A Surprise That Keeps You Awake: Overnight Returns After Earnings Announcements[a]

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Abstract

I dissect stock returns after earnings announcements into their overnight and intraday components and document strong positive abnormal overnight returns for several weeks after both large positive and negative earnings surprises. This finding is in line with attention-induced buying pressure. Consistently, the effect exists only when retail investors are net buyers and pay attention to the surprise. Corresponding intraday returns have the opposite sign, which makes this pattern invisible in close-to-close returns. Finally, results are stronger during high sentiment periods as well as for hard-to-arbitrage firms and weaker if the average investor holds the stock at a gain.

Keywords: Investor Attention, Large Earnings Surprises, Overnight and Intraday Stock Returns, Retail and Institutional Investor Trading, Disposition Effect

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1 Introduction

How do individual investors trade after large earnings surprises and how does this affect stock prices? Using discount brokerage trading data, Hirshleifer et al. (2008) find that retail investors are net buyers after both positive and negative earnings surprises for more than five weeks which is consistent with attention-induced buying pressure (Barber and Odean, 2008).[1] However, when looking at the price impact of this behavior, there seems to be no clear evidence. Is the aggregate impact of retail investors' trading decisions not powerful enough to temporarily move prices or is there no such trading behavior at all?

I contribute to this discussion by dissecting close-to-close returns into their overnight and intraday components. There are strong positive abnormal overnight returns for several weeks (event time $t+2$ to $t+31$) after both large positive (top 5%) and large negative (bottom 5%) earnings surprises. This pattern is consistent with buying pressure after attention-grabbing earnings surprises. However, corresponding intraday returns have the opposite sign and are of similar magnitude. Thus, in most cases the attention-induced buying pressure after large absolute earnings surprises is not visible in close-to-close returns. I depict these patterns in Figure 1.

[Insert Figure 1 about here]

The effect is economically large: The 10% most surprising earnings announcements are associated with abnormal DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted overnight returns of 4.10% from event time day 2 up to day 31. This result is robust to controlling for a battery of firm and event characteristics as well as using day- and firm-fixed effects.

My analysis is motivated by the literature that divides close-to-close returns into their overnight and intraday components (e.g., Cliff et al., 2008 and Branch and Ma, 2012). Recently, Lou et al. (2018) document that most cross-sectional anomalies are entirely driven by one of these two components.[2] Moreover, there seems to be a strong 'tug of war' between intraday and overnight returns, meaning that intraday returns typically go in the opposite direction as overnight returns which indicates a strong clientele effect. Based on their finding that institutional ownership increases more with intraday rather than overnight returns, they argue that institutions are more likely to trade intraday whereas retail investors are more likely to submit orders overnight.[3] A simple explanation for

[1]See also Lee (1992) who finds high buying activity in small trades after large absolute surprises and related studies of Lamont and Frazzini (2007) and Lawrence et al. (2017).

[2]Lou et al. (2018) also examine earnings announcements. However, contrary to my study, they assume a linear relationship between earnings surprises and overnight/intraday returns and thus are not able to detect the effects from attention-induced buying pressure after both large negative and positive surprises.

[3]Lou et al. (2018) further show that small trades (presumably by retailer investors) occur more near the market open while large trades (presumably by institutions) occur more near the market close for the pre-2000 time period, during which trade size proxies reasonable well for investor types. Linnainmaa (2010)

this might be that retail investors are relatively more likely to make trading decisions in the evening after work that are executed at the next open compared to institutional investors who prefer to trade intraday or at the close (e.g. Cushing and Madhavan, 2000 and Bogousslavsky and Muravyev, 2019).

Based on this reasoning, my findings provide an important potential explanation for why the previous literature is not able to detect any clear price impact: If an earnings surprise attracts substantial retail investor attention it is also likely that sophisticated investors are aware of this event and should thus trade against any noise traders' behavior in a timely manner. Although in this case markets are relatively efficient (related to the concept of "efficiently inefficient" markets of Pedersen, 2015), looking at overnight and intraday returns separately seems to reveal systematic return patterns that reflect the price impact of different investor types.

In order to examine this investor clientele channel more directly, I look at the actual trading behavior of retail investors after large earnings surprises. To do so, I use subpenny price improvements in order to identify retail order flow as proposed by Boehmer et al. (2019). This measure has the advantage of being available for all stocks in my sample for a long time period. I first confirm that retail investors are net buyers after large earnings surprises. Most importantly, the overnight/intraday return patterns after large earnings surprises exist only if retail investors are net buyers after the surprise. This is in line with the notion that retail investors' buying behavior is indeed driving the large positive overnight returns. Consistently, I further document that large earnings surprises are associated with a following decrease in institutional holdings.

To examine the attention channel in more detail, I use direct proxies for retail investor attention, namely Google search volume for firm tickers (Da et al., 2011) and Wikipedia page views (Focke et al., 2018)) for company pages. Indeed, I show that the overnight/intraday return patterns only exist if a large earnings surprise actually attracts retail investors' attention. Moreover, consistent with the notion that any attention shock should be temporary, the overnight buying pressure vanishes over time if there is no new attention-stimulus in the meantime.

Furthermore, overnight returns are especially high after *extreme* absolute earnings surprises, indicating a u-shaped pattern. Thus, my findings also contribute to the literature that tries to identify the actual drivers of retail investor attention and firm visibility.[4]

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finds that individual investors submit a substantial portion of their limit orders before the trading session starts. Aboody et al. (2018) show that overnight returns possess characteristics of a firm-specific retail investor sentiment measure. Recently, Akbas et al. (2019) find that that stocks with more pronounced overnight/intraday 'tug of war' patterns earn higher future returns which is consistent with noise trader risk being priced.

[4]Bali et al. (2019) argue that large absolute earnings surprises are a driver of investor attention but do not examine the exact functional form. Kumar et al. (2016) and Ungeheuer (2017) show that stocks which have large positive and negative returns or that are ranked as daily winners or losers experience spikes in attention. Since stocks that have large earnings surprises also are more likely to be daily winners or losers, I show that the results also hold for stocks that are not ranked. Thus, both large earnings surprises

One of the most robust empirical findings is the post-earnings announcement drift (PEAD hereafter).[5] The usual interpretation of the PEAD is an initial underreaction to fundamental news and a following drift towards the true value. Since I document that intraday returns are strongly negative after large negative earnings surprises, intraday returns seem to reflect the rational correction of overnight price pressure. Contrarily, after large positive surprises (top 10%), intraday returns are on average close to zero. Thus, the price pressure that occurs overnight may help price discovery after positive surprises to some degree. However, after very large positive surprises (top 5% and top 1%) that generate substantial retail investor attention, intraday returns are strongly negative. This effect can result in even negative close-to-close returns for very glamorous positive announcements. Thus, for extreme positive surprises, intraday returns seem to prevent prices from 'overshooting'.

I document that the overnight/intraday patterns after large earnings surprises are much stronger for stocks with higher limits to arbitrage, i.e. small stocks with low institutional ownership, low analyst coverage, low book-to-market ratio, and high idiosyncratic volatility (see, for example, Lakonishok and Shleifer (1994), Nagel (2005), Baker and Wurgler (2006), Pontiff (2006), Kumar (2009), and Stambaugh et al. (2012)). Moreover, especially small stocks are often less visible *ex ante* (see, for example, Fang and Peress (2009)) which potentially amplifies the attention-generating effect of having a large earnings surprise. Further, the overnight price pressure is more pronounced during high sentiment periods which is consistent with the notion that temporary overpricing should be more pronounced during these periods (Stambaugh et al. (2012)).

Moreover, I analyze the profitability of a simple trading strategy based on the documented effects. Of course, trading on these patterns requires substantial re-balancing and profitability heavily relies on trading costs. However, transaction costs have declined sharply over the last decade, especially for institutions (Frazzini et al. (2015)). For instance, Lachance (2015) estimates that investing overnight is associated with daily costs between 1.5 and 3.1 basis points which results in annual costs of about 4-8%. Since a simple long-only strategy based on these patterns earns an annualized raw return of 39.85% (DGTW-adjusted alpha of 32.46%) before trading costs, this strategy is most likely also profitable after costs.

An alternative interpretation of the overnight return price pressure could be that large earnings surprises proxy for an increase in overnight risk, potentially related to inventory holding risk (see, for instance, Hendershott and Menkveld, 2014). This might seem reasonable since most fundamental company news are announced overnight, e.g. earnings announcements. However, I document that the results still hold after controlling

and being ranked are distinct important drivers of retail investor attention.

[5]The term PEAD refers to the empirically documented positive abnormal returns after a positive earnings surprise and the negative abnormal returns after a negative surprise (e.g., Ball and Brown (1968) and Bernard and Thomas (1989)).

for the volatility of overnight returns. Moreover, the volatility of overnight returns on average does not change after large earnings surprises. Finally, this interpretation does not directly explain why the effect is conditional on retail net buying and retail investor attention.

Apparently, the findings in Figure 1 suggest that the buying pressure seems to be larger for negative surprises than for positive ones. Attention generated by large earnings surprises might not only attract new investors but also affect existing investors' behavior. The fundamental immediate price reaction at a large earnings surprise can push existing investors into the gain or loss domain. There is evidence that especially retail investors are prone to the 'disposition effect' which is the tendency to sell winner stocks 'too early' and hold on to loser stocks for 'too long' (e.g., Shefrin and Statman, 1985, Odean, 1998, and Frazzini, 2006).

