CAR*(0,1)×*FracSat* on buy-sell imbalance around announcements. Specifically, we have two findings: (1) *CAR*(0,1) itself generates a buying pressure, suggesting that investors buy stocks on good news; (2) *CAR*(0,1)×*FracSat* generates a selling pressure. These findings not only provide direct evidence for our argument, but also show that our results are not merely driven by the mechanical relation between *CAR*(0,1) and *FracSat.* That is, if *FracSat* just captures extreme *CAR*(0,1), *CAR*(0,1)×*FracSat* should generate stronger buying pressure which goes against our findings (see Section 3.3 for details).

In the main tests, we use DGTW-adjusted daily returns to compute *CAR*(0,1), *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61). To check the robustness of our results to different return adjustments, we also adjust daily returns by Fama-French six benchmark portfolios formed on size and book-to-market ratio and repeat our main analyses in Table 4. Our results are robust to this alternative specification. These results are reported in Appendix Table A.1.

3.3. Trading Volume

In this section, we investigate trading volume patterns around earnings announcements in order to provide direct evidence on our argument. Intuitively, our mechanism should be driven by the selling pressure from investors who anchor at their target prices and are satisfied with their investment outcomes once the market price exceeds their target-price anchors. Therefore, for a given level of positive news, stocks with a high fraction of satisfied investors should experience higher abnormal trading volume and more sell-initiated trades (i.e., lower buy-sell imbalance) around earnings announcements than those with a low *FracSat*.

To test these predictions, we use Trade and Quote (TAQ) database, which contains intraday transactions data (trades and quotes) for all securities listed on all U.S. equity exchanges. Following standard literature on market microstructure, we include the following filters for trades:

(1) Market-hour trades, i.e., trades happened between 9:30 to 16:00;

(2) Trades with positive price and positive share volume;

(3) Trades issued in NYSE, AMEX or NASDAQ;

(4) Good trades (Correction Indicator = 0, 1, or 2);

(5) Condition of sales should not fall in to the following categories: "Opened Last (O)", "Sold Sale (Z)", "Bunched (B)", "Pre- and Post-Market Close Trades (T)", "Sold last (L)", "Bunched sold (G)", "Average Price Trades (W)", "Rule 127 trade (J)", and "Rule 155 trade (K)".

We first study abnormal trading volume around the earnings announcement. We construct *Abnormal Trading Volume* (*Abn_Vol*) as the ratio of the average daily trading volume from day 0 and day 1 to the average daily trading volume from day −40 to day −11. *Abnormal Dollar Trading Volume* (*Abn_DVol*) is defined as the ratio of the average daily dollar trading volume from day 0 and day 1 to the average daily dollar trading volume from day −40 to day −11. Dollar trading volume is defined as the product of executed price and traded shares for each trade.

To further investigate the role of *FracSat* in buying and selling activities, we use the algorithm of Lee and Ready (1991) to infer the direction of trades as buy- initiated or sell-initiated. The methodology involves a two-step approach: a quote test first (compare trade price to the mid-point of bid and ask five seconds ago, i.e., the 5-second rule), then a tick test (compare current trade price with previous price). *Buy-Sell Imbalance* (*BSI*) is defined as:

$$BSI = (Buy - Sell)/(Buy + Sell), \tag{3}$$

where we compute buy-initiated (sell-initiated) trading volume as the total buy-initiated (sell-initiated) trading volume from day 0 and day 1. We define *Dollar Buy-Sell Imbalance* (*DBSI*) similarly by replacing trading volume with dollar trading volume:

$$DBSI = (DBuy - DSell)/(DBuy + DSell). \tag{4}$$

We estimate panel regressions on *RankCAR*(0,1), *FracSat*, *FracSat* × *RankCAR*(0,1), and the same set of control variables as in equation (1):

$$Proxy_{i,t} = \alpha + \beta_1 \times RankCAR(0,1)_{i,t} + \beta_2 \times FracSat_{i,t} \times RankCAR(0,1)_{i,t}$$

$$+ \beta_3 \times FracSat_{i,t} + \gamma_1 \times \boldsymbol{X}_{i,t} + \gamma_2 \times RankCAR(0,1)_{i,t} \times \boldsymbol{X}_{i,t} + \varepsilon_{i,t}\ , \tag{5}$$

where i indexes firms and t indexes time. $Proxy_{i,t}$ refers to *Abn_Vol*, *Abn_DVol*, *BSI*, or *DBSI*. When we use *Abn_Vol* and *Abn_DVol* as the dependent variables, we expect β_2 to be positive and significant; when we use *BSI* and *DBSI* as the dependent variables, we expect β_2 to be negative and significant.

[Table 7 Here]

The results presented in Table 7 are consistent with our conjecture. For *Abn_Vol* (*Abn_DVol*), the coefficient estimate on the interaction term *FracSat* × *RankCAR*(0,1) is 0.883 (1.368) with a t-statistic of 2.83 (3.34). This shows that, for a given level of positive news, stocks with a high *FracSat* experience more trading volume than stocks with a low *FracSat*. For *BSI* (*DBSI*), the coefficient estimate on the interaction term *FracSat* × *RankCAR*(0,1) is −0.007 (−0.007) with a t-statistic of −2.55 (−2.59). This shows that, for a given level of positive news, stocks with a high *FracSat* experience more sell-initiated trades than stocks with a low *FracSat*. The results on *BSI* and *DBSI* also confirm that our main results based on *FracSat* and *CAR*(0,1) are not purely driven by the potential mechanical relation between *FracSat* and *CAR*(0,1).

Specifically, columns 3 and 4 show two patterns: (1) *CAR*(0,1) itself generates a buying pressure (β_1 is positive), suggesting that investors buy stocks on good news; (2) *CAR*(0,1)×*FracSat* generates a selling pressure (β_2 is negative). These results cannot be obtained if *FracSat* merely captures extremely high *CAR*(0,1). That is, if *FracSat* just captures extreme *CAR*(0,1), *CAR*(0,1)×*FracSat* should generate stronger buying pressure (both β_1 and β_2 should be positive), which goes against our findings.

We show in Section 4.1 that the effect of *FracSat* on the price drift is concentrated on stocks with low institutional ownership. Therefore, it is natural to expect that the results documented here tend to be driven by increased sell-initiated trades from retail investors. However, we have no access to any database that can directly identify investor types for each trade. As suggested by Lee and Radhakrishna (2000), trades with dollar size less than 5,000 USD (small trades) can be used as a proxy for individual investor trades. Nevertheless, the literature argues that this methodology is only efficient before 2001, due to the introduction of decimalization in 2000 and the growing use of computerized trading algorithms (for instance, see Hvidkjaer, 2008; Barber, Odean, and Zhu, 2009; Han and Kumar, 2013; among others). Thus, we can only conduct this analysis for the first two years in our sample. Despite limited observations, we still find that, for a given level of positive news, stocks with a high *FracSat* experience more sell-initiated trades from retail investors. This is consistent with the results in Section 4.1, which shows that the effect of *FracSat* is concentrated on stocks with low institutional ownership. These results are reported in Appendix Table A.2.

3.4. Trading Strategy based on FracSat and CAR(0,1)

In this section, we develop an improved PEAD trading strategy based on the previous empirical evidence. Specifically, at the end of each calendar month *t*, we select stocks that have made earnings announcements in the past two months (i.e., month $t-1$ and month *t*) and a price no less than \$5 at the end of month *t*. We focus on the sample with a positive *CAR*(0,1), and then sort these stocks into quintiles based on *CAR*(0,1). Within each quintile, stocks are further divided into two groups based on *FracSat.* Because the distribution of *FracSat* is such that it equals zero until the 65th percentile, we categorize an observation as having a "High Satisfied Fraction" if *FracSat* is above the 80th percentile and as having a "Low Satisfied Fraction" otherwise. In untabulated results, we find that our results are robust for different cutoffs from the 70th percentile to the 85th percentile. We require that each of the ten portfolios should consist of at least five stocks. We hold these ten portfolios for one month and study their equal-weighted return patterns in month $t+1$. We report Fama-French (1993) three-factor adjusted returns in Panel A of Table 8, and Fama-French-Carhart four-factor adjusted returns in Panel B of Table 8. Newey-West (1987) adjusted standard errors are reported in parentheses.

[Table 8 Here]

Panel A of Table 8 shows that a trading strategy which longs stocks with a high *FracSat* in the top *CAR*(0,1) quintile and shorts stocks with a high *FracSat* in the bottom *CAR*(0,1) quintile yields a three-factor adjusted return of 0.68% per month (*t*-statistic = 2.01). On the contrary, the difference in returns between the stocks with a low *FracSat* in the top *CAR*(0,1) and the stocks with a low *FracSat* in the low *CAR*(0,1) is −0.27% and is not statistically significant (*t*-statistic = −1.28). The difference between these two long-short trading strategies is 0.95% per month and statistically significant (*t*-statistic = 2.56). Results are similar when we adjust portfolio returns with the four-factor model, which are shown in Panel B of Table 8. We report value-weighted results in the Appendix Table A.3, which are qualitatively similar.

This evidence is consistent with our previous argument that investors do have a target price in mind as a forward-looking anchor, and once the stock price exceeds the target price, they are more likely to sell the stock, generating a price drift.

3.5. Discussions of Alternative Explanations

An alternative explanation for our results is that high *FracSat* may be associated with high idiosyncratic volatility, and existing research has documented that the PEAD is stronger in stocks with high idiosyncratic volatility (Mendenhall, 2004). This is not the case. On one hand, in Panel B of Table 1, we report that the correlation between *FracSat* and idiosyncratic volatility is only −0.04, indicating that *FracSat* captures a very different perspective apart from idiosyncratic volatility. On the other hand, in untabulated results, we include idiosyncratic volatility and its interaction with *CAR*(0,1) into regressions but still find similar results as reported in Table 4.

Another alternative explanation is based on analyst responsiveness. Zhang (2008) reports that the PEAD is stronger in stocks with unresponsive analysts. In Zhang (2008), if at least one analyst updates his earnings forecast within one-day window after the earnings announcement, the firm is defined to have responsive analysts. Lack of analyst responsiveness presumably generates stale target prices, which may in turn drive *FracSat*. Our results cannot be explained by this mechanism based on the following reasons. First of all, we construct *FracSat* using the most recent analyst-target-price forecasts *before* the earnings announcement, which mitigates analysts' timing behavior in forecast revisions (e.g., analysts may have timing behavior and update target price/earnings forecasts immediately after announcements). We further check the correlation between *FracSat* and analyst responsiveness measure of Zhang (2008), which is fairly low (0.04). In untabulated results, we control analyst responsiveness and its interaction with *CAR*(0,1) in the regressions and find similar results as reported in Table 4.