Since investors have to be aware of the fact that they are holding a stock at a gain or loss, attention that is created by a large earnings surprise might be an important trigger for actual trading decisions based on the disposition effect (Yuan, 2015). Thus, the attention-induced buying pressure and the disposition effect might sometimes go in opposite directions. This is most likely the case after large positive surprises. Here the large attention-grabbing positive surprise is expected to attract new investors which results in positive buying pressure. However, the fundamental price movement at the announcement makes it also more likely that existing investors are holding the stock at a gain which might result in increased selling pressure due to the disposition effect.

In line with this reasoning, the overnight/intraday return patterns are strongly mediated by whether investors on average hold the stock at a gain or at a loss after the earnings surprise. More precisely, overnight returns after large surprises are higher if investors on average hold the stock at a loss after the announcement (both effects are supposed to go in the same direction). Moreover, the asymmetry in overnight buying pressure between negative and positive large surprises in relative terms is reduced significantly compared to the unconditional analysis (from 70.1% to 23.0%). The fact that the asymmetry is still not completely eliminated might be consistent with the 'negativity bias' which refers to the notion that negative news have a stronger impact on attention (see, for example, Pratto and John (1991) and Baumeister et al. (2001)).[6] Indeed, Hirshleifer et al. (2008) find that net purchases of retail investors are larger after negative surprises compared to positive ones.[7]. Consistently, I document that the patterns are symmetric if surprises attract the same amount of retail investor attention.

Contrary, overnight returns are substantially reduced if existing investors on average

[6]This can also lead to a catering effect: For instance, the media covers firms with negative news more extensively than those with positive news (e.g., Niessner (2017) and Garcia (2015)).

[7]Besides that, in my sample the mean forecast error in forecast error decile 1 is -2.3% whereas it is 1.4% in decile 10. Thus, there are on average more extreme attention-grabbing surprises in forecast error decile 1 than in decile 10.

hold the stock at a gain (both effects are supposed to go in opposite directions). Depending on which effect is stronger, this can lead to different conclusions regarding the overall price impact of the trading behavior of individuals. This finding highlights that it is important to separate the two effects.

Taking the main findings together and using the terminology of Lou et al. (2018), there seems to be a strong 'tug of war' between overnight and intraday returns after large earnings surprises which indicates a clientele effect. Attention-induced buying pressure as well as the disposition effect are both solely reflected in overnight returns. Apparently, overnight returns seem to reflect the price impact of trading behavior that is usually attributed to noise traders. Contrary, intraday returns seem to reflect rational corrections of this behavior.

To the best of my knowledge, these patterns in overnight and intraday returns after both negative and positive large earnings surprises have not yet been documented before. Analyzing only close-to-close returns might hide important systematic patterns in stock returns that stem from trading behavior of noise traders. Therefore, my findings may have broader implications for analyzing the price impact of other types of non-rational trading patterns that are based on other behavioral biases of investors like overconfidence, sentiment or mental-accounting (Thaler, 1999).

2 Related Literature

In general, my findings contribute to the literature on investor attention and the resulting implications for asset pricing. Bayesian surprises seem to be a strong attractor of human attention (Itti and Baldi, 2009). Since attention is limited (Kahneman, 1973) but also a necessary prerequisite for any trading activity, this finding from the psychology literature should also apply to financial investors. Especially retail investors do not have the capacities to constantly monitor all potential investment opportunities. Thus, unexpected events like earnings surprises should attract substantial investor attention towards a specific stock. In line with this reasoning, Koester et al. (2016) show that large positive earnings surprises can increase firm visibility up to three years.

In order to describe the expected influence of retail investor attention on market prices, Barber and Odean (2008) propose the price pressure hypothesis. Based on the argument that individual investors on average hold portfolios with a small number of stocks (e.g. Goetzmann and Kumar (2008) find that retail investors hold four different stocks on average) and do not engage in short selling, retail investor attention should be more important for the buy-decision than for the sell-decision. In the presence of limits to arbitrage (e.g., Shleifer and Vishny (1997)), this can result in temporary buying pressure (see, for example, Barber and Odean (2008) and Da et al. (2011)).

In line with this reasoning, Berkman et al. (2012) find that retail investors buy overnight after attention-grabbing trading days, which results in positive overnight returns that are then reversed during the following day. Yet, contrary to my study, Berkman et al. (2012) do not analyze earnings surprises and thus are not able to answer the question whether there is a price impact of attention-induced buying pressure after large negative and positive earnings surprises. Moreover, they only use indirect market-based measures of attention like squared past returns whereas I use direct measures of retail investor attention and explicitly control for indirect attention measures. Furthermore, they focus only on the next day reaction (where the open is necessarily the first opportunity to trade) whereas I document that the overnight price pressure consists for several weeks after the surprise which is more consistent with a general overnight/intraday trading clientele effect as documented in Lou et al. (2018). Last, they do not examine the moderating role of the disposition effect.

There is also a literature (see, for example, Lamont and Frazzini (2007) and Chapman (2018)) that proposes investor attention as a potential explanation for the earnings announcement premium which is the empirical finding that stock prices on average rise in the days around earnings announcement (see, for example, Beaver (1968), and Ball and Kothari (1991)). However, my findings are different since the earnings announcement premium also exists for announcements without any surprise and the overnight/intraday return patterns after large surprises also exist if there is no or even a negative effect on close-to-close returns.

Another strand of the literature on investor attention argues that inattention to fundamental news ('too little' attention) can lead to an initial under-reaction and a following drift towards the true fundamental value. For example, Hirshleifer et al. (2009), DellaVigna and Pollet (2009) and Hou et al. (2007) show that the PEAD is strongest if investors are more likely to be distracted at the announcement. Consistent with the explanation that is based on investor inattention, Fricke et al. (2014) find that an increase in Google search volume for stock tickers is associated with a stronger initial stock price reaction and Peress (2008) finds that more newspaper coverage reduces the PEAD.

However, Ben-Rephael et al. (2017) find no predictive power of retail investor attention after controlling for institutional investor attention. Hence, their finding suggests that the temporary underreaction to fundamental news due to inattention is mainly explained by inattention of institutional investors whereas the role of retail investor attention on stock prices remains unclear. Most importantly, all of these studies examine a linear relationship between retail investor attention and earnings surprises and thus assess whether retail investor attention leads to more efficient prices immediately at the announcement and less drift in the following period ('too little' attention) instead of analyzing potential buying pressure after both positive and negative surprises.[8]

[8]An exception is the recent study of Lawrence et al. (2016). They find that an increase in Yahoo Finance search volume at the earnings announcement is associated with relatively higher returns during

Looking at the actual trading behavior of retail investors, Hirshleifer et al. (2008) use trading data from one major discount broker in the US from 1991 to 1996. They document that retail investors are net buyers after large earnings surprises which is consistent with attention-induced buying behavior. However, Kaniel et al. (2012) use a trading data set of only NYSE stocks from 2000 to 2003 and find that individual investors trade in a news-contrarian way after earnings surprises.

My findings might also help to explain the partly contradicting evidence from these two studies. First, I document that the buying pressure is stronger for non-NYSE stocks (which are on average smaller and have higher limits-to-arbitrage) that are not covered in Kaniel et al. (2012) but in Hirshleifer et al. (2008). Second, Kaniel et al. (2012) mainly analyze the bottom and top 20% of surprises whereas I find that the overnight buying pressure is strongest after extreme surprises (largest 10%, 5% and 1%). Finally, I document that the overnight attention-induced buying pressure might be reduced or even reversed due to the disposition effect. However, Hirshleifer et al. (2008) and Kaniel et al. (2012) do not explicitly account for the disposition effect. Hence, if investors in these two samples differ with respect to their average gain/loss, e.g. due to the dot com bubble, there might be different overall net effects on their trading behavior.

3 Data and Methodology

In this section, I introduce the way I measure unexpected earnings surprises, overnight and intraday returns, and investor attention as well as other datasets that I use in my empirical analysis.

3.1 Earnings Surprises

I use quarterly earnings announcements from I/B/E/S and Compustat. Whenever the announcement date in I/B/E/S differs from the one recorded in Compustat, I follow DellaVigna and Pollet (2009) and use the earlier date. If an announcement has an hourly time stamp in I/B/E/S that indicates that the announcement was after the closing hour, I assign it to the next trading day (analogous to Berkman and Truong (2009)).

I use the difference between the actual announced earnings per share as recorded in I/B/E/S ($E_{i,q}$) and the analyst consensus earnings forecast ($F_{i,q}$) as the estimate of the earnings surprise (analyst-based earnings surprise). The consensus forecast is defined as the median forecast among all analysts in I/B/E/S. This difference is then normalized

the following quarter. However, they analyze only close-to-close returns and thus still find negative returns after negative surprises that attracted investor attention (although relatively larger) and they do not observe any reversal patterns. Thus, it is difficult to disentangle irrational buying pressure from a drift towards the fundamental value.

by the share price at the end of the previous corresponding fiscal quarter ($P_{i,q}$), following Kothari (2001) and Hirshleifer et al. (2009):

$$FE_{i,q} = \frac{E_{i,q} - F_{i,q}}{P_{i,q}} \tag{1}$$

In order to exclude stale forecasts, I use only one- or two-quarter ahead forecasts that are issued or reviewed during the last 60 cays before the actual earnings announcement and only the most recent forecast of each analyst is used. Moreover, following Ben-Rephael et al. (2017), I use only observations where at least two analysts have made a forecast during this period in order to get a more robust measure of the median forecast. Following Hirshleifer et al. (2009), I also exclude all observations for which the absolute value of the earnings forecast or the actual earnings per share is larger than the price at the end of the previous fiscal quarter.

In order to account for potential outliers and nonlinearities in the relation between earnings surprises and returns, I follow the literature (see, for example, Kothari (2001)) and use decile ranks in some analyses. Thus, I classify earnings announcements into 10 portfolios based on quarterly sorts by FE (FE *Decile*), respectively by the absolute value of FE (*Abs* FE *Decile*). During my main analysis, I use an indicator variable that takes the value one if the earnings surprise is in the top decile/vigintile/percentile (largest 10%/5%/1%) based on quarterly sorts by absolute forecast error as my main independent variable (*Abs* FE 10/*Abs* FE 5/*Abs* FE 1).

In total, my sample consists of 217,884 observations during the period June 1992 - December 2016.

3.2 Returns

I use all stocks with a share code of 10 or 11 in the Center for Research in Securities Prices (CRSP) database. I exclude stocks with a price smaller than 1 USD at the end of the fiscal quarter for which the earnings announcement is made in order to reduce the impact of microstructural issues like the bid-ask-bounce. Following Lou et al. (2018), I dissect total close-to-close returns from CRSP into their overnight (close-to-open) and intraday (open-to-close) components:

$$r^i_{intraday,\tau} = \frac{P^i_{close,\tau}}{P^i_{open,\tau}} - 1 \tag{2}$$

$$r^i_{total,\tau} = (1 + r^i_{overnight,\tau})(1 + r^i_{intraday,\tau}) - 1 \tag{3}$$

Since the close-to-close return from CRSP is adjusted for dividends, share splits and some other corporate events, I assume that these events happen overnight.[9]

I use open prices from CRSP. They reflect the first trading price of the day, including the opening auction, and are available starting from June 1992. They are directly sourced from TAQ. There might be some concerns that the first transaction price of a day might be associated with very small trading volume and thus might be subject to any stale price problems, especially for illiquid stocks. Although it is not obvious how this could create the systematic patterns in overnight and intraday returns *conditional* on earnings surprises, I address this issue by including various control variables for the illiquidity of a stock as well as excluding small and illiquid stocks during robustness tests. Furthermore, following Lou et al. (2018), I also use the volume-weighted average price ($VWAP$) of the first half hour of trading (9:30 am - 10:00 am) as an alternative open price to show the robustness of my results with respect to the choice of the open price. To be conservative, I exclude all observations with fewer than 1,000 shares traded in the first half hour for this test. The data is sourced from the Algoseek minute trade bar database which is available to me for the whole NYSE/AMEX/NASDAQ common stocks universe from 2007 to 2015. Nevertheless, I decide to use the CRSP open price for my main analyses for the following reasons: First, based on the idea that there is a clientele effect and some investors prefer to place their trades after the close, for sufficiently liquid stocks the open price should exactly reflect this behavior. For liquid stocks, it might be the case that the other clientele starts already trading in response to the observed open price during the first half hour which might lead to distortions. Second, the $VWAP$ open price cannot be used in order to implement a trading strategy since the needed weights are based on trading volume that is not known ex ante.

When dissecting the cross-sectional expected value (for instance the mean) of total close-to-close returns, it becomes apparent that because of compounding effects there are not only the components of the expected value of overnight and intraday returns but also the expected value of the interaction term $r^i_{overnight,\tau} \times r^i_{intraday,\tau}$ ($Interaction\ ON/ID$):

$$\mathbb{E}[r^i_{total,\tau}] = \mathbb{E}[(1 + r^i_{overnight,\tau}) \times (1 + r^i_{intraday,\tau}) - 1] \tag{4}$$

$$\mathbb{E}[r^i_{total,\tau}] = \mathbb{E}[r^i_{overnight,\tau}] + \mathbb{E}[r^i_{intraday,\tau}] + \mathbb{E}[r^i_{overnight,\tau} \times r^i_{intraday,\tau}] \tag{5}$$

This interaction effect captures the 'tug of war' between intraday and overnight returns *within* a given event window. A large negative interaction term indicates that intraday returns go in the opposite direction as the corresponding overnight returns for a given earnings announcement of a firm. Thus, the interaction term is informative. For instance, it might be the case that overnight returns are positive for half of the sample whereas intraday returns are negative for the other half of the sample. On average, overnight

[9]Lou et al. (2018) check this assumption and find no violation.

returns would be positive and intraday returns would be negative, but there would be no 'tug of war' behavior within a stock. However, in order to make sure that the choice of using non-log versus log returns is not driving the results, I also use log returns as a robustness test. Nevertheless, I stick to using non-log returns during my main analyses in order to exactly track the performance of an investor who follows a trading strategy of only investing overnight or intraday.

When comparing the magnitude of the average overnight and the average intraday returns in order to see which effect dominates, one has to keep in mind that by definition overnight returns always precede intraday returns on day τ. To give an example of the implications, assume that a stock has a fundamental value of 100. Assume further that on given day overnight returns of +20% irrationally push up prices up to 120. In order to correct this mispricing completely, it requires less than -20% in intraday returns to get back to a price of 100, which solely comes from the compounding effects and this effect is captured in the interaction term. According to my findings, overnight returns are on average positive after large surprises. Thus, even if intraday returns fully reverse this effect, the average intraday return would be smaller in absolute terms because of these compounding effects.

In order to account for systematic risk and well-known cross-sectional patterns in stock returns, I use DGTW adjusted returns (Daniel et al. (1997), and Wermers (2003)).[10] Therefore, I subtract the total/overnight/intraday return of a matched portfolio based on size, industry-adjusted book-to-market, and momentum from the total/overnight/intraday raw stock return. I exclude stocks without book-to-market information in Compustat. As an example, the abnormal buy-and-hold overnight returns during the drift period beginning from day h up to day H relative to the announcement date are defined as follows:

$$BHAR[h,H]^{i,q}_{overnight} = \prod_{\tau=t+h}^{t+H} (1 + r^{i}_{overnight,\tau}) - \prod_{\tau=t+h}^{t+H} (1 + r^{p}_{overnight,\tau}) \tag{6}$$

where t is the actual date of the earnings announcement of fiscal quarter q for firm i.

Instead of analyzing the initial impact directly at the announcement date, I mainly look at the return reactions during the following weeks (drift period). There are various reasons for this decision: First, this procedure makes my analysis predictive and thus allows me to test the profitability of a potential trading strategy as well as the semi-strong form of market efficiency. Second, a large portion of earnings announcements actually takes place after the closing hour (about 40%, see Berkman and Truong (2009)). Therefore, if

[10] For a robustness test, I use raw returns and report the results in Table A2. The results are nearly unchanged. In general, abnormal returns in short-horizon event studies do not so much depend on the choice of the systematic risk adjustment. This applies especially to my findings since the economic size of the effects are large.

markets are at least semi-strong efficient, all of the fundamental price adjustment should take place immediately at the next market opening. This makes it difficult to disentangle fundamental price reactions from attention-driven buying behavior at the announcement date. Thus, during my main analysis, I focus solely on the following drift period. Of course, attention-induced price pressure might also occur directly at the announcement date. However, this should bias against finding an attention effect on stock prices at all.

Similar to Ben-Rephael et al. (2017), I focus on the drift period up to 31 days ($H = 31$) after the announcement date in order to reduce the impact of confounding events but still being able to capture potential persistent effects of increased visibility. Moreover, this horizon is motivated by the finding of Hirshleifer et al. (2008) who show that retail investors seem to be net buyers after large earnings surprises for more than 25 trading days. However, I also test various additional drift periods to show the robustness of my results. Since there are no hourly timestamps of the announcements in I/B/E/S for the beginning of my sample period, I exclude the first day after the announcement (event time $t + 1$) to not capture the initial reaction for announcements that took place after the closing hour (following Berkman and Truong (2009)).

Last, I winsorize returns at the 0.01% level in order to make sure that extreme values or potential data errors, e.g. erroneous open prices, are not driving my results.

3.3 Direct Investor Attention Measures

In order to test whether the documented overnight/intraday patterns are driven by retail investor attention, I use attention proxies based on investors' Internet searching behavior as more direct measures (see, for example, Da et al. (2011) compared to measures that are directly linked to market outcomes like abnormal trading volume or absolute returns.

For the first measure within this category, I use Google search volume for stock tickers.[11] Retail investors are expected to use Google whereas institutional investors are more likely to gather information using more professional services like Bloomberg terminals (Ben-Rephael et al., 2017). As proposed by Da et al. (2011), I use stock tickers instead of firm names as search terms since they are in general less ambiguous. In order to further reduce the problem of ambiguity, I also exclude all tickers that are also listed in the Merriam-Webster dictionary. Following Drake et al. (2012), I calculate abnormal search volume by using the difference between the search volume index ($SVI_{i,t}$) and the median search volume index value of the same day-of-the-week over the previous 10 weeks in order to account for intraweekly seasonality in Internet search behavior. This difference is then normalized by the median search volume index value of the same day-of-the-week over the previous 10 weeks. I take the natural logarithm of this ratio to reduce skewness. In order to also include days with zero attention (i.e. $SVI = 0$), I add one before taking

[11] Google provides this data on their webpage www.trends.google.com.

the logarithm:

$$Abn.\ Google_{i,t} = ln(1 + \frac{SVI_{i,t} - median(SVI_{i,t,\ same\ day-of-the-week,\ previous\ 10\ weeks})}{median(SVI_{i,t,\ same\ day-of-the-week,\ previous\ 10\ weeks})}) \quad (7)$$

In order to make sure that extreme values are not driving my results, I winsorize $ASVI$ at the 1%-level. Google search volume data is available starting from 2004.