4. Further Discussions

4.1. FracSat and Institutional Ownership

We next investigate how our results vary with institutional ownership. Since individual investors generally have limited information sources and insufficient skills analyzing firms' fundamentals and analyst target-price forecasts are readily available from financial media, they are more likely to anchor their expectations on future stock prices at analyst-target-price forecasts. In contrast, institutional investors have professional in-house research teams and should rely less on target prices estimated by analysts. Therefore, analyst-target-price forecasts should better approximate the distribution of investors' target prices on stocks with low institutional ownership. Meanwhile, the low institutional ownership implies that there is little arbitraging activity to correct the mispricing. Thus, we conjecture that our results should be stronger within the subsample with low institutional ownership.

To test this conjecture, we sort our sample based on institutional ownership in each quarter: those with an institutional ownership below the 30^{th} percentile ("Low IO") and those with an institutional ownership above the 70^{th} percentile ("High IO"). We conduct the same panel regressions as specified in Equation 1 and Table 4 for both subsamples. Results are reported in Panel A of Table 9.

[Table 9 Here]

Consistent with our hypothesis, we find that results are stronger in the subsample with low institutional ownership. When we use *CAR*(2,61) as the dependent variable, the coefficient estimates on the interaction of *FracSat* and *RankCAR*(0,1) are 0.010 (*t*-statistic = 3.71) and 0.005 (*t*-statistic = 1.48) for the low IO subsample and the high IO subsample, respectively. The difference between the two coefficient estimates is 0.005 (*t*-statistic = 1.79).[16] Similar results are obtained when we replace *CAR*(2,61) with *CAR*(2,30) or *CAR*(2,45) as the dependent variable.

4.2. FracSat and Uncertainty

We further conjecture that the effect of *FracSat* on PEAD should be stronger for stocks with high uncertainty. For stocks with high uncertainty, investors have difficulty collecting and processing related information and are more likely to anchor their expectations of future stock prices at target prices estimated by analysts. Therefore, analyst-target-price forecasts can better approximate the distribution of investors' target prices on stocks with high uncertainty. Meanwhile, stocks with high uncertainty are usually associated with high arbitraging costs and tend to have greater mispricing. Thus, we expect target prices to have greater impacts on the subsample of stocks with high uncertainty.

We use idiosyncratic volatility to capture firm-level uncertainty and compute it using raw daily returns from day −40 to −11, where day 0 is the earnings announcement day, or the ensuing day if the announcement is made on a non-trading day or after market-hours. We regress these raw daily returns on Fama-French (1993) three-factor model and take the standard deviation of the residuals as idiosyncratic volatility before the earnings announcement. We require at least 15 daily

[16] In order to estimate the statistical significance for the difference in coefficient estimates on *FracSat*×*RankCAR*(0,1) between the low IO and high IO subsamples, we create a dummy variable that equals 0 for the low IO subsample, and equals 1 for the high IO subsample. We interact all variables with this dummy and conduct the analysis by adding these additional interaction terms to our main regression.

returns to compute this measure. Then, we sort our sample based on idiosyncratic volatility in each quarter: those with an idiosyncratic volatility below the 30th percentile ("Low IV") and those with an idiosyncratic volatility above the 70th percentile ("High IV"). We conduct the same panel regressions as specified in Equation 1 and Table 4 for both subsamples. Results are reported in Panel B of Table 9.

We find that our previously documented results are stronger in the subsample with high idiosyncratic volatility. For example, when we use *CAR*(2,61) as the dependent variable, the coefficient estimates on the interaction of *FracSat* and *RankCAR*(0,1) are 0.003 (*t*-statistic = 1.35) and 0.010 (*t*-statistic = 2.87) for the low IV subsample and the high IV subsample, respectively. The difference between the two coefficient estimates is 0.007 (*t*-statistic = 1.99).[17] Similar results are obtained when we replace *CAR*(2,61) with *CAR*(2,30) or *CAR*(2,45) as the dependent variable. This subsample analysis suggests that the effect of *FracSat* on the PEAD is stronger for firms under great uncertainty.

4.3. FracSat and General Price Drift

Although we have focused on post-earnings-announcement drift as the main test setting, our mechanism can be extended to explain price drifts more broadly. Specifically, a high positive stock return (e.g., due to positive news) with a high *FracSat* should be accompanied with a disproportionately higher subsequent return drift than a stock with the same level of high positive return, but a low *FraSat*.

[17] In order to estimate the statistical significance for the difference in coefficient estimates on *FracSat*×*RankCAR*(0,1) between the low IV and high IV subsamples, we create a dummy variable which equals 0 for the low IV subsample, and equals 1 for the high IV subsample. We interact all variables with this dummy and conduct the analysis by adding these additional interaction terms to our main regression.

To test this conjecture, *FracSat* is now measured as the fraction of analysts whose target price forecasts are exceed by the price at the end of month *t*. We focus on 12-month target price forecasts announced within the 90-day period prior to month *t*. Again, we include target price forecasts that are higher than the price at the time the forecast is announced. This requirement is based on the assumption that only optimistic investors hold a long position in a stock.[18]

We construct the following trading strategy based on *FracSat* and short-term monthly returns. At the end of each month *t*, we select stocks with a positive return from the current month (*Return*(*t*) > 0) and assign them into quintiles based on *Return*(*t*). Among the stocks from the top *Return*(*t*) quintile, we long those with a *FracSat* above the 80th percentile and short those with a *FracSat* below the 80th percentile. The portfolios are equally-weighted and held for one, two or three months. We follow Jegadeesh and Titman (1993) to track the long-short portfolio performance. We report the value-weighted results in the Appendix Table A.4.

[Table 10 Here]

Table 10 reports performance statistics for the long-short portfolio returns. The economic significance of the target price effect is substantial. For the one-month holding period, the long-short portfolio trading strategy earns abnormal returns of 0.65% per month in terms of Fama and French's (1993) three-factor alpha (*t*-statistic = 2.52), and 0.44% per month in terms of Fama-French-Carhart's (1997) four-factor alpha (*t*-statistic = 1.96). When increasing the holding period to three months, the three-factor alpha is 0.77% per month (*t*-statistic = 3.56) and four-factor alpha is 0.58% per month (*t*-statistic = 3.31).

5. Conclusion

[18] This requirement is not crucial. We obtain similar results if we remove it.

We argue that investors have target prices in mind for the stocks that they own. Target prices serve as forward-looking anchors for investors, and once a stock's trading price exceeds their target prices, investors are satisfied and more likely to sell the stock. This increased willingness to sell once the target price has been met and, correspondingly, the reluctance to sell a stock whose target price has not yet been met, can lead to a sluggish market reaction to news and generate a price drift after the announcement.

Overall, the results presented in our paper are consistent with this conjecture. We find that among stocks with a positive earnings surprise, those with a high fraction of satisfied investors exhibit positive return drifts. In comparison, among stocks with a low fraction of satisfied investors, the price reacts fully and immediately. Moreover, we show that this phenomenon is stronger among stocks with low institutional ownership and high uncertainty. The effect can also be generalized to explain the general price drift following positive returns.

Meanwhile, for a given level of positive news, we find that stocks with a high *FracSat* also experience higher abnormal trading volume and more sell-initiated trades (i.e., lower buy-sell imbalance) around the earnings announcement than stocks with a low *FracSat*. This further supports our conjecture that, for stocks with a high *FracSat*, the majority of the current investors are willing to sell.

Our empirical results focus on positive news due to data limitation. However, our mechanism should also be able to explain the market underreaction following negative news. Therefore, investors' target-price anchors may help explain the phenomenon that negative information diffuses only gradually across the investing public (e.g., Hong, Lim, and Stein, 2000).

References

Amihud, Y., 2002. Illiquidity and Stock Returns: Cross-section and Time-series Effects, *Journal of Financial Markets* 5(1), 31-56.

An, L., 2015. Asset pricing when traders sell extreme winners and losers. *Review of Financial Studies*, 29(3), 823-861.

An, L., Wang, H., Wang, J., and Yu, J., 2017. Lottery-Related Anomalies: The Role of Reference-Dependent Preferences. PBCSF-NIFR Research Paper No. 15-04. Available at SSRN: https://ssrn.com/abstract=2636610 or http://dx.doi.org/10.2139/ssrn.2636610

Asquith, P., Mikhail, M.B., and Au, A.S., 2005, Information Content of Equity Analyst Reports, *Journal of Financial Economics* 75(2), 245-282.

Baker, M., Pan, X., and Wurgler, J., 2012, The Effect of Reference Point Prices on Mergers and Acquisitions, *Journal of Financial Economics* 106, 49–71.

Barber, B. M., Odean, T., and Zhu, N., 2009, Do retail trades move markets?, *Review of Financial Studies* 22, 151–186.

Barberis, N., Mukherjee, A., and Wang, B. 2016. Prospect theory and stock returns: an empirical test. *Review of Financial Studies*, 29(11), 3068-3107.

Barberis, N., and Richard T., 2005, A Survey of Behavioral Finance, in George M. Constantinides, Milton Harris, and Rene Stulz, eds.: *Handbook of the Economics of Finance* (North Holland, Amsterdam).

Banerjee, S., 2011, Learning from Prices and the Dispersion in Beliefs. *Review of Financial Studies*, 24(9),3025– 3068, 2011.

Banerjee, S., Kaniel, R., and Kremer, I.,2009, Price Drift as An Outcome of Differences in Higher-Order Beliefs, *Review of Financial Studies*, 22(9), 3707–3734.

Banerjee, S., and Kremer, I., 2010, Disagreement and Learning: Dynamic Patterns of Trade, *Journal of Finance*, 65(4), 1269-1302.

Bhattacharya, U., Holden, C. W., and Jacobsen, S. 2012. Penny wise, dollar foolish: Buy–sell imbalances on and around round numbers. *Management Science*, 58(2), 413-431.

Birru, J., 2015, Psychological Barriers, Expectational Errors, and Under-reaction to News, Charles A. Dice Center Working Paper No. 2014-03; Fisher College of Business Working Paper No. 2014-03-03. Available at SSRN: https://ssrn.com/abstract=2352474.

Bradshaw, Mark. T., 2002, The Use of Target Prices to Justify Sell-Side Analysts' Stock Recommendations, *Accounting Horizons* 16(1), 27-41.

Carhart, M.M., 1997, On Persistence in Mutual Fund Performance. *Journal of Finance* 52(1), 57-82.

Cohen, L., and Lou, D., 2012, Complicated firms. *Journal of Financial Economics*, 104(2), 383-400.

Da, Z., Hong, K.P., and Lee, S., 2016. What drives target price forecasts and their investment value? *Journal of Business Finance & Accounting*, 43(3-4), 487–510.

Da, Z. and Schaumburg, E., 2011, Relative Valuation and Analyst Target Price Forecasts, *Journal of Financial Markets*, 14, 161-192.

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R., 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *Journal of Finance* 52, 1035–1058.