It might take some time until the information of an earnings surprise actually reaches retail investors. For instance, the media may reports about the surprise on the next day. In line with this, Peress (2008) documents that the fraction of covered firms in the WSJ increases nearly nine fold on event time day $t + 1$ compared to the average coverage. Therefore, I follow Peress (2008), and use the cumulative abnormal search volume from event time day t to day $t+1$, i.e., up to one day after the announcement. This is especially important if the earnings announcement was in the evening and the print media can only react on this during the next day. Last, since Google aggregates daily search volume from midnight-to-midnight in Pacific Standard Time, one might be worried that the search volume after the close on day $t + 1$ reflects fundamental information that is reflected in the next opening price. Although my analysis would still be predictive in this case, I redo my base analysis with an event window that starts from day $t + 3$ in order to show that this is not driving my results.

To test the robustness of my results, I use a second measure based on Internet search behavior of retail investors, namely daily Wikipedia page views of firms. This dataset includes hourly page views for Wikipedia pages of US firms traded on NYSE, AMEX and NASDAQ and was introduced in Focke et al. (2018), Ungeheuer (2017) and Hillert and Ungeheuer (2016). Wikipedia page views as a measure of attention may have several advantages over Google search volume. First less frequently searched firms often do no have a valid SVI in Google. Moreover, using Wikipedia firm pages reduces the problem of potentially noisy tickers.[12] The hourly availability also allows me to aggregate page views from close-to-close. I exclude Wikipedia pages with less than 1000 page views during the previous month in order to reduce the impact of outliers for pages with few views.[13] I calculate abnormal Wikipedia pageviews ($AWIKI$) in the same way as the Google search volume measure, apply the same adjustments and also use cumulative abnormal page views from event time day t to day $t + 1$. I add one to the number of pageviews on each day in order to also include observations where the median of previous pageviews was zero[14] Wikipedia data is available starting from January 2008.

[12]For an extensive discussion of the potential advantages as well as a detailed description of the data gathering process, see Focke et al. (2018).

[13]For instance, these pages might be heavily affected by non-human visitors like webcrawlers.

[14]I do not do this adjustment when using Google data since Google uses an arbitrary and unknown threshold when calculating the daily pageviews. If the daily search volume is below this threshold, Google

During some tests, I use abnormal requests for firm filings on the SEC EDGAR server as a proxy for institutional investor attention (see, for instance, Drake et al. (2015) and Loughran and Mcdonald (2015)). I use the SEC EDGAR log file data that is provided by James Ryans.[15] This data is already cleaned for non-human views as described in Ryans (2017). I calculate abnormal EDGAR institutional attention (*Abn. EDGAR*) in the same way as abnormal Google search volume. SEC EDGAR data is available starting from January 2003.

3.4 Other Variables

In order to examine the role of the disposition effect, I use the market-based measure of Grinblatt and Han (2005). It proxies for the aggregate unrealized capital gains overhang (CGO) of the investors who are currently holding the stock. By using past trading volume, one can determine a proxy for the probability that a certain investor who bought a share at a point in time for a certain price is still holding this share. This hypothetical purchase price is then used as reference price for the mental account.[16] I calculate a daily version of this measure and use CGO at the close of the earnings announcement date t in order to capture the effect of the initial announcement price reaction on investors' gains and losses. Since very distant prices have nearly no influence on the reference price, I follow Grinblatt and Han (2005) and truncate the estimation at 1,250 trading days. Hence, the measure is calculated in the following way:

$$CGO_{i,t} = \frac{P_{i,t} - RP_{i,t}}{P_{i,t}} \tag{8}$$

$$RP_{i,t} = \frac{1}{k} \sum_{n=1}^{1250} (Vol_{i,t-1-n} \prod_{\tau=1}^{n-1} [1 - Vol_{i,t-1-n+\tau}]) P_{i,t-1-n} \tag{9}$$

where $RP_{i,t}$ is the reference price and $P_{i,t}$ the stock price at the close at the earnings announcement date t and k is a constant such that weights sum up to one.[17] In order to reduce the potential impact of outliers, I follow Birru (2015) and use quintile ranks based on quarterly sorts by CGO.

In order to measure the trading behavior of retail investors, I rely on a proxy that has been proposed by Boehmer et al. (2019). They exploit the fact that due to regulatory

just reports a SVI of zero. Thus, contrary to Wikipedia pageviews, a median Google search volume of zero is not meaningful and quite noisy. For this reason, I exclude these observations.

[15] I thank James Ryans for providing this data. The data can be accessed at http://www.jamesryans.com

[16] For a detailed discussion about the CGO measure and the underlying model, please see Grinblatt and Han (2005).

[17] I do not adjust stock prices since there is evidence that retail investors fail to split-adjust their reference point (Birru (2015) and do not properly account for dividends (Hartzmark (2019)).

restrictions (Reg NMS) in the U.S. only retail but not institutional order flow can receive sub-penny price improvements. Nearly all of these price improvements take place off-exchange[18]. Hence, following Boehmer et al. (2019), I use Trade Reporting Facility (TRF) data and classify a transaction as a retail buy if the transaction price is slightly below the round penny ($> .6$) and as a sell if the price is slightly above the round penny ($<$ .4). To be conservative, I followg Boehmer et al. (2019) and exclude transactions that are executed around and at the midpoint (between .4 and .6). This allows me to extract marketable retail investor orders. An advantage of this retail trading measure is that it covers all stocks in my sample for a relatively large time period and that it is most likely representative for the total population of retail investors[19]. I then construct retail buy-sell imbalances by looking at the difference between the number of traded shares that are classified as a buy and those that are classified as a sell. I scale the buy-sell imbalances by the total number of shares outstanding to make the measure comparable across different stocks ($ScaledRetailBSI$). I aggregate the buy-sell imbalances over event time days $t+2$ to $t+31$ by summing up in order to measure retail investor trading behavior after earnings announcements. Finally, I winsorize this scaled aggregate measure at the 1% level to reduce the impact of potential outliers. Moreover, I also use a more robust dummy variable ($RetailBuy$) that takes the value one if the buy-sell imbalance is positive (net buying) and zero otherwise. Due to the introduction and implementation time of the Reg NMS legal framework, data on retail investor trading is available starting in January 2007.

I use institutional ownership data from 13f filings at the end of the respective previous quarter. Similar to Nagel (2005) and Kumar et al. (2016), during some analyses I use the residuals from cross-sectional regressions of the logit transformation of institutional ownership on size, size squared and the Amihud (2002) illiquidity ratio in order to create variation in institutional ownership when keeping size and liquidity largely fixed. This data is available to me up to Q3/2015.

In order to measure abnormal trading volume at the announcement, I take the logarithm of the ratio of the stock's trading volume at the announcement date ($Vol_{i,t}$) to its average trading volume over the previous 252 trading days:

$$Abn.\ Volume_{i,t} = \ln(\frac{Vol_{i,t}}{Average\ Vol_{i,t-1,t-252}}) \tag{10}$$

If not stated explicitly otherwise, all continuous control variables are winsorized at the 0.1% level in order to reduce the impact of large outliers and to make the linear OLS

[18]According to Boehmer et al. (2019), also the majority of retail trades are internalized or executed by a wholesaler and thus executed off-exchange. Moreoever, most of the retail orders actually get sub-penny price improvements.

[19]Boehmer et al. (2019) validate their proxy by comparing it with a sample of actual proprietary Nasdaq retail trading (TRF) data that is also used in Menkveld et al. (2017)

regression estimates more robust.

3.5 Summary Statistics

A detailed description of all variables can be found in Table A1 in the Appendix. Summary statistics are displayed in Table 1. Panel A shows the univariate distributions of the main variables and Panel B shows the respective pairwise Pearson correlation coefficients.

[Insert Table 1 about here]

Abnormal close-to-close returns are on average slightly positive (7 basis points) after earnings announcements which is consistent with the finding of Lamont and Frazzini (2007) that there seems to exist an earnings announcement premium during the month of the announcement. On average, all proxies for abnormal attention are positive at earnings announcements and some announcements seem to generate large spikes in abnormal attention which is indicated by the positive skewness of these variables. Moreoever, in Panel C, I show that the pairwise Pearson correlation coefficients between the indirect proxies for attention (abnormal trading volume, number of analysts) and direct proxies for attention (Google search volume, Wikipedia pageviews and SEC EDGAR filing downloads) are all positive but still far from being perfectly correlated.

4 Baseline Empirical Analysis

4.1 Main Results

I start my empirical analysis by looking at the mean buy-and-hold total, overnight, and intraday abnormal returns by FE decile rank ($FE\ Decile$) during the event window day $t+2$ to $t+31$. The decile ranks are based on quarterly sorts by earnings forecast errors (FE). I show the results of this analysis in Table 2, Panel A.

[Insert Table 2 about here]

The increasing close-to-close returns ($Total\ BHAR\ [2,31]$) from decile 1 (most negative surprises) to decile 10 (most positive surprises) confirm the existence of the well-documented post-earnings announcement drift (e.g., Bernard and Thomas (1989)) in my sample. More importantly, when dissecting close-to-close returns into their overnight and intraday components, a striking pattern appears: There are large positive overnight returns ($ON\ BHAR\ [2,31]$) after both large negative (3.45% for $FE\ Decile = 1$) and large positive (2.02% for $FE\ Decile = 10$) surprises. This is consistent with buying pressure due to the attention-grabbing effect of large earnings surprises. Moreover, this price pressure is economically large and exceeds the close-to-close post-earnings announcement drift returns by far in magnitude.

This result is consistent with Hirshleifer et al. (2008) who find that retail investors are net buyers after both positive and negative earnings surprises for more than 25 trading days after the announcement. It seems plausible that it takes some time until retail investors are aware of the surprise. For instance, the media might cover the event during the next days (e.g., Peress (2008)). Further, it might take some time until retail traders implement their trades since the increase in visibility of the stock does not necessarily indicate that investors have to react fast on this event. For this reason, an increase in visibility can lead to buying-pressure over the next weeks (see, for instance, Gervais et al. (2001), and Koester et al. (2016)).

In contrast, there is no indication of buying pressure when looking at intraday returns. In fact, intraday returns are highly negative after negative surprises (-1.67% for $FE\ Decile$ 1) and close to zero for positive surprises (0.04% for $FE\ Decile = 10$). The usual interpretation of the post-earnings announcement drift is that there is an initial underreaction to fundamental news and a following drift towards the fundamental value. Since the intraday returns during the drift period are almost monotonically increasing from decile 1 to 9, it seems like intraday returns are pushing prices towards their fundamental value except for very positive surprises.

Because of the large overnight buying-pressure after very negative surprises, there exists a strong 'tug of war' behavior for large negative surprises. Contrary, for positive surprises, the increased buying-pressure in overnight returns is not necessarily leading to mispricing. Thus, the price pressure that occurs overnight may help price discovery after positive surprises to some degree if investors initially underreact to the announcement. Only if the buying-pressure is so large that prices start 'overshooting', intraday returns should go in the opposite direction when they are reflecting rational corrections. Apparently, Figure 1 already shows that overnight returns are much more positive for extreme ranks and corresponding intraday returns become negative after very large positive surprises (top 5%). This is consistent with the notion that very large positive surprises can lead to overshooting prices during the overnight period and intraday returns seem to correct them.

In order to explore this hypothesis in more detail, I examine more extreme surprises and look at the top and bottom vigintiles and percentiles. I report the results in Panel B of Table 2. Consistent with the idea that extreme surprises should lead to more buying pressure, overnight returns are much higher after both extreme negative surprises (7.85% for the bottom 1%) and extreme positive surprises (4.17% for the top 1%) compared to large surprises (3.45% for the bottom 10% and 2.02% for the top 10%). Consistent with the notion that more buying-pressure after positive surprises leads to a higher probability of 'overshooting' prices, intraday returns after extreme positive surprises are strongly negative (-2.46% for the top 1%) which is not the case for large positive surprises (0.04% for the top 10%). Thus, there exists a strong 'tug of war' between overnight and intraday returns for extreme earnings surprises. This is also indicated by the interaction term between intraday and overnight returns ($Interaction$) that shows the 'tug of war' *within* the event window of an announcement of a firm. This interaction term is much more negative after both large negative and positive earnings surprises.

Apparently, the buying pressure seems to be larger for negative surprises than for positive surprises. There is a large literature in psychology that examines the 'negativity bias' which refers to the notion that negative happenings have a stronger impact on a person's behavior and cognition like attention (see, for example, Pratto and John (1991) and Baumeister et al. (2001)). This can also lead to a catering effect: For instance, the media covers firms with negative news more extensively than those with positive news (see, for example, Niessner (2017) and Garcia (2015)) which might lead to the fact that negative surprises generate more attention. Indeed, Hirshleifer et al. (2008) document that net purchases of retail investors are actually larger after negative surprises compared to positive surprises.[20]

To control for important other factors that might affect both intraday/overnight returns and earnings surprises, I do OLS regression analyses. Since I want to test the hypothesis that both negative and positive earnings surprises lead to overnight price-pressure and based on the results in Figure 1, I do quarterly sorts by *absolute* forecast errors.[21] I then use an indicator variable that takes the value one if the absolute forecast error is in the top decile (largest 10%) as my main independent variable ($Abs.\ FE$ 10). Thus, this variable indicates whether an earnings announcement is a large surprise and reflects both large negative and large positive surprises.[22] Using an indicator variable provides a robust way of testing the economic effect of having a large earnings surprise without heavily relying on the definition of the forecast error and the underlying functional form. Due to the seemingly u-shaped patterns this approach might be more appropriate than assuming a linear relationship.[23]

I add various control variables in order to test whether my results are driven by any omitted variable. I control for firm size, book-to-market ratio, market beta, idiosyncratic volatility, Amihud (2002) illiquidity ratio, abnormal trading volume, number of analysts and aggregate capital gains overhang (Grinblatt and Han (2005)). Furthermore, I control

[20]Besides that, the mean forecast error in decile 1 is -2.3% whereas the mean forecast error in decile 10 is 1.4%. Thus, there are on average more extreme attention-grabbing surprises in forecast error decile 1 than in decile 10. Consistently, I document in Chapter 4 that the effects are symmetric when controlling for the amount of attention generated. Moreover, I examine the role of the disposition effect as another source of this asymmetry in Chapter 4 as well in more detail.

[21]Furthermore, I report the results when separating negative and positive large surprises in Table 10.

[22]Although the mean FE within the top absolute FE decile is -0.0056, the number of announcements with positive surprises (9,919) is comparable to the number of announcements with negative surprises (11,818).

[23]However, I show in robustness tests that nearly identical results occur when using raw absolute forecast errors, squared absolute forecast errors, or decile ranks based on absolute forecast errors. I report the results in Table A2.

for the volatility of the earnings forecast in order to proxy for differences in opinion among investors (Diether et al., 2002).

Even after controlling for these variables, overnight returns are still significantly higher (2.095, t-stat: 13.40) after large earnings surprises whereas intraday returns are significantly lower (-1.684, t-stat: -9.20), confirming the documented 'tug of war' behavior (see Panel C of Table 2). In columns 3 and 4, I use firm-fixed effects in order to control for all time-invariant firm characteristics that might be related to overnight/intraday return patterns. The results show that even *within* a firm, having a large earnings surprises is associated with larger overnight returns and lower intraday returns. In columns 5 to 8, I look at more extreme earnings surprises (largest 5% and largest 1%). Consistent with the idea that larger surprises should on average be associated with larger price pressure, overnight returns increase significantly. Perhaps even more striking is the finding that intraday returns become much more negative for extreme surprises in relative terms. Whereas intraday returns reverse about 42% of overnight returns for the 10% largest surprises, they correct 74% for the 5% largest surprises and more than 100% for the 1% largest surprises.[24]

Next, I analyze how overnight/intraday returns after large earnings surprises evolve at longer time horizons. For this reason, I look at the event windows $t+32$ to $t+61$ and $t+62$ to $t+91$. I report the results in Panel D of Table 2. Up to event day $t+61$, overnight buying-pressure seems to be quite persistent. However, this changes when looking at the period up to day $t+91$: Now overnight returns after large surprises are reduced by more than 50% compared to the previous period (0.595% compared to 1.245%). This is consistent with temporary price-pressure that should flatten out in the long run if there is no new attention stimulus in the meantime[25].

Nevertheless, the overnight buying-pressure is seemingly not completely eliminated up to day $t+91$. In general, attention effects could also lead to a quite persistent increase in visibility[26]. However, increasing the event window increases the risk of including confounding events. A large absolute earnings surprise in one quarter is positively correlated with a large absolute earnings surprise next quarter[27] which can be a confounding new attention stimulus. Thus, in columns (5) and (6) I control for a forward-looking indicator variable ($F1$ *Abs.* FE 10) that takes the value one if the earnings announcement of the next quarter is a large absolute surprise (i.e., *Abs.* FE 10 of the next fiscal quarter takes the value one). After controlling for this variable, the long-term effect of having a large earnings surprise is almost completely eliminated and statistically insignificant from zero.

[24]Since the event window starts at event time day $t+2$, initial price pressure directly at the announcement date is not reflected which makes the interpretation of the total effect difficult.

[25]Note that there is no long-term reversal since overnight price pressure is already reversed during the corresponding intraday periods.

[26]Koester et al. (2016) show that large positive earnings surprises can increase firm visibility up to three years

[27]I document a Pearson correlation coefficient of 0.43 in my sample.

This result supports the reasoning that attention-induced buying-pressure should die out in the long run if there is no new attention stimulus in the meantime.

All in all, there is strong evidence of temporary buying-pressure after large earnings surprises that is reflected solely in overnight returns. Corresponding intraday returns go in the opposite direction and seem to drive prices towards their fundamental value if overnight buying-pressure pushes prices away from their true fundamental value, which is most likely the case after negative and extremely positive surprises.

4.2 Robustness Tests and Alternative Interpretations

I run various tests in order to check the robustness of my previously documented main results. The results can be seen in Table A2 in the Appendix.

Fist, in Panel A, I address the concern that the effect might be entirely driven by very small and low-price stocks for which micro-structural or liquidity issues might play a substantial role. Since I am using transaction data, one might for instance be worried that the results simply reflect the bid-ask bounce.

I therefore exclude all firms that are in the bottom size quintile (using NYSE breakpoints based on the market capitalization at the end of the previous fiscal quarter) and include only observations with a share price above 10 USD at the end of the previous fiscal quarter. Although the magnitude of the coefficients is reduced, the effects are still economically and statistically highly significant at the 1% level.