Diether, K. B., Malloy, C. J., and Scherbina, A., 2002, Differences of Opinion and the Cross Section of Stock Returns. *Journal of Finance*, 57(5), 2113-2141.

Donaldson, G., Kim, H., 1993. Price barriers in the Dow–Jones industrial average. *Journal of Financial and Quantitative Analysis* 28, 313–330.

Eyster, E., Rabin, M., and Vayanos, D., 2018, Financial Markets Where Traders Neglect the Informational Content of Prices. *Journal of Finance*, 74 (1), 371-399.

Fama, E. F., and French, K. R., 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3–56.

Fama, E.F., and MacBeth, J.D., 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy*, 81(3), 607-636.

Frazzini, A. 2006., The Disposition Effect and Under-reaction to News, *Journal of Finance*, 61,2017–2046.

Gao, X., and Ritter, J., 2010, The Marketing of Seasoned Equity Offerings, *Journal of Financial Economics* 97, 33–52.

George, T.J. and Hwang, C.Y., 2004, The 52-week High and Momentum Investing, *Journal of Finance* 59(5), 2145-2176.

George, T.J., Hwang, C.Y., and Li, Y., 2015, Anchoring, the 52-Week High and Post Earnings Announcement Drift, Available at SSRN: https://ssrn.com/abstract=2391455.

Grinblatt, M., Keloharju, M., 2001. What makes investors trade?, *Journal of Finance* 56, 589–616.

Grinblatt, M., and Han, B., 2005, Prospect Theory, Mental Accounting, and Momentum, *Journal of Financial Economics* 78, 311–339.

Han, B. and Kumar, A., 2013, Speculative Retail Trading and Asset Prices, *Journal of Financial and Quantitative Analysis* 48, 377–404.

Hirshleifer, D., 2001, Investor Psychology and Asset Pricing, *Journal of Finance* 56, 1533–1597.

Hirshleifer, D, Lim S. S., and Teoh, S. H., 2009, Driven to Distraction: Extraneous Events and Under-reaction to Earnings News, *Journal of Finance* 64, 2289–2325.

Hong, X., Jordan, B. D., and Liu, M. H. 2015. Industry information and the 52-week high effect. *Pacific-Basin Finance Journal*, 32, 111-130.

Hong, H., and Lim,T. and Stein., J., 2000, Bad News Travels Slowly: Size, Analyst Coverage and the Profitability of Momentum Strategies, *Journal of Finance* (55), 265–295.

Hou, K., 2007, Industry information diffusion and the lead-lag effect in stock returns. *The Review of Financial Studies*, 20(4), 1113-1138.

Hou, K., and Moskowitz, T. J., 2005, Market frictions, price delay, and the cross-section of expected returns. *The Review of Financial Studies*, 18(3), 981-1020.

Huang, S., Lin, T.C., and Xiang, H., 2018, Psychological Barrier and Cross-Firm Return Predictability. Available at SSRN: https://ssrn.com/abstract=3115934 or http://dx.doi.org/10.2139/ssrn.3115934

Huddart, S., Lang, M., and Yetman, M. H. 2009. Volume and price patterns around a stock's 52-week highs and lows: Theory and evidence. *Management Science*, 55(1), 16-31.

Hvidkjaer, S., 2008, Small Trades and the Cross-section of Stock Returns, *Review of Financial Studies* 21, 1123–1151.

Jegadeesh, N., 1990, Evidence of Predictable Behavior of Security Returns, *Journal of Finance* 45, 881–898.

Jegadeesh, N. and Titman, S., 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65–91.

Kahneman, D., 1992. Reference points, anchors, norms, and mixed feelings. *Organizational Behavior and Human Decision Processes*, 51, 296–312.

Kőszegi, B., and Rabin, M., 2006, A Model of Reference-Dependent Preferences, *Quarterly Journal of Economics*, 121, 1133–1165.

Kőszegi, B., and Rabin, M., 2007, Reference-Dependent Risk Attitudes, *American Economic Review*, 97(4), 1047–1073.

Kőszegi, B., and Rabin, M., 2009, Reference-Dependent Consumption Plans, *American Economic Review*, 99, 909–936.

Lee, C. and Ready, M.J., 1991, Inferring Trade Direction from Intraday data, *Journal of Finance*, 46(2), 733-746.

Lee, C.M. and Radhakrishna, B., 2000, Inferring Investor Behavior: Evidence from TORQ Data, *Journal of Financial Markets*, 3(2), 83-111.

Lehmann, B., 1990, Fads, Martingales and Market Efficiency, *Quarterly Journal of Economics*, 105, 1–28.

Li, J., and Yu, J. 2012. Investor attention, psychological anchors, and stock return predictability. *Journal of Financial Economics*, 104(2), 401-419.

Livnat, J., and Mendenhall, R. R., 2006, Comparing the Post-Earnings Announcement Drift for Surprises Calculated from Analyst and Time Series Forecasts, *Journal of Accounting Research* 44, 177–205.

Lou, D., 2012, A flow-based explanation for return predictability. *The Review of Financial Studies*, 25(12), 3457-3489.

Lou, D., 2014, Attracting investor attention through advertising. *The Review of Financial Studies*, 27(6), 1797-1829.

Ma, Q., Whidbee, D.A., and Zhang, W.A., 2018, Acquirer Reference Prices and Acquisition Performance. *Journal of Financial Economics*, forthcoming. Available at SSRN: https://ssrn.com/abstract=2716329 or http://dx.doi.org/10.2139/ssrn.2716329

Mendenhall, R. (2004), Arbitrage Risk and Post-Earnings-Announcement Drift, *Journal of Business*, Vol. 77, 875-894

Meng, J. and Weng, X., 2017. Can Prospect Theory Explain the Disposition Effect? A New Perspective on Reference Points. *Management Science*.

Newey, W. K., and West, K. D., 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, 55, 703–708.

Odean, T., 1998, Are Investors Reluctant to Realize Their Losses?, *Journal of Finance* 53, 1775–1798.

Tversky, A., and Kahneman, D., 1974. Judgment under Uncertainty: heuristics and biases. *Science* 185, 1124–1131.

Shefrin, H., and Statman, M., 1985, The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence, *Journal of Finance* 40, 777–791.

Wang, H., Yan, J., & Yu, J., 2017. Reference-dependent preferences and the risk–return trade-off. *Journal of Financial Economics*, 123(2), 395-414.

Wermers, R., 2005, Is Money Really Smart? New Evidence on the Relation between Mutual Fund Flows, Manager Behavior, and Performance Persistence, unpublished manuscript, University of Maryland.

Zhang, Y. (2008), Analyst Responsiveness and the Post-Earnings-Announcement Drift, *Journal of Accounting and Economics*, 46, 201-215

Figure 1

This figure illustrates the distribution of investors' target prices. In Figure 1a, the black and gray curves depict the distribution of investor target prices for stocks A and B respectively. In Figure 1b, the shaded area represents the fraction of satisfied investors when the price becomes $11 for stock A. In Figure 1c, the shaded area represents the fraction of satisfied investors when the price becomes $11 for stock B. Figure 1d illustrates the scenario with negative price shocks.