Moreover, a random bid-ask bounce alone does not result in overnight returns that are on average larger than intraday returns *conditional* on large earnings surprises, especially when controlling for various firm characteristics and using firm-fixed effects. After all, the economic size of the effects that I document seems too large to be explained by the bid-ask-spread alone. All in all, it seems very unlikely that the bid-ask-bounce alone can explain my finding.

In Panel B, I exclude all observations within the bottom and top 1% of forecasts errors as well as within the bottom and top 0.1% of abnormal returns to make sure that extreme observations and potential outliers are not driving the results. Although I document that among those very extreme surprises the effects are strongest, I still find that the documented patterns and their magnitude is similar as in the baseline regressions when excluding those very extreme observations.

In Panel C, I address the concern that the interaction term between overnight and intraday returns that stems from discrete compounding is distorting. For this reason, I use log-returns. Log-returns are additive over time and hence, there is no interaction term. The results are qualitatively the same.

In Panel D, I use raw returns in order to show that the results are not sensitive to the way how returns are adjusted for systematic risk. The results in Panel D are similar as when using DGTW adjusted returns.

Panel E examines the robustness of the choice of the open price. Following Lou et al. (2018), I use the volume-weighted average price ($VWAP$) of the first half hour of trading (9:30 am - 10:00 am) as an alternative open price in order to test whether any stale price problems of illiquid stocks might drive the results. In fact, the choice of the open price does not drive the results although the statistical significance is slightly reduced due to the smaller sample (but still highly significant at the 0.1% level). The economic size of the effect is slightly reduced which might indicate that for very liquid stocks, returns during the first half trading hour already go against previous overnight returns.

Kumar et al. (2016) show that stocks that are ranked as daily winners or losers (DWL) are associated with temporary attention-induced overpricing due to retail investor buying pressure. It seems plausible that stocks with large earnings surprises are also more likely to be a daily winner or loser at the announcement date. In order to test whether the overnight buying pressure after large earnings surprises is solely due to the fact that these stocks are also a daily winner or loser, I take a very conservative approach and exclude all stocks that ranked in the top or bottom 100 in the full CRSP universe at the announcement date t or at the next trading day $t+1$. Panel F in Table A2 shows that the attention effects due to earnings surprises still exists when excluding these stocks. Thus, the effect of having a large earnings surprise is not driven by a daily winner or loser effect.

In Panel G, I exclude all stocks with an absolute announcement date return (t and $t+1$) that is larger than the 30th percentile of all absolute announcement date returns. Furthermore, I control for the absolute announcement date return. The results show that it really seems to be the large earnings surprise *per se* that is driving the overnight price pressure and not the announcement date return which helps to identify earnings surprises as an important driver of investor attention.

In Panel H, I control for cumulative past intraday and overnight returns before the earnings announcement (event time day $t-32$ up to $t-1$) as well as the previous earnings surprise (lagged $AbsFE10$) in order to account for pre-announcement effects that might lead to spurious findings.

In Panel I, I employ various additional control variables. Further controls are the cumulative raw return and the mean turnover during the five trading days preceeding the announcement (Aboody et al. (2010) and Akbas (2016)) as well as the logarithm of one plus the number of days between the fiscal quarter end and the announcement (Chambers and Penman, 1984).

Next, I test different alternative ways of defining large earnings surprises as the main independent variable instead of using an indicator variable. For this reason, in Panel J, I use the raw value of the absolute forecast error. In Panel K, I use the squared raw value of the absolute forecast error in order to fit the convex (concave) overnight (intraday) patterns that I document in Table 2 more accurately. Last, I use decile ranks based on quarterly sorts by the absolute value of the forecast error (FE) and use these ranks as my main independent variable (*Abs.* FE *Decile*) and the results are shown in Panel L.

Moreover, I analyze whether the baseline effect does still exist in recent years. I do a sample split and examine the periods 1992 - 2004 and 2005 - 2016 separately. In Panel M, I show that the statistical significance of the coefficients is very similar in both sub-periods. However, the economic size of the effect seems to be smaller in the recent sub-period which might indicate that markets have become more efficient in recent years, e.g. because of high-frequency algorithmic trading that might already correct prices at the open. However, in unreported results I also make sure that the effects have a similar economic size when only looking at the very most recent sub-period from 2014-2016 which indicates that the findings are still relevant nowadays.

All in all, the baseline effect shown in Table 2 seems to be very robust with respect to various concerns regarding micro-structural issues, liquidity and data errors.

A remaining concern might be that earnings surprises reflect uncertainty about the true value of the firm. Correspondingly, investors might require a premium in order to compensate them for any kind of systematic risk that is related to this uncertainty. Cliff et al. (2008) and Kelly and Clark (2011) empirically show that the US equity premium over the last decade is mainly realized during overnight periods. Thus, it might be that the relation between positive overnight returns and large earnings surprises is spurious and the overnight returns are actually compensating for this systematic risk. However, overnight returns on average seem to be less volatile than intraday returns (Kelly and Clark, 2011). Most importantly, this potential explanation is not consistent with the finding that total close-to-close returns after negative earnings surprises are actually negative.

However, having a large earnings surprise might be associated with an increase in overnight risk, potentially related to inventory holding risk (see, for instance, Hendershott and Menkveld, 2014). Since most fundamental company news are released overnight, e.g. earnings announcements, this might be relevant. Hence, in panel N, I additionally control for the volatility of overnight returns before the announcement (event time $t-32$ to $t-2$) as well as after the announcement (event time $t+2$ to $t+31$) and show that this does not affect the results. Moreover, I find that the volatility of overnight returns does not change after having a large earnings surprise (2.03% before and 1.97% after). These results are robust to using winsorized (1%) measures of overnight return volatility. Hence, it seems unlikely that the patterns reflect a compensation for overnight risk.

Finally, in Panel O, I show that the results also hold when only using stocks that are traded on the NYSE where the open price is determined by a single opening auction. This addresses any concerns that the results might be distorted by the opening cross procedure at the Nasdaq exchange.

4.3 Announcement Date Reaction and Alternative Horizons

So far, I analyze abnormal returns during the period $t+2$ up to $t+31$ in event time for my baseline analysis. In order to test the robustness of this choice and to get additional insights when exactly the overnight/intraday patterns are occurring, I examine various alternative horizons. I report the results in Table 3

[Insert Table 3 about here]

In columns (1) and (2), I look at the effect directly at the announcement date.[28] If markets are semi-strong efficient, all fundamental reaction should happen immediately at that date. Thus, it is hard to disentangle price-pressure from fundamental reaction to the earnings news, especially since some earnings announcements occur intraday whereas others occur after the close. Nevertheless, I observe that overnight returns directly at the announcement of large surprises are larger (-0.16%) than intraday returns (-0.44%). Since the surprises include both negative and positive ones, it seems that part of the large overnight returns might stem from attention-induced buying behavior. It might be that positive surprises are occurring more frequently after the close whereas negative surprises might be systematically occurring more frequently intraday. However, there is various evidence in the literature (see, for example, Patell and Wolfson (1981)) that exactly the opposite is happening: Managers strategically release bad news after the close and good news intraday, which is also known under the "good news during, bad news after" hypothesis.

In columns (3) and (4), I look at the day directly after the announcement. For the beginning of the sample when no timestamp is available in I/B/E/S, this day might still reflect the initial announcement date reaction if the announcement happened after the close. In line with this, both overnight and intraday returns are still negative since the average forecast error is negative. Nevertheless, overnight returns (-0.06%) are again relatively larger than intraday returns (-0.14%). However, when looking at event time day $t+2$, overnight returns become clearly positive (0.06%) and significant (t-stat: 3.28). In contrast, the following intraday returns are insignificant (t-stat: -1.33). Only from day $t+3$ onwards the previously documented 'tug of war' pattern clearly occurs.

In Panel B, I show that the effects also exist when choosing a different event window, e.g. from day $t+2$ up to $t+11$ or $t+21$ and that the results are not entirely driven by the first day of the drift period $t+2$ or the first ten trading days after the announcement. Therefore, the overnight/intraday return patterns after large earnings surprises seem to be robust with respect to the exact choice of the event window.

[28]Note that for this analysis, I lag the control variable CGO by one day to not encounter any forward-looking bias.

4.4 The Role of Retail Investor Trading

In this subsection, I examine the investor clientele channel more directly by looking at the role of actual trading behavior of retail investors after large earnings surprises. I rely on a proxy for retail investor trading that is recently proposed by Boehmer et al. (2019). More precisely, I use sub-penny price improvements in order to identify retail order flow.[29] This allows me to construct daily retail buy-sell imbalances for a stock. Further, imbalances are scaled by the number of shares outstanding to make the measure comparable across stocks. I aggregate these daily buy-sell imbalances for event time day $t + 2$ to $t + 31$ in order to relate it to the return patterns and winsorize this measure at the 1% level to make it more robust with respect to potential outliers. First, I examine retail investor trading behavior after large earnings surprises in general. The results can be seen in Table 4.

[Insert Table 4 about here]

First, the findings in columns (1) and (2) in Panel B confirm that retail investors are indeed net buyers after large earning surprises. The mean scaled retail BSI after large earnings surprises is significantly positive (0.28, t-stat: 5.93) and is significantly larger than the BSI after small surprises (difference = 0.4, t-stat: 8.8). This is in line with the findings of Hirshleifer et al. (2008).

Next, I link retail investor trading to the documented overnight/intraday return patterns. If the overnight/intraday return patterns after large earnings surprises reflect buying pressure of retail investors, then one would expect that these patterns should only exist if retail investors are indeed net buyers.

In order to test this, I look at the interaction between having a large earnings surprise and an indicator variable that takes the value one if retail investors are net buyers after the surprise. I additionally control for all variables used in the previous analyses and employ firm-fixed effects. The results can be seen in Panel B of Table 4.

First, the strong baseline effect of retail buying on overnight returns (1.34, t-stat: 22.21) is in line with the hypothesis that retail investors' trading behavior in general is reflected in overnight returns. Most importantly, I document that the baseline effect of having a large earnings surprise completely vanishes after one includes the interaction term with retail net buying. Hence, there are no abnormal positive overnight and negative intraday returns after large earnings surprises if retail investors are net sellers. Contrary, the overnight/intraday patterns after large earnings surprises are strong and highly significant (2.48, t-stat: 6.68 for overnight returns and -2.52, t-stat: -5.68 for intraday returns) if retail investors are net buyers. Finally, one might wonder why the interaction term between $AbsFE10$ and $RetailBuy$ is still significant if retail investor trading is the only

[29] For details about the construction process as well as the regulatory framework, please see Section 3 as well as Boehmer et al. (2019).

channel. However, $RetailBuy$ is only an indicator variable. Columns (3) and (4) of Panel B show that the actual retail BSI is on average much stronger after large earnings surprises. Hence, $AbsFE10$ proxies also for the strength of the retail buying pressure which explains the highly significant positive interaction term.

Overall, these results are consistent with the explanation that it is indeed price-pressure induced by retail investors that is driving the overnight/intraday patterns after large earnings surprises.

4.5 Changes in Institutional Ownership

In order to examine the robustness of the previously documented retail investor trading results, I also examine the association between large earnings surprises and changes in institutional ownership. If the positive overnight returns after large earnings surprises really reflect buying pressure of retail investors, then one would expect that the fraction of institutional holdings should decrease after large earnings surprises. In order to test this, I use data on institutional holdings from 13f filings and regress the change in institutional holdings from fiscal quarter $t-1$ to quarter $t+1$ on the indicator variable for having a large earnings surprises. I winsorize the change in institutional holdings at the 1% level in order to get a more robust measure. I additionally control for all variables used in the previous analyses and employ firm-fixed effects. The results can be seen in Table 5.

[Insert Table 5 about here]

Consistent with the hypothesis that large earnings surprises attract net-buying of retail investors, the fraction of institutional investors' holdings decreases after large surprises. This effect gets stronger the larger the absolute earnings surprise is. For instance, an earnings surprise in the largest 10% decile is associated with a 0.443% decrease in institutional ownership (t-stat: -17.44) whereas an earnings surprise in the largest 1% is associated with a 0.848% decrease (t-stat: -10.61). This effect is economically significant as a standard deviation of the distribution of the change in institutional holdings is 2.16%.

I test the robustness of this finding by excluding the observations with the largest and smallest 1% of institutional holding changes. I report the results in columns 7 and 8 and they indicate that the effects are not driven by extreme institutional holding changes.

4.6 Periods of High Market Sentiment

In this subsection, I examine the time-series variation of the overnight/intraday baseline effect of large earnings surprises. More precisely, I analyze whether the effect depends on the overall level of market sentiment. Stambaugh et al. (2012) show that especially the short leg returns of various cross-sectional anomalies become higher after periods of high investor sentiment. They argue that this stems from larger overpricing during high sentiment periods because of more over-optimistic noise traders. Thus, it seems reasonable that also the attention-induced buying pressure after large earnings surprises is more pronounced during periods of high investor sentiment. In order to test this hypothesis, I do sample splits based on the orthogonalized Baker and Wurgler (2006) monthly market sentiment index.[30] I classify an earnings announcement as a high sentiment announcement if the sentiment index at the announcement date is within the top quintile (20%) and as a very high sentiment announcement if the sentiment index is within the top decile (10%) based on the distribution of the sentiment index. I report the results in Table 6.

[Insert Table 6 about here]

The results show that the documented overnight/intraday return patterns after large surprises are much more pronounced during high sentiment periods. For instance, overnight returns more than double after large earnings surprises during very high sentiment periods (5.059%, t-stat: 6.92) and corresponding intraday returns offset these returns completely (-5.749%, t-stat: -7.59). In order to make sure that the previously documented results are not entirely driven by very high sentiment periods, I show that the baseline effects still exist during non-high sentiment periods, although smaller in magnitude. Overall, this is consistent with the notion that during periods of high sentiment noise traders are more optimistic which is why the resulting overnight price pressure is larger.

5 What Drives the Results?

5.1 The Role of Limits to Arbitrage

In this subsection, I test whether the observed overnight/intraday patterns after large earnings surprises are stronger for firms with higher limits to arbitrage. This would be consistent with the notion that overnight/intraday reversals reflect temporary overnight attention-induced buying pressure.

I interact the large absolute earnings surprise indicator variable (*Abs FE* 10) with quintile ranks of firm characteristics that are typically associated with higher limits to arbitrage. I also include the interactions of all other control variables with *Abs FE* 10 to avoid documenting spurious relations. In order to make the interpretation of the baseline effect still meaningful in the presence of various interaction terms, I demean each quintile rank variable (see, for example, Jaccard (2003). Thus, a demeaned quintile rank of zero corresponds to firms in the median quintile of that particular firm characteristic. The superscript Q indicates that a variable is constructed in this way.

[30]For details, see Baker and Wurgler (2006). The sentiment index that is orthogonalized to several macroeconomic conditions can be downloaded from the web page of Jeffrey Wurgler at people.stern.nyu.edu/jwurgler and is available until September 2015.

I use firm size[31], idiosyncratic volatility, book-to-market ratio, and residual institutional ownership as proxies for limits to arbitrage. These firm characteristics are suggested by the previous literature: Small stocks are usually associated with larger limits to arbitrage which makes temporary mispricing more pronounced Baker and Wurgler (2006) and they typically should have a larger price impact of price pressure due to retail trader activity (see, for example, Kumar and Lee (2006) and Da et al. (2011)). For instance, the dollar traded volume needed to move prices for small stocks is smaller. Furthermore, firm size is also an important proxy for firm visibility (see, for instance, Fang and Peress (2009) and Hillert and Ungeheuer (2016)). Idiosyncratic volatility is often used as a proxy for limits to arbitrage (Stambaugh et al. (2012), and Pontiff (2006). Besides that, especially retail investors might have a preference for lottery-like stocks (Kumar, 2009). Stocks with low book-to-market stocks should be more difficult to arbitrage since their valuation is more subjective. Moreover, especially retail investors might be attracted to 'glamorous' growth stocks (see, for example, Lakonishok and Shleifer (1994)) and Baker and Wurgler (2006)). Last, firms with larger institutional ownership are also associated with higher limits to arbitrage since they have more binding short-selling constraints (Nagel, 2005). I report the results of this analysis in Table 7.

[Insert Table 7 about here]

Overall, the overnight/intraday patterns after large earnings surprises are much more pronounced for firms with higher limits to arbitrage. For instance, the coefficient estimate on $Abs\ FE\ 10 \times Size^{\mathrm{Q}}$ (-1.270, t-stat: -5.39 in column 3) shows that the overnight return reactions are significantly more sensitive to earnings surprises of small firms as compared to large firms. In contrast, for intraday returns the sensitivity to earnings surprises is more negative for small firms (0.854, t-stat: 3.50 in column 4). Similar patterns exist for idiosyncratic volatility, book-to-market, and residual institutional ownership. Although intraday returns after large earnings surprises become more negative for firms that are more difficult to arbitrage, they reverse less of the overnight price pressure in *relative* terms which might indicate the more binding limits to arbitrage. For instance, the coefficient on $Abs\ FE\ 10 \times IVOLA^{\mathrm{Q}}$ is 1.121 for overnight returns but only -0.432 for intraday returns (see columns 3 and 4).

My results indicate that overnight buying pressure is largest for small stocks with *ex ante* low visibility. Among those stocks, an attention-grabbing earning surprise has the largest effect since most investors might not have recognized them before.

Finally, when looking at the interaction terms between *Abs FE* 10 and the additional control variables, some other interesting patterns occur: Overnight returns conditional on

[31] I use quintile ranks based on NYSE quintile breakpoints for market capitalization in order to account for the fact that the universe of I/B/E/S firms consists of only mainly large firms, especially for firms that are covered by at least two analysts as required in my sample.

large earnings surprises are more positive for announcements with large abnormal trading volume at the announcement and firms that are covered by more analysts. Both variables are often used as proxies for attention (Barber and Odean (2008) and Hou and Moskowitz (2005)). Nevertheless, there is only weak evidence that intraday returns are more negative after large abnormal volume announcements. Since abnormal volume is only an indirect market-based measure of investor attention, it might also proxies for various other economic concepts like differences in opinion about an earnings announcement (Garfinkel and Sokobin, 2006) which makes an ultimate interpretation difficult. Therefore, I examine the role of retail investor attention as the potential channel in more detail in subsection 5.3 when employing direct measures of attention.

The overnight/intraday patterns conditional on large earnings surprises are less pronounced for illiquid stocks. Large earnings surprises of very illiquid stocks might also be less visible for retail investors and appear in general less attractive to buy. This is also evidence against the concern that the results might be driven by any microstructural issues that should be largest for the most illiquid stocks.

Systematic risk as measured with market beta does not seem to play a large role since the interaction is insignificant in most cases. Finally, I document that the overnight-intraday patterns conditional on large earnings surprises are in fact less pronounced for stocks with high analyst forecast dispersion. This is consistent with the notation that an earnings surprise might be less surprising if there was already a lot of uncertainty about the earnings before the actual announcement.