Figure 1a

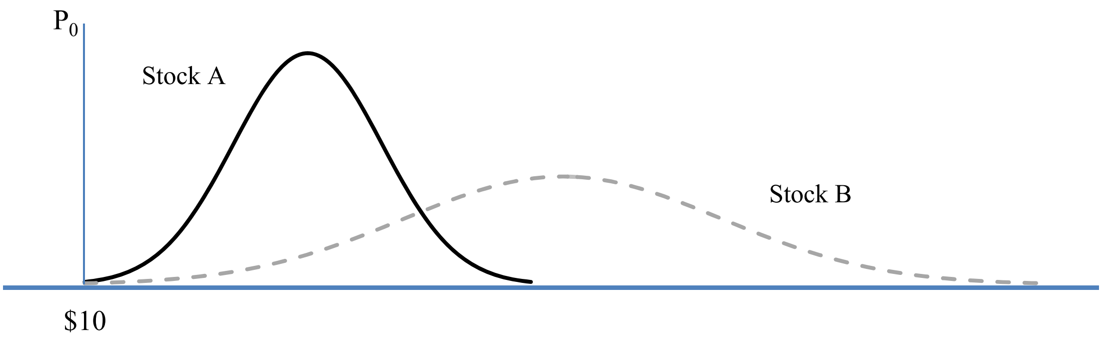

Figure 1b

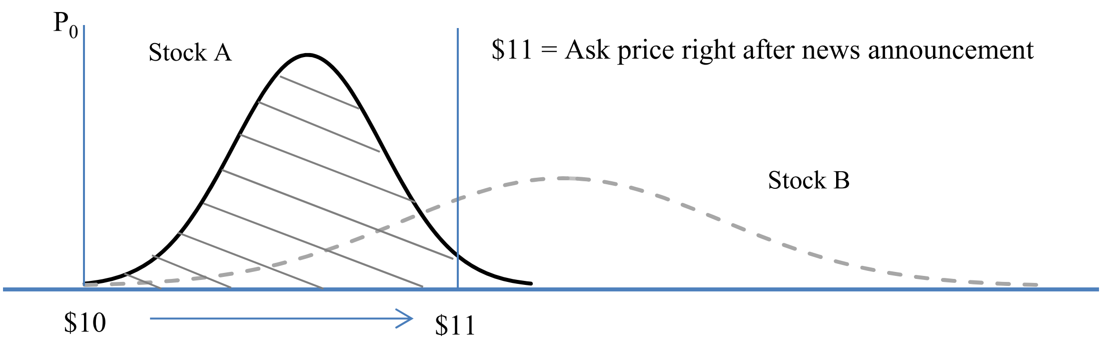

Figure 1c

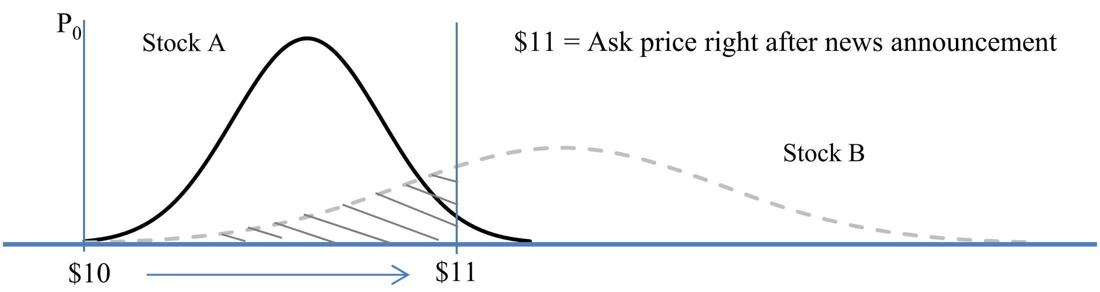

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Figure 1 – *Continued*

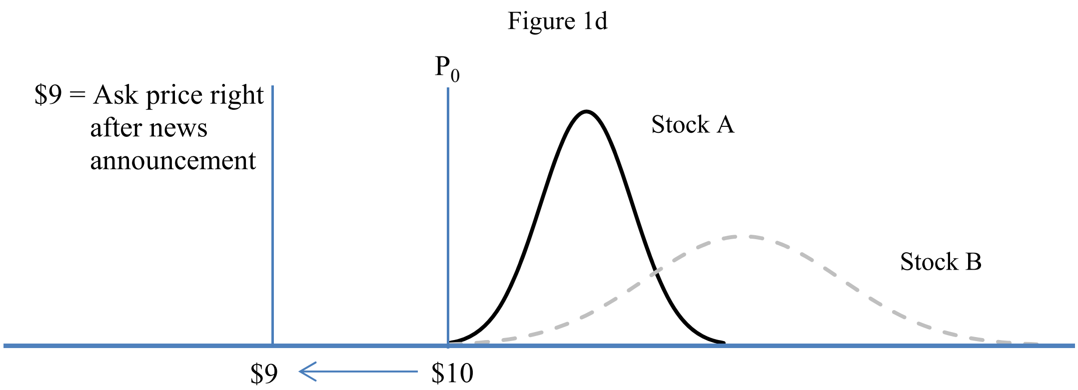


Table 1
Descriptive Statistics

This table reports descriptive statistics of *Cumulative Abnormal Returns* around quarterly earnings announcements, *FracSat* and lagged firm characteristics, as well as the determinants of *FracSat*. The sample contains all quarterly earnings announcements in I/B/E/S from 1999 to 2015 that have a positive *CAR*(0,1), a price-per-share greater than $5 and data available to compute the *FractSat* measure. Daily abnormal return is computed as the raw daily return minus the daily value-weighted return on a portfolio of firms with similar size, book-to-market ratio and momentum. *CAR*(0,1) is the sum of daily abnormal returns from day 0 to day 1, where day 0 is the earnings announcement day or the ensuing trading day if news is announced on a non-trading day or after market-hours. *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) are the sum of daily abnormal returns from day 2 to day 30, day 45, and day 61, respectively. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of day 1; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. *Capital Gain Overhang* is the percentage deviation of the stock price at the end of day 1 from the aggregate purchase price of mutual funds (Frazzini 2006). *Market Capitalization* (in million $) is measured as of the most recent June. *Book-to-Market* is the firm's book-to-market ratio, where book value is measured as of the fiscal year end in calendar year *t*-1, and market value is measured as of December of calendar year *t*-1; the book-to-market ratio so computed is matched with earnings announcements from July of year *t* to June of year *t*+1. *Past Return*(*t*−7, *t*−1) is the raw return over the six-month period ending one month prior to the month of the earnings announcement. *Institutional Ownership* is the fraction of total shares outstanding held by institutional investors as of the end of the quarter prior to the earnings announcement. *Nearness to 52-week High* is the ratio of closing price on day −11 to the highest closing price from the prior 52 weeks. *Turnover* is measured as the average of daily ratios of the number of shares traded to the total number of shares outstanding from day −40 to day −11. *Amihud Ratio* is the average of daily ratios of absolute stock return to its dollar volume from day −40 to day −11. *SUE*1 is the difference in earnings per share before extraordinary items between quarter *t* and quarter *t*−4, scaled by the price at quarter *t*. *SUE*2 is the standardized unexpected earnings, defined as the difference between the actual earnings per share and the median of analyst forecasts in the 90 days prior to the earnings announcement, scaled by price. *Earnings Volatility* is measured as the standard deviation of quarterly earnings surprises based on a seasonal random walk model over the preceding four years. *Earnings Persistence* is the first-order auto-regressive coefficient of quarterly earnings-per-share over the preceding four years. *Reporting Lag* is the number of days between the fiscal quarter-end date and the actual earnings announcement date. *# of Analysts* is the number of analysts reporting earnings-per-share forecasts for the corresponding earnings announcement. *# of Announcements* is the number of firms announcing earnings on the same earnings announcement day. Panel A reports summary statistics, and Panel B reports the correlation between *FracSat* and firm characteristics. In Panel C, we report the coefficient estimates from panel regressions of *FracSat* on firm characteristics. We include time and industry fixed effects with standard errors clustered by time (reported in parentheses). *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Panel A: Summary Statistics

Variable	N	Mean	St. Dev.	P5	Q1	Median	Q3	P95
CAR(0,1)	52,071	0.056	0.054	0.003	0.017	0.039	0.076	0.169
CAR(2,30)	52,071	0.011	0.113	−0.164	−0.045	0.010	0.066	0.194
CAR(2,45)	52,071	0.013	0.145	−0.217	−0.057	0.013	0.085	0.246
CAR(2,61)	52,071	0.016	0.171	−0.261	−0.068	0.015	0.100	0.290
FracSat	52,071	0.178	0.303	0.000	0.000	0.000	0.278	1.000
Capital Gain Overhang	52,071	0.012	0.415	−0.701	−0.057	0.061	0.241	0.455
Market Capitalization	52,071	6582	16631	130	470	1378	4576	29948
Book-to-Market	52,071	0.556	0.439	0.099	0.268	0.457	0.726	1.319
Past Return(*t*−7,*t*−1)	52,071	0.101	0.384	−0.377	−0.096	0.061	0.233	0.681
Institutional Ownership	52,071	0.669	0.212	0.248	0.544	0.710	0.832	0.947
Nearness to 52-week High	52,071	0.811	0.187	0.426	0.714	0.864	0.953	1.000

(Continued)

Table 1 -- *Continued*

Panel A: Summary Statistics

Variable	N	Mean	St. Dev.	P5	Q1	Median	Q3	P95
Turnover	52,071	0.008	0.007	0.001	0.004	0.007	0.011	0.022
Amihud Ratio	52,071	0.032	0.183	0.000	0.000	0.002	0.008	0.101
*SUE*1	52,071	0.002	0.089	−0.028	−0.002	0.002	0.006	0.031
*SUE*2	52,071	0.002	0.005	−0.003	0.000	0.001	0.003	0.009
Earnings Volatility	52,071	0.031	0.096	0.001	0.003	0.008	0.022	0.124
Earnings Persistence	52,071	0.288	0.371	−0.254	0.003	0.252	0.570	0.921
Reporting Lag	52,071	30	10	16	22	28	35	50
# of Analysts	52,071	7	6	1	3	6	10	20
# of Announcements	52,071	226	131	31	125	220	305	460

Panel B: Correlation

	CAR (0,1)	*Capital Gain Overhang*	*Market Cap*	*Book-to-Market*	*Past Return*	*Institutional Ownership*	*Nearness to 52-week High*	*IV*	*SUE*1	*SUE*2
FracSat	0.21	0.09	-0.05	0.05	0.08	0.02	0.17	-0.04	0.02	0.09

Panel C: Determinants of *FracSat*

Variable	(1)	(2)
Capital Gain Overhang	-0.037***	-0.044***
	(0.009)	(0.009)
Nearness to 52-week High	0.334***	0.380***
	(0.019)	(0.022)
Analyst Dispersion		0.153***
		(0.032)
Ln(*Market Capitalization*)		-0.011***
		(0.001)
Ln(*Book-to-Market*)		-0.009***
		(0.002)
Past Return(t−7,t−1)		0.027***
		(0.008)
Institutional Ownership		-0.010
		(0.009)
Idiosyncratic Volatility		1.718***
		(0.220)
Observations	52,071	52,071
R^2	0.114	0.123

Table 2
Informativeness of Analyst Target Prices: Fama-MacBeth Regressions

This table reports the time-series mean of coefficient estimates from quarterly cross-sectional regressions of *Cumulative Abnormal Returns* around analyst *Target Price Revision, Earnings Forecast Revision* and *Recommendation Revision*. The sample contains all analyst target price revisions with a price-per-share greater than $5 from 1999 through 2015. *CAR*(0,1) is the sum of daily abnormal returns from the target price revision day to the ensuing trading day, where daily abnormal return is the daily raw return minus the daily value-weighted return on a portfolio of firms with similar size, book-to-market ratio and past performance. *Target Price Revision* is the percentage change in the analyst-target-price forecasts. *Earnings Forecast Revision* is the percentage change in the analyst annual earnings-per-share forecast. *Recommendation Revision* is the change in the analyst recommendation levels. *Recommendation Upgrade* is an indicator variable that equals one when the recommendation revision is an upgrade and zero otherwise. *Recommendation Downgrade* is an indicator variable that equals one when the recommendation revision is a downgrade and zero otherwise. *T*-statistics are computed using Newey-West (1987) standard errors and are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)
	CAR(0,1)	*CAR*(0,1)	*CAR*(0,1)
Target Price Revision	0.110***	0.088***	0.086***
	(0.010)	(0.009)	(0.009)
Earnings Forecast Revision		0.003**	0.003**
		(0.001)	(0.001)
Recommendation Revision		0.009***	
		(0.001)	
Recommendation Upgrade			0.011***
			(0.002)
Recommendation Downgrade			-0.016***
			(-0.002)
Average Adj. R^2	0.146	0.173	0.175

Table 3

FracSat and the Post Earnings Announcement Drift

This table reports the time-series mean of *CAR*(2,30), *CAR*(2,45) , and *CAR*(2,61) for portfolios based on *CAR*(0,1) and *FracSat*. The final sample contains all quarterly earnings announcements in I/B/E/S from 1999 to 2015 that have a positive *CAR*(0,1), a price-per-share greater than $5 and data available to compute the *FracSat* measure. Daily abnormal return is computed as the raw daily return minus the daily value-weighted return on a portfolio of firms with similar size, book-to-market ratio and momentum. *CAR*(0,1) is the sum of daily abnormal returns from day 0 to day 1, where day 0 is the earnings announcement day or the ensuing trading day if news is announced on a non-trading day or after market-hours. *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) are the sum of daily abnormal returns from day 2 to day 30, day 45, and day 61, respectively. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of day 1; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. In each calendar quarter, we first assign stocks with a positive earnings surprise into five groups based on *CAR*(0,1) quintiles. Within each group, we divide stocks into two parts: those with a *FracSat* above the 80th percentile ("High Fraction Satisfied") and those with a *FracSat* below the 80th percentile ("Low Fraction Satisfied"). Then, we compute the equally-weighted *CAR*(2,30) (Panel A), *CAR*(2,45) (Panel B), and *CAR*(2,61) (Panel C) for these ten portfolios sorted by *CAR*(0,1) and *FracSat*, as well as the difference between top- and bottom-quintile-*CAR*(0,1) portfolios. *T*-statistics are computed using Newey-West (1987) standard errors and are reported in parentheses.

Panel A. *CAR*(2,30)					Panel B. *CAR*(2,45)				
CAR (0,1)	Low *FracSat*	High *FracSat*	H−L	*t*-stat	*CAR* (0,1)	Low *FracSat*	High *FracSat*	H−L	*t*-stat
P1	0.22%	−0.30%	−0.52%	(−1.72)	P1	0.12%	−0.11%	−0.23%	(−0.48)
P2	0.33%	0.24%	−0.09%	(−0.27)	P2	0.28%	0.24%	−0.04%	(−0.09)
P3	0.69%	0.33%	−0.36%	(−1.31)	P3	0.57%	0.50%	−0.07%	(−0.17)
P4	0.28%	0.70%	0.42%	(1.43)	P4	0.32%	1.03%	0.71%	(1.41)
P5	0.76%	1.44%	0.68%	(1.80)	P5	0.39%	1.73%	1.34%	(2.21)
H−L	0.54%	1.75%	1.21%	(3.40)	H−L	0.28%	1.84%	1.56%	(2.39)
	(1.88)	(4.50)				(0.65)	(3.42)		

Panel C. *CAR* (2,61)				
CAR (0,1)	Low *FracSat*	High *FracSat*	H−L	*t*-stat
P1	0.12%	0.10%	−0.02%	(−0.02)
P2	0.34%	0.41%	0.07%	(0.13)
P3	0.54%	0.51%	−0.03%	(−0.07)
P4	0.17%	0.98%	0.81%	(1.29)
P5	0.62%	2.30%	1.68%	(2.42)
H−L	0.50%	2.20%	1.70%	(2.11)
	(1.12)	(3.25)		

Table 4
FracSat and the Post-Earnings-Announcement Drift: Panel Regressions

This table reports the coefficient estimates from panel regressions of *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) on *FracSat*, *CAR*(0,1), and the interaction between *FracSat* and *CAR*(0,1), respectively. The final sample contains all quarterly earnings announcements in I/B/E/S from 1999 to 2015 that have a positive *CAR*(0,1), a price-per-share greater than $5 and data available to compute the *FracSat* measure. Daily abnormal return is computed as the raw daily return minus the daily value-weighted return on a portfolio of firms with similar size, book-to-market ratio and momentum. *CAR*(0,1) is the sum of daily abnormal returns from day 0 to day 1, where day 0 is the earnings announcement day or the ensuing trading day if news is announced on a non-trading day or after market-hours. *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) are the sum of daily abnormal returns from day 2 to day 30, day 45, and day 61, respectively. In each calendar quarter *t*, we assign stocks into quintile portfolios based on *CAR*(0,1). *RankCAR*(0,1) equals one for stocks from the bottom *CAR*(0,1) quintile, and five for stocks from the top *CAR*(0,1) quintile. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of day 1; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. All control variables are as described in Table 1. We also control for all the interactions between control variables and *RankCAR*(0,1). We include time and industry fixed effects with standard errors clustered by time (reported in parentheses). *, **, and *** denote significance at 10%, 5% and 1%, respectively.

	(1) *CAR*(2,30)	(2) *CAR*(2,45)	(3) *CAR*(2,61)
RankCAR(0,1)	0.002	0.002	0.004
	(0.005)	(0.007)	(0.009)
FracSat × *RankCAR*(0,1)	0.003**	0.004***	0.006***
	(0.001)	(0.001)	(0.002)
FracSat	-0.009**	-0.011**	-0.015**
	(0.004)	(0.005)	(0.007)
Capital Gain Overhang	-0.009	-0.007	-0.002
	(0.007)	(0.009)	(0.012)
Ln(*Market Capitalization*)	0.001	0.001	0.002
	(0.001)	(0.001)	(0.002)
Ln(*Book-to-Market*)	-0.001	-0.002	-0.002
	(0.002)	(0.002)	(0.003)
Past Return($t-7$,$t-1$)	0.007	0.011	0.012
	(0.007)	(0.008)	(0.010)
Institutional Ownership	0.000	0.011	0.014
	(0.007)	(0.008)	(0.010)
Nearness to 52-week High	-0.013	-0.013	-0.033
	(0.017)	(0.022)	(0.027)
Turnover	-0.145	-0.452	-0.412
	(0.287)	(0.360)	(0.396)
Amihud Ratio	-0.019*	-0.020	-0.005
	(0.010)	(0.014)	(0.020)

(Continued)

Table 4 -- *Continued*

	(1) *CAR*(2,30)	(2) *CAR*(2,45)	(3) *CAR*(2,61)
SUE	0.654*	1.428***	1.726***
	(0.368)	(0.463)	(0.575)
Earnings Volatility	-0.013	-0.009	-0.031
	(0.022)	(0.028)	(0.035)
Earnings Persistence	0.004	0.008**	0.012***
	(0.003)	(0.004)	(0.004)
Reporting Lag	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)
Ln(1+ *# of Analysts*)	-0.001	-0.004	-0.006
	(0.002)	(0.003)	(0.004)
# of Announcements	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Friday	0.004	0.007	0.007
	(0.004)	(0.005)	(0.006)
Intact with *RankCAR(0,1)*	Yes	Yes	Yes
Observations	52,071	52,071	52,071
R^2	0.017	0.016	0.016

Table 5
Alternative Proxies of *FracSat* and the Post-Earnings-Announcement Drift

This table reports the correlation coefficients between alternative measures of *FracSat* and firm characteristics in Panel A and the coefficient estimates from panel regressions of *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) on an alternative proxy for *FracSat*, *CAR*(0,1), and the interaction between *FracSat* and *CAR*(0,1), respectively in Panel B. *FracSat*1 is the fraction of analysts whose target price forecasts are exceeded by the stock price one week before the earnings announcement; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. *FracSat*2 is defined as the difference between the stock price at the end of day 1 and the minimum target price, over the difference between the maximum and the minimum target price. If only one target price is available, this proxy is set to 1 if the stock price at day 1 exceeds the target price, and zero otherwise. If the stock price at the end of day 1 is below the minimum target price, this variable is set to zero. *FracSat*3 is a dummy variable that equals one if the stock price at the end of day 1 exceeds the mean target price, and zero otherwise. *FracSat*4 is a dummy variable that equals one if the stock price at the end of day 1 exceeds the median target price, and zero otherwise. The final sample contains all quarterly earnings announcements in I/B/E/S from 1999 to 2015 that have a positive *CAR*(0,1), a price-per-share greater than $5, and data available to compute the *FracSat* measure. Daily abnormal return is computed as the raw daily return minus the daily value-weighted return on a portfolio of firms with similar size and similar book-to-market ratio. *CAR*(0,1) is the sum of daily abnormal returns from day 0 to day 1, where day 0 is the earnings announcement day or the ensuing trading day if news is announced on a non-trading day or after market-hours. *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) are the sum of daily abnormal returns from day 2 to day 30, day 45, and day 61, respectively. In each calendar quarter *t*, we assign stocks into quintile portfolios based on *CAR*(0,1). *RankCAR*(0,1) equals one for stocks from the bottom *CAR*(0,1) quintile, and five for stocks from the top *CAR*(0,1) quintile. All control variables are the same as in Table 4 and are as described in Table 1. We also control for all the interactions between control variables and *RankCAR*(0,1). We include time and industry fixed effects with standard errors clustered by time (reported in parentheses). *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Panel A. *Correlation*

	*FracSat*1	*FracSat*2	*FracSat*3	*FracSat*4
CAR(0,1)	−0.01	0.19	0.23	0.23

Panel B1. *FracSat*1: One Week Before the Earnings Announcement

	(1) *CAR*(2,30)	(2) *CAR*(2,45)	(3) *CAR*(2,61)
RankCAR(0,1)	0.007	0.009	0.017**
	(0.005)	(0.006)	(0.007)
*FracSat*1 × *RankCAR*(0,1)	0.003**	0.004*	0.006**
	(0.002)	(0.002)	(0.003)
*FracSat*1	-0.015***	-0.018***	-0.024***
	(0.005)	(0.007)	(0.008)
Controls	Yes	Yes	Yes
Intact with *RankCAR*(0,1)	Yes	Yes	Yes
Observations	52,071	52,071	52,071
R^2	0.017	0.016	0.015

(Continued)

Table 5 --*Continued*

Panel B2. *FracSat*2: (Prc-Min[TP])/(Max[TP]-Min[TP])

	(1)	(2)	(3)
	CAR(2,30)	*CAR*(2,45)	*CAR*(2,61)
RankCAR(0,1)	0.002	0.002	0.005
	(0.005)	(0.007)	(0.009)
*FracSat*2 × *RankCAR*(0,1)	0.002**	0.002*	0.003**
	(0.001)	(0.001)	(0.001)
*FracSat*2	-0.007**	-0.006	-0.009*
	(0.003)	(0.004)	(0.005)
Controls	Yes	Yes	Yes
Intact with *RankCAR*(0,1)	Yes	Yes	Yes
Observations	52,071	52,071	52,071
R^2	0.017	0.016	0.015

Panel B3. *FracSat*3: I(Prc ≥ Mean[TP])

	(1)	(2)	(3)
	CAR(2,30)	*CAR*(2,45)	*CAR*(2,61)
RankCAR(0,1)	0.001	0.001	0.004
	(0.005)	(0.007)	(0.009)
*FracSat*3 × *RankCAR*(0,1)	0.003***	0.004***	0.006***
	(0.001)	(0.001)	(0.002)
*FracSat*3	-0.010***	-0.015***	-0.019***
	(0.004)	(0.005)	(0.006)
Controls	Yes	Yes	Yes
Intact with *RankCAR*(0,1)	Yes	Yes	Yes
Observations	52,071	52,071	52,071
R^2	0.017	0.016	0.016

Panel B4. *FracSat*4: I(Prc ≥ Median[TP])

	(1)	(2)	(3)
	CAR(2,30)	*CAR*(2,45)	*CAR*(2,61)
RankCAR(0,1)	0.001	0.002	0.005
	(0.005)	(0.007)	(0.009)
*FracSat*4 × *RankCAR*(0,1)	0.002**	0.004***	0.006***
	(0.001)	(0.001)	(0.001)
*FracSat*4	-0.007**	-0.012***	-0.016***
	(0.004)	(0.005)	(0.006)
Controls	Yes	Yes	Yes
Intact with *RankCAR*(0,1)	Yes	Yes	Yes
Observations	52,071	52,071	52,071
R^2	0.017	0.016	0.016

Table 6

Alternative Proxies for Earning Surprise: Seasonal Earnings Growth and Analyst Consensus

This table reports correlation coefficients between alternative measures of earnings surprise and firm characteristics in Panel A and the coefficient estimates from panel regressions of *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) on *FracSat*, *SUE* measures, and the interaction between *FracSat* and *SUE* measures, respectively in Panel B. *SUE*1 is defined from a seasonal random walk model, i.e., the difference between earnings per share before extraordinary items in quarter t and $t-4$, scaled by the price at quarter t. *SUE*2 is defined as the difference between the actual earnings per share and the median of analyst forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement, scaled by price. Following the previous analysis, the final sample contains all quarterly earnings announcements in I/B/E/S from 1999 to 2015 that have a positive *SUE*, a price-per-share greater than $5, and data available to compute the *FracSat* measure. In each calendar quarter t, we assign stocks into quintile portfolios based on *SUE*. *RankSUE* equals one for stocks from the bottom *SUE* quintile, and five for stocks from the top *SUE* quintile. Daily abnormal return is computed as the raw daily return minus the daily value-weighted return on a portfolio of firms with similar size and similar book-to-market ratio. *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) are the sum of daily abnormal returns from day 2 to day 30, day 45, and day 61, respectively, where day 0 is the earnings announcement day or the ensuing trading day if news is announced on a non-trading day or after market-hours. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of day 1; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. We include *CAR*(0,1) and all control variables applied in Table 4 in the regressions. We also control for all the interactions between control variables and *RankCAR*(0,1). We include time and industry fixed effects with standard errors clustered by time (reported in parentheses). *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Panel A. *Correlation*

	*SUE*1	*SUE*2
FracSat	0.02	0.09

Panel B1. *SUE*1- Seasonal Earnings Growth

	(1) *CAR*(2,30)	(2) *CAR*(2,45)	(3) *CAR*(2,61)
*RankSUE*1	0.004	0.007	0.003
	(0.005)	(0.006)	(0.008)
FracSat × *RankSUE*1	0.004***	0.004**	0.005***
	(0.001)	(0.002)	(0.002)
FracSat	-0.005	-0.001	-0.003
	(0.004)	(0.005)	(0.005)
Controls	Yes	Yes	Yes
Intact with *RankCAR*(0,1)	Yes	Yes	Yes
Observations	60,630	60,630	60,630
R^2	0.018	0.019	0.017

(Continued)

Table 6 --*Continued*

Panel B2. *SUE*2 - Analyst Consensus

	(1)	(2)	(3)
	CAR(2,30)	*CAR*(2,45)	*CAR*(2,61)
*RankSUE*2	0.013***	0.011*	0.016**
	(0.004)	(0.006)	(0.007)
FracSat × *RankSUE*2	0.003**	0.003**	0.003*
	(0.001)	(0.001)	(0.002)
FracSat	-0.006	-0.005	-0.004
	(0.005)	(0.006)	(0.006)
	0.013***	0.011*	0.016**
Controls	Yes	Yes	Yes
Intact with *RankCAR*(0,1)	Yes	Yes	Yes
Observations	63,133	63,133	63,133
R^2	0.015	0.015	0.013

Table 7
FracSat and Trading

This table reports the coefficient estimates from panel regressions of *Abn_Vol*, *Abn_DVol*, *BSI*, and *DBSI* on *FracSat*, *CAR*(0,1), and the interaction between *FracSat* and *CAR*(0,1), respectively. *Abn_Vol* is abnormal trading volume, defined as the average trading volume from day 0 and day 1 over the average trading volume from day −40 to day −11; *Abn_DVol* is abnormal dollar trading volume, defined as the average dollar trading volume from day 0 and day 1 over the average dollar trading volume from day −40 to day −11, where day 0 is the earnings announcement day or the ensuing trading day if earnings are announced on a non-trading day. *BSI* is buy-sell imbalance, defined as the difference between buy-initiated trading volume and sell-initiated trading volume over the sum of these two. Buy-initiated and sell-initiated trades are identified using Lee and Ready (1991)'s algorithm and are summed from day 0 to day 1, respectively. *DBSI* is dollar value buy-sell imbalance, which is defined similar to *BSI* by replacing buy-initiated and sell-initiated trading volume with buy-initiated and sell-initiated dollar trading volume. The final sample contains all quarterly earnings announcements in I/B/E/S from 1999 to 2015 that have a positive *CAR*(0,1), a price-per-share greater than $5, data available to compute the *FracSat* measure, and data available to compute the dependent variables from TAQ. In each calendar quarter *t*, we assign stocks into quintile portfolios based on *CAR*(0,1). *RankCAR*(0,1) equals one for stocks from the bottom *CAR*(0,1) quintile, and five for stocks from the top *CAR*(0,1) quintile. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of day 1; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. All control variables are the same as in Table 4 and are as described in Table 1. We also control for all the interactions between control variables and *RankCAR*(0,1). We include time and industry fixed effects with standard errors clustered by time (reported in parentheses). *, **, and *** denote significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
	Abn_Vol	*Abn_DVol*	*BSI*	*DBSI*
RankCAR(0,1)	1.012***	1.808**	0.034***	0.034***
	(0.339)	(0.814)	(0.010)	(0.010)
FracSat × *RankCAR*(0,1)	0.883***	1.368***	-0.007**	-0.007**
	(0.312)	(0.410)	(0.003)	(0.003)
FracSat	-1.980**	-2.778***	0.020*	0.020*
	(0.874)	(1.041)	(0.011)	(0.011)
Controls	Yes	Yes	Yes	Yes
Intact with *RankCAR*(0,1)	Yes	Yes	Yes	Yes
Observations	47,363	47,363	43,045	43,045
R^2	0.018	0.017	0.103	0.101

Table 8
Trading Strategy Based on *FracSat* and *CAR(0,1)*

This table reports the three-factor and four-factor adjusted returns for a trading strategy based on *CAR*(0,1) and *FracSat*. The final sample contains all quarterly earnings announcements in I/B/E/S from 1999 to 2015 that have a positive *CAR*(0,1), a price-per-share greater than \$5, and data available to compute the *FracSat* measure. At the end of each calendar month *t*, we select stocks in our sample that have made earnings announcements in the past two months (i.e., month *t*−1 and month *t*) and a price no less than \$5 at the end of month *t*. We then sort these stocks into five groups based on *CAR*(0,1) quintiles. Within each of the five groups, stocks are further divided into two parts: those with a *FracSat* above the 80th percentile ("High Fraction Satisfied") and those with a *FracSat* below the 80th percentile ("Low Fraction Satisfied"). We require that each of the ten portfolios should consist of at least five stocks. We hold these ten portfolios for one month and compute their equal-weighted return patterns in month *t*+1. We report Fama-French (1993) three-factor adjusted returns in Panel A, and Fama-French-Carhart four-factor adjusted returns in Panel B. Daily abnormal return is computed as the raw daily return minus the daily value-weighted return on a portfolio of firms with similar size, book-to-market ratio and momentum. *CAR*(0,1) is the sum of daily abnormal returns from day 0 to day 1, where day 0 is the earnings announcement day or the ensuing trading day if news is announced on a non-trading day or after market-hours. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of day 1; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. Newey-West (1987) adjusted standard errors are reported in parentheses.

Panel A: Three-factor Adjusted Returns				Panel B: Four-factor Adjusted Returns			
CAR (0,1)	Low *FracSat*	High *FracSat*	H−L	*CAR* (0,1)	Low *FracSat*	High *FracSat*	H−L
P1	0.00%	0.10%		P1	0.09%	−0.03%	
P2	0.03%	0.24%		P2	0.08%	0.13%	
P3	−0.03%	0.27%		P3	−0.01%	0.14%	
P4	−0.20%	0.20%		P4	−0.14%	0.06%	
P5	−0.27%	0.77%		P5	−0.17%	0.72%	
H−L	−0.27%	0.68%	0.95%	H−L	−0.26%	0.76%	1.01%
	(−1.28)	(2.01)	(2.56)		(−1.22)	(2.22)	(2.72)

Table 9
Subsample Analysis on Institutional Ownership and Idiosyncratic Volatility

This table reports the coefficient estimates from panel regressions of *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) on *FracSat*, *CAR*(0,1), and the interaction between *FracSat* and *CAR*(0,1), respectively, for institutional ownership subsamples and for idiosyncratic volatility subsamples. In each calendar quarter, we sort our sample based on institutional ownership (idiosyncratic volatility): those with an institutional ownership (idiosyncratic volatility) below the 30^{th} percentile and those with an institutional ownership (idiosyncratic volatility) above the 70^{th} percentile . The final sample contains all quarterly earnings announcements in I/B/E/S from 1999 to 2015 that have a positive *CAR*(0,1), a price-per-share greater than $5, and data available to compute the *FracSat* measure. Daily abnormal return is computed as the raw daily return minus the daily value-weighted return on a portfolio of firms with similar size, book-to-market ratio and momentum. *CAR*(0,1) is the sum of daily abnormal returns from day 0 to day 1, where day 0 is the earnings announcement day or the ensuing trading day if news is announced on a non-trading day or after market-hours. *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) are the sum of daily abnormal returns from day 2 to day 30, day 45, and day 61, respectively. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of day 1; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. We assign stocks into quintile portfolios based on *CAR*(0,1) independently. *RankCAR*(0,1) equals one for stocks from the bottom *CAR*(0,1) quintile, and five for stocks from the top *CAR*(0,1) quintile. All control variables are the same as in Table 4 and are as described in Table 1. We also control for all the interactions between control variables and *RankCAR*(0,1). We include time and industry fixed effects with standard errors clustered by time (reported in parentheses). *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Panel A. IO Subamples

	CAR(2,30)		*CAR*(2,45)		*CAR*(2,61)	
	Low IO	High IO	Low IO	High IO	Low IO	High IO
	(1)	(2)	(3)	(4)	(5)	(6)
RankCAR(0,1)	0.011	-0.000	-0.001	-0.010	-0.000	-0.001
	(0.008)	(0.012)	(0.012)	(0.016)	(0.014)	(0.020)
FracSat × *RankCAR*(0,1)	0.005***	0.002	0.009***	0.003	0.010***	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
FracSat	-0.014**	-0.008	-0.022***	-0.008	-0.024***	-0.009
	(0.006)	(0.007)	(0.007)	(0.009)	(0.009)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Intact with *RankCAR*(0,1)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,335	17,357	17,335	17,357	17,335	17,357
R^2	0.031	0.031	0.033	0.029	0.034	0.026

(Continued)

Table 9 --*Continued*

Panel B. IV Subsamples

	CAR(2,30)		*CAR*(2,45)		*CAR*(2,61)	
	Low IV	High IV	Low IV	High IV	Low IV	High IV
	(1)	(2)	(3)	(4)	(5)	(6)
RankCAR(0,1)	-0.006	0.006	-0.010	-0.004	-0.018	0.002
	(0.008)	(0.011)	(0.010)	(0.014)	(0.013)	(0.017)
FracSat × *RankCAR(0,1)*	0.003**	0.006**	0.002	0.008**	0.003	0.010***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)
FracSat	-0.013***	-0.021**	-0.013**	-0.024*	-0.016**	-0.027*
	(0.004)	(0.010)	(0.005)	(0.013)	(0.006)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Intact with *RankCAR*(0,1)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,335	17,357	17,335	17,357	17,335	17,357
R^2	0.076	0.028	0.086	0.028	0.072	0.030

Table 10
Trading Strategy Based on *FracSat* and Short-Term Return

This table reports performance statistics for trading strategies based on *FracSat*. The sample contains common stocks from 1999 to 2015 that have a positive *Return*(*t*), price-per-share greater than $5 and data available to compute the *FracSat* measure. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of month *t*; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. At the end of each month, we assign stocks into quintiles based on the return of that month, *Return*(*t*). We then focus on stocks from the top *Return*(*t*) quintile. Among the stocks from the top *Return*(*t*) quintile, we long those with a *FracSat* above the 80th percentile and short those with a *FracSat* below the 80th percentile. The portfolios are equally-weighted and held for one, two or three months. We report performance statistics of the long-short portfolio returns. *T*-statistics are computed using Newey-West (1987) standard errors and are reported in parentheses.

	1 month		2 months		3 months	
Raw Return	0.63%	(2.30)	0.74%	(3.12)	0.71%	(3.08)
Three-Factor Alpha	0.65%	(2.52)	0.79%	(3.54)	0.77%	(3.56)
Four-Factor Alpha	0.44%	(1.96)	0.58%	(3.23)	0.58%	(3.31)

Table A.1
Robustness Check: Fama-French size and book-to-market portfolio adjusted *CAR*

This table reports the coefficient estimates from panel regressions of *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) on *FracSat*, *CAR*(0,1), and the interaction between *FracSat* and *CAR*(0,1), respectively, based on Fama-French size/book-to-market portfolio adjusted *Cumulative Abnormal Returns* around quarterly earnings announcements. The final sample contains all quarterly earnings announcements in I/B/E/S from 1999 to 2015 that have a positive *CAR*(0,1), a price-per-share greater than $5, and data available to compute the *FracSat* measure. Daily abnormal return is computed as the raw daily return minus the daily value-weighted return on a portfolio of firms with similar size and similar book-to-market ratio. *CAR*(0,1) is the sum of daily abnormal returns from day 0 to day 1, where day 0 is the earnings announcement day or the ensuing trading day if news is announced on a non-trading day or after market-hours. *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) are the sum of daily abnormal returns from day 2 to day 30, day 45, and day 61, respectively. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of day 1; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. In each calendar quarter *t*, we assign stocks into quintile portfolios based on *CAR*(0,1). *RankCAR*(0,1) equals one for stocks from the bottom *CAR*(0,1) quintile, and five for stocks from the top *CAR*(0,1) quintile. All control variables are the same as in Table 4 and are as described in Table 1. We also control for all the interactions between control variables and *RankCAR*(0,1). We include time and industry fixed effects with standard errors clustered by time (reported in parentheses). *, **, and *** denote significance at 10%, 5% and 1%, respectively.

	(1) *CAR*(2,30)	(2) *CAR*(2,45)	(3) *CAR*(2,61)
RankCAR(0,1)	−0.000	−0.000	−0.001
	(0.001)	(0.001)	(0.001)
FracSat × *RankCAR*(0,1)	0.004***	0.006***	0.008***
	(0.001)	(0.002)	(0.002)
FracSat	−0.012***	−0.017***	−0.022***
	(0.004)	(0.006)	(0.007)
Controls	Yes	Yes	Yes
Intact with *RankCAR*(0,1)	Yes	Yes	Yes
Observations	52,590	52,590	52,590
R^2	0.017	0.019	0.020

Table A.2
FracSat and Small Trades

This table reports the coefficient estimates from panel regressions of small trade *BSI* and *DBSI* on *FracSat*, respectively. The final sample contains all quarterly earnings announcements in I/B/E/S in 1999 and 2000 that have a positive *CAR*(0,1), a price-per-share greater than $5, data available to compute the *FracSat* measure, and data available to compute the dependent variables from TAQ. We use small trades to compute *BSI*, and *DBSI*. As suggested by Lee and Radhakrishna (2000), trades with dollar size less than 5,000 USD (small trades) are used as a proxy for individual investor trades. Following Barber, Odean and Zhu (2009), trade size is based on 1991 real dollars and adjusted using the Consumer Price Index. *BSI* is small buy-sell imbalance, defined as the difference between small buy-initiated trading volume and small sell-initiated trading volume over the sum of these two. Buy-initiated and sell-initiated trades are identified using Lee and Ready (1991)'s algorithm and are summed from day 0 to day 1 respectively, where day 0 is the earnings announcement day or the ensuing trading day if earnings are announced on a non-trading day. *DBSI* is dollar value small buy-sell imbalance, which is defined similar to *BSI* by replacing small buy-initiated and small sell-initiated trading volume with small buy-initiated and small sell-initiated dollar trading volume. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of day 1; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. In each calendar quarter *t*, we assign stocks into quintile portfolios based on *CAR*(0,1). *RankCAR*(0,1) equals one for stocks from the bottom *CAR*(0,1) quintile, and five for stocks from the top *CAR*(0,1) quintile. All control variables are the same as in Table 4 and are as described in Table 1. We include time and industry fixed effects with standard errors clustered by time (reported in parentheses). *, **, and *** denote significance at 10%, 5% and 1%, respectively.

	(1)	(2)
	BSI	*DBSI*
RankCAR(0,1)	0.049***	0.049***
	(0.003)	(0.003)
FracSat × *RankCAR*(0,1)	−0.019*	−0.020*
	(0.011)	(0.011)
FracSat	0.061	0.062
	(0.044)	(0.044)
Controls	Yes	Yes
Observations	3,858	3,858
R^2	0.079	0.078

Table A.3

Trading Strategy Based on *FracSat* and *CAR*(0,1): Value-weighted

This table reports the three-factor and four-factor adjusted value-weighted returns for a trading strategy based on *CAR*(0,1) and *FracSat*. The final sample contains all quarterly earnings announcements in I/B/E/S from 1999 to 2015 that have a positive *CAR*(0,1), a price-per-share greater than $5, and data available to compute the *FracSat* measure. Daily abnormal return is computed as the raw daily return minus the daily value-weighted return on a portfolio of firms with similar size, book-to-market ratio and momentum. *CAR*(0,1) is the sum of daily abnormal returns from day 0 to day 1, where day 0 is the earnings announcement day or the ensuing trading day if news is announced on a non-trading day or after market-hours. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of day 1; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. At the end of each calendar month *t*, we select stocks in our sample that have made earnings announcements in the past two months (i.e., month *t*−1 and month *t*) and a price no less than $5 at the end of month *t*. We then sort these stocks into five groups based on *CAR*(0,1) quintiles. Within each of the five groups, stocks are further divided into two parts: those with a *FracSat* above the 80th percentile ("High Fraction Satisfied") and those with a *FracSat* below the 80th percentile ("Low Fraction Satisfied"). We require that each of the ten portfolios should consist of at least five stocks. We hold these ten portfolios for one month and compute their value-weighted return patterns in month *t*+1. We report Fama-French (1993) three-factor adjusted returns in Panel A, and Fama-French-Carhart four-factor adjusted returns in Panel B. Newey-West (1987) adjusted standard errors are reported in parentheses.

Panel A: Three-factor Adjusted Returns				Panel B: Four-factor Adjusted Returns			
CAR (0,1)	Low *FracSat*	High *FracSat*	H−L	*CAR* (0,1)	Low *FracSat*	High *FracSat*	H−L
P1	0.00%	0.14%		P1	0.03%	−0.01%	
P2	0.04%	0.26%		P2	0.06%	0.15%	
P3	−0.04%	0.21%		P3	−0.03%	0.08%	
P4	−0.19%	0.14%		P4	−0.15%	0.03%	
P5	−0.08%	0.79%		P5	0.01%	0.72%	
H−L	−0.08%	0.65%	0.73%	H−L	−0.03%	0.74%	0.76%
	(−0.38)	(1.88)	(1.92)		(−0.13)	(2.13)	(2.00)

Table A.4

Trading Strategy Based on *FracSat* and Short-Term Return: Value-weighted

This table reports performance statistics for value-weighted trading strategies based on *FracSat*. The sample contains common stocks from 1999 to 2015 that have a positive *Return*(*t*), a price-per-share greater than $5, and data available to compute the *FracSat* measure. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of month *t*; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. At the end of each month, we assign stocks into quintiles based on the return of that month, *Return*(*t*). We then focus on stocks from the top return quintile. Among the stocks from the top return quintile, we long those with a *FracSat* above the 80th percentile and short those with a *FracSat* below the 80th percentile. The portfolios are value-weighted and held for one, two or three months, separately. We report performance statistics of the long-short portfolio returns. *T*-statistics are computed using Newey-West (1987) standard errors and are reported in parentheses.

	1 month		2 months		3 months	
Raw Return	0.69%	(2.04)	0.66%	(2.46)	0.55%	(2.16)
Three-Factor Alpha	0.72%	(2.31)	0.69%	(2.75)	0.61%	(2.61)
Four-Factor Alpha	0.48%	(1.72)	0.48%	(2.25)	0.42%	(2.13)

Table A.5
FracSat and the Post-Earnings-Announcement Drift: Panel Regressions

This table reports the coefficient estimates from panel regressions of *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) on *FracSat*, *CAR*(0,1), and the interaction between *FracSat* and *CAR*(0,1), respectively. The final sample contains all quarterly earnings announcements in I/B/E/S from 1999 to 2015 that have a positive *CAR*(0,1), a price-per-share greater than $5 and data available to compute the *FracSat* measure. Daily abnormal return is computed as the raw daily return minus the daily value-weighted return on a portfolio of firms with similar size, book-to-market ratio and momentum. *CAR*(0,1) is the sum of daily abnormal returns from day 0 to day 1, where day 0 is the earnings announcement day or the ensuing trading day if news is announced on a non-trading day or after market-hours. *CAR*(2,30), *CAR*(2,45), and *CAR*(2,61) are the sum of daily abnormal returns from day 2 to day 30, day 45, and day 61, respectively. In each calendar quarter *t*, we assign stocks into quintile portfolios based on *CAR*(0,1). *RankCAR*(0,1) equals one for stocks from the bottom *CAR*(0,1) quintile, and five for stocks from the top *CAR*(0,1) quintile. *FracSat* is the fraction of analysts whose target price forecasts are exceeded by the stock price at the end of day 1; we focus on 12-month target price forecasts announced within 90 days prior to the earnings announcement. All control variables are as described in Table 1. We also control for all the interactions between control variables and *RankCAR*(0,1). We include time and industry fixed effects with standard errors clustered by time (reported in parentheses). *, **, and *** denote significance at 10%, 5% and 1%, respectively.

	(1) *CAR*(2,30)	(2) *CAR*(2,45)	(3) *CAR*(2,61)
RankCAR(0,1)	0.002	0.002	0.004
	(0.005)	(0.007)	(0.009)
FracSat × *RankCAR*(0,1)	0.003**	0.004***	0.006***
	(0.001)	(0.001)	(0.002)
FracSat	-0.009**	-0.011**	-0.015**
	(0.004)	(0.005)	(0.007)
Capital Gain Overhang	-0.009	-0.007	-0.002
	(0.007)	(0.009)	(0.012)
Ln(*Market Capitalization*)	0.001	0.001	0.002
	(0.001)	(0.001)	(0.002)
Ln(*Book-to-Market*)	-0.001	-0.002	-0.002
	(0.002)	(0.002)	(0.003)
Past Return($t-7$,$t-1$)	0.007	0.011	0.012
	(0.007)	(0.008)	(0.010)
Institutional Ownership	0.000	0.011	0.014
	(0.007)	(0.008)	(0.010)
Nearness to 52-week High	-0.013	-0.013	-0.033
	(0.017)	(0.022)	(0.027)
Turnover	-0.145	-0.452	-0.412
	(0.287)	(0.360)	(0.396)
Amihud Ratio	-0.019*	-0.020	-0.005
	(0.010)	(0.014)	(0.020)

(Continued)

Table A.5 -- ***Continued***

	(1) $CAR(2,30)$	(2) $CAR(2,45)$	(3) $CAR(2,61)$
SUE	0.654*	1.428***	1.726***
	(0.368)	(0.463)	(0.575)
Earnings Volatility	-0.013	-0.009	-0.031
	(0.022)	(0.028)	(0.035)
Earnings Persistence	0.004	0.008**	0.012***
	(0.003)	(0.004)	(0.004)
Reporting Lag	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)
Ln(1+ *# of Analysts*)	-0.001	-0.004	-0.006
	(0.002)	(0.003)	(0.004)
# of Announcements	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Friday	0.004	0.007	0.007
	(0.004)	(0.005)	(0.006)
Capital Gain Overhang	-0.000	-0.001	-0.003
×*RankCAR*(0,1)	(0.002)	(0.002)	(0.002)
Ln(*Market Capitalization*)	-0.001*	-0.001*	-0.001**
×*RankCAR*(0,1)	(0.000)	(0.000)	(0.000)
Ln(*Book-to-Market*)	0.000	0.001	0.001
×*RankCAR*(0,1)	(0.001)	(0.001)	(0.001)
Past Return(t−7,t−1)	-0.000	-0.000	-0.000
×*RankCAR*(0,1)	(0.002)	(0.002)	(0.003)
Institutional Ownership	-0.000	-0.003	-0.005*
×*RankCAR*(0,1)	(0.002)	(0.003)	(0.003)
Nearness to 52-week High	0.006	0.010*	0.016**
×*RankCAR*(0,1)	(0.004)	(0.006)	(0.007)
Turnover	-0.031	-0.012	-0.019
×*RankCAR*(0,1)	(0.077)	(0.098)	(0.110)
Amihud Ratio	0.003	0.005	0.001
×*RankCAR*(0,1)	(0.003)	(0.004)	(0.006)
SUE	0.078	-0.124	-0.176
×*RankCAR*(0,1)	(0.093)	(0.119)	(0.145)
Earnings Volatility	-0.001	-0.004	-0.002
×*RankCAR*(0,1)	(0.006)	(0.008)	(0.010)
Earnings Persistence	-0.001	-0.002	-0.002*
×*RankCAR*(0,1)	(0.001)	(0.001)	(0.001)

(Continued)

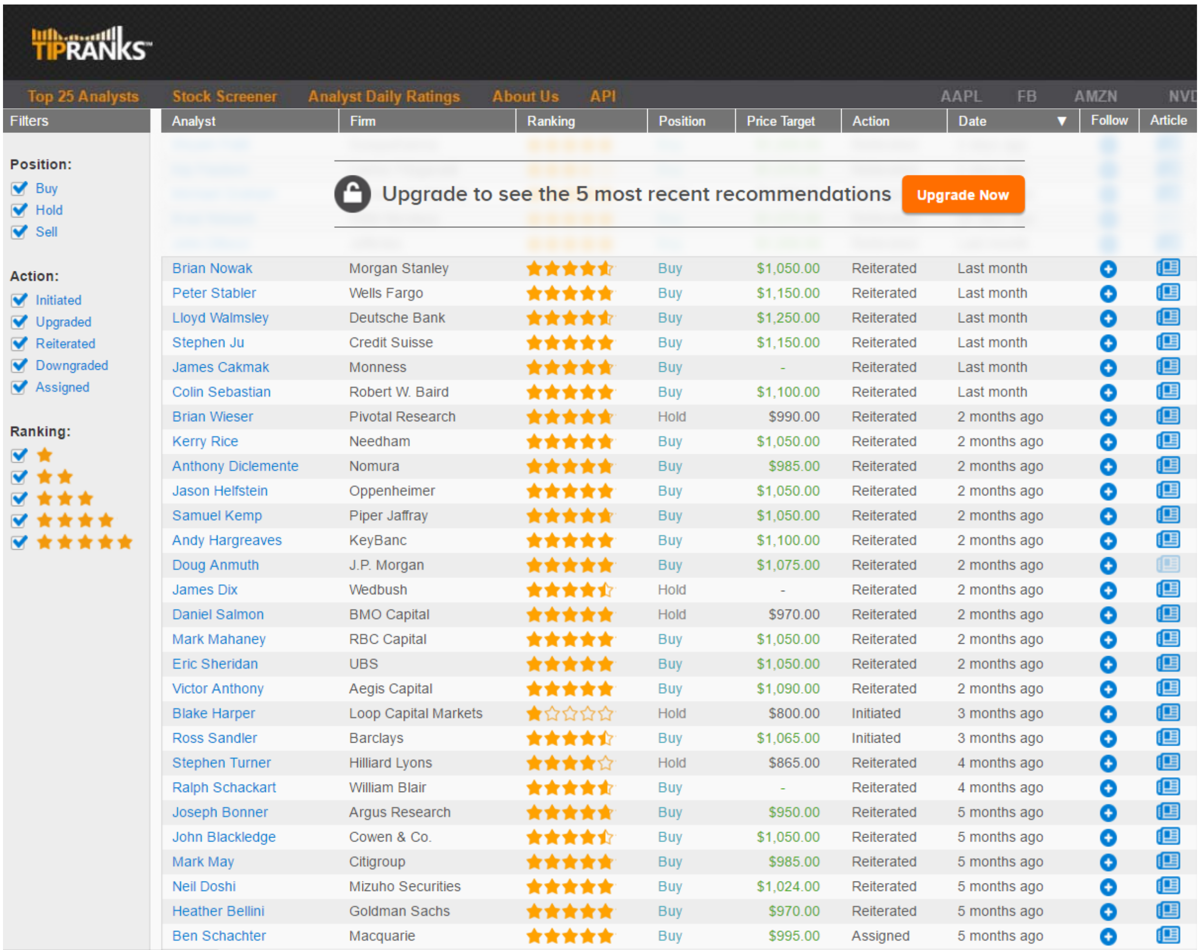
Table A.5 -- ***Continued***

	(1) *CAR*(2,30)	(2) *CAR*(2,45)	(3) *CAR*(2,61)
Reporting Lag ×*RankCAR*(0,1)	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Ln(1+ *# of Analysts*) ×*RankCAR*(0,1)	0.000	0.002*	0.002*
	(0.001)	(0.001)	(0.001)
# of Announcements ×*RankCAR*(0,1)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Friday ×*RankCAR*(0,1)	-0.003*	-0.003*	-0.004**
	(0.001)	(0.002)	(0.002)
Observations	52,071	52,071	52,071
R^2	0.017	0.016	0.016

Figure A.1

Analyst-Target-Price Forecasts for Alphabet Inc (Ticker: GOOGL) from *TIPRANKS*

This figure shows detailed analyst-target-price forecasts for Alphabet Inc (Ticker: GOOGL) from *TIPRANKS*. *TIPRANKS* (https://www.tipranks.com/) is a financial media specialized in providing detailed analyst forecasts and research articles to the public. On the stock summary page, each forecast record consists of the name of the analyst, the brokerage firm where the analyst is from, recommendation level, target prices, action, and the date the forecast is announced. Almost all forecast records are free and can be openly accessed.



Analyst	Firm	Ranking	Position	Price Target	Action	Date	Follow	Article
Brian Nowak	Morgan Stanley		Buy	$1,050.00	Reiterated	Last month		
Peter Stabler	Wells Fargo		Buy	$1,150.00	Reiterated	Last month		
Lloyd Walmsley	Deutsche Bank		Buy	$1,250.00	Reiterated	Last month		
Stephen Ju	Credit Suisse		Buy	$1,150.00	Reiterated	Last month		
James Cakmak	Monness		Buy	-	Reiterated	Last month		
Colin Sebastian	Robert W. Baird		Buy	$1,100.00	Reiterated	Last month		
Brian Wieser	Pivotal Research		Hold	$990.00	Reiterated	2 months ago		
Kerry Rice	Needham		Buy	$1,050.00	Reiterated	2 months ago		
Anthony Diclemente	Nomura		Buy	$985.00	Reiterated	2 months ago		
Jason Helfstein	Oppenheimer		Buy	$1,050.00	Reiterated	2 months ago		
Samuel Kemp	Piper Jaffray		Buy	$1,050.00	Reiterated	2 months ago		
Andy Hargreaves	KeyBanc		Buy	$1,100.00	Reiterated	2 months ago		
Doug Anmuth	J.P. Morgan		Buy	$1,075.00	Reiterated	2 months ago		
James Dix	Wedbush		Hold	-	Reiterated	2 months ago		
Daniel Salmon	BMO Capital		Hold	$970.00	Reiterated	2 months ago		
Mark Mahaney	RBC Capital		Buy	$1,050.00	Reiterated	2 months ago		
Eric Sheridan	UBS		Buy	$1,050.00	Reiterated	2 months ago		
Victor Anthony	Aegis Capital		Buy	$1,090.00	Reiterated	2 months ago		
Blake Harper	Loop Capital Markets		Hold	$800.00	Initiated	3 months ago		
Ross Sandler	Barclays		Buy	$1,065.00	Initiated	3 months ago		
Stephen Turner	Hilliard Lyons		Hold	$865.00	Reiterated	4 months ago		
Ralph Schackart	William Blair		Buy	-	Reiterated	4 months ago		
Joseph Bonner	Argus Research		Buy	$950.00	Reiterated	5 months ago		
John Blackledge	Cowen & Co.		Buy	$1,050.00	Reiterated	5 months ago		
Mark May	Citigroup		Buy	$985.00	Reiterated	5 months ago		
Neil Doshi	Mizuho Securities		Buy	$1,024.00	Reiterated	5 months ago		
Heather Bellini	Goldman Sachs		Buy	$970.00	Reiterated	5 months ago		
Ben Schachter	Macquarie		Buy	$995.00	Assigned	5 months ago		