To sum up, firm characteristics that proxy for limits to arbitrage seem to be important cross-sectional determinants of the documented overnight/intraday patterns after large earnings surprises. Overnight price pressure is especially pronounced among small stocks with low institutional holdings, high idiosyncratic volatility and low book-to-market ratios. Since any noise-trader based mispricing patterns are expected to be more pronounced among stocks with those characteristics, this finding is consistent with the hypothesis that the documented large positive overnight returns after earnings surprises reflect temporary attention-induced buying pressure.

5.2 The Role of the Disposition Effect

In this subsection, I test whether the observed overnight/intraday patterns after large earnings surprises are mediated by whether existing investors on average hold the stock at a gain or at a loss after the announcement. After a large negative earnings surprise investors are more likely to hold the stock at a loss whereas after a positive earnings surprise investors are more likely to hold the stock at a gain. This can have important implications: Based on the previous analyses, it seems like positive price-pressure from noise traders due to attention-generating earnings surprises manifests solely overnight.

Another behavioral trading pattern of retail traders that is extensively documented in the behavioral finance literature is the disposition effect (see, for instance, Shefrin and Statman (1985) and Odean (1998)). It refers to the tendency of investors to hold loser stocks 'too long' and sell winner stocks 'too early'.

However, it is not exactly clear *when* investors are actually making trading decisions according to the disposition effect. In a recent paper, Yuan (2015) shows that market-wide attention might be an important trigger for the disposition effect since especially retail investors are not continuously monitoring the performance of their holdings. Thus, large earnings surprises that generate attention might trigger trading decisions according to the disposition effect. Moreover, the fundamental information of an earnings surprise leads to a potentially large price reaction at the announcement which additionally pushes investors in the gain or loss domain (see, for example, Frazzini (2006)).

In order to test whether the disposition effect also has a different impact on overnight and intraday returns following large earnings surprises, I use the market-based measure of Grinblatt and Han (2005). This measure proxies for the aggregate unrealized capital gains overhang (CGO) of the investors at the earnings announcement date.

As a first test, I sort earnings announcements independently by forecast error decile ranks (FE *Decile*) and CGO quintile and decile ranks. Then, I test whether there is a difference between large earnings surprise where investors on average hold the stock at a gain (top CGO quintile/decile) and large earnings surprises where investors on average hold the stock at a loss (bottom CGO quintile/decile). I visualize the results for the decile rank analysis in Figure 2.

[Insert Figure 2 about here]

The results indicate that the positive overnight returns after large earnings surprises are much higher if investors on average hold the stock at a loss (both effects work in the same direction) whereas overnight returns are dramatically reduced and are close to zero when investors on average hold the stock at a gain (the effects work in opposite directions). Moreover, the asymmetry in the effect between negative and positive large surprises in relative terms is reduced significantly compared to the unconditional analysis (from 70.1% to 23.0%).

In order to test this relationship within a proper statistical framework and controlling for other cross-sectional determinants, I also run OLS regressions as in the baseline analysis and add the interaction between CGO and earnings surprises (*Abs* FE 10) to the model. I report the results Table 8.

[Insert Table 8 about here]

Indeed, if investors on aggregate hold the stock at a gain after a large earnings surprise, the corresponding overnight returns during the following weeks are more negative (coefficient of -1.038%, t-stat: -11.37). This is consistent with the notion that investors are realizing their gains and thus selling. This seems to happen exclusively overnight. Again, corresponding intraday returns go in the opposite direction (0.852%, t-stat: 7.74) and seem to reverse the pricing impact of this non-rational behavioral pattern nearly fully. Hence, the pricing impact of the disposition effect seems to manifest mainly in overnight returns.

Moreover, attention caused by large earnings surprises seems to be an important trigger for actual trading decisions according to the disposition effect (since the interaction with $Abs\ FE$ 10 is much stronger than the baseline effect of capital gains overhang (e.g. -1.038 compared to -0.323 in column 1)). This is consistent with the finding of Yuan (2015) who looks at the role of market-wide attention. The economic size of this effect is large. If attention-induced buying pressure and disposition effect are supposed to go in opposite directions, the effect from the disposition effect can dominate the baseline effect. In this case, overnight returns actually decrease after large earnings surprises. Thus, accounting for the role of the disposition effect seems crucial when examining any attention-induced buying pressure.

5.3 The Role of Retail Investor Attention

Next, I examine the mediating role of retail investor attention as a potential channel in more detail. Although the previous results show that large earnings surprises seem to generate large attention spikes which results in large overnight returns, not every large earning surprise necessarily attracts the same amount of attention. If these overnight returns indeed reflect attention-induced buying pressure, they should be especially strong for large earnings surprises that actually attract high retail investor attention. In order to test this, I look at the interaction between having a large earnings surprise and abnormal Google search volume of stock tickers as a direct measure of retail investor attention (Da et al. (2011), and Ben-Rephael et al. (2017)).

As in the previous tests, I include the set of control variables that might be related to both large earnings surprises and differences in overnight and intraday returns. I demean and standardize the Google attention measure such that it has a mean of zero and a standard deviation of one in order to allow for an easier interpretation. I report the results in Table 8.

[Insert Table 9 about here]

In Panel A, I show the results from the baseline analysis. In all specifications, the same strong pattern appears: The interaction variable between Google attention and earnings surprise has a statistically highly significant mediating role (t-stat of 3.25 for overnight returns, -3.73 for intraday returns in columns 1 and 2). The economic size of this effect is large: A one standard deviations increase in abnormal Google attention nearly doubles the baseline effect. Contrary, an earnings surprise with abnormally low attention is associated with almost no overnight price pressure.

Even after controlling for all other interactions between control variables (including indirect measures of attention as abnormal volume) and employing firm-fixed effects, the effects remain statistically significant at the 5% level. In fact, with firm-fixed effects having a large earnings surprise is only associated with overnight buying pressure if there is also abnormal Google search volume.

Correspondingly, intraday returns are more negative if retail investor attention is high after large earnings surprises. After controlling for the interactions with all characteristics that might be related to limits to arbitrage, intraday returns revers about 100% of the corresponding overnight returns. Taken together, there is a much stronger 'tug of war' between overnight and intraday returns if a large earnings surprise actually generates high retail investor attention.

As a robustness test, I use Wikipedia pageviews for company names instead of Google search volume for tickers as an alternative direct measure of retail investor attention (see, for example, Focke et al. (2018) and Ungeheuer (2017)). The results can be found in Table A3 in the Appendix. The significance of the coefficients is statistically and economically similar to the analyses with Google search volume.

The recent literature on investor attention highlights the importance of distinguishing between retail investor attention and institutional investor attention (see, for example, Ben-Rephael et al. (2017)). Since proxies for retail investor attention (like Google and Wikipedia) and proxies for institutional investor attention (SEC Edgar) are positively correlated (see Table 1), one might be worried that the mediating role of retail investor attention that I document is driven solely by institutional investor attention. In order to test this, I use abnormal SEC EDGAR filing downloads for firms at the announcement date (see, for example, Drake et al. (2015)) as a proxy for institutional investor attention. I then include abnormal SEC Edgar as well as its interaction with the large earnings surprise variable ($AbsFE10$) to my model and report the results in Panel B of Table 9.

The results indicate that institutional investor attention does not have a strong mediating role for large earnings surprises when additionally controlling for retail investor attention[32]. At first sight it seems odd that the corresponding intraday returns are similar across low and high institutional investor attention announcements. It might be tempting to expect that intraday returns should be more negative when institutional investor attention is high. However, low institutional attention *at* the announcement date does not necessarily imply that institutional investors are not recognizing attention-induced mispricing during the following weeks.

[32]This is consistent with the finding of Ben-Rephael et al. (2017) who report that the magnitude of the earnings surprise seems not to be a primary driver of institutional investor attention.

Most importantly, the results suggest that retail investor attention has a unique mediating role for large earnings surprises, consistent with the overnight buying-pressure hypothesis, and that it is probably not the trading behavior of institutions after large earnings surprises that is triggering the patterns. Moreover, Ben-Rephael et al. (2017) show that there is no following post-earnings announcement drift in close-to-close returns after earnings surprises when institutional investor attention at the announcement is high. Hence, the results imply that attention-induced overnight buying-pressure also exist among those earnings surprises for which the initial price reaction at the announcement date already pushes prices to their true fundamental value. This is consistent with the reasoning that any attention-induced buying pressure should not be directly related to the initial fundamental reaction to the announcement.

5.4 Separating Negative and Positive Large Surprises

In this subsection, I analyze the effect of negative and positive large earnings surprises on future overnight and intraday returns separately. The patterns in Table 2 already indicate that there is large buying pressure in overnight returns after both negative and positive surprises. This is the reason why I employ one indicator variable for both negative and positive large surprises. Nevertheless, in this subsection I test the validity of this approach. These tests are important since the price pressure hypothesis explicitly states that attention to *both* negative and positive events should result in buying pressure. First, I construct separate indicator variables for negative (bottom 10%, $FE1$) and positive (top 10%, $FE10$) surprises based on quarterly sorts on the forecast error and redo my main analysis. I report the results in Panel A of Table 10.

[Insert Table 10 about here]

It becomes apparent that both negative and positive surprises are associated with larger overnight returns. Again, high retail investor attention as measured with Google amplifies this effect for both large negative and positive surprises.

Moreover, compared to the baseline results in Table 2, the patterns after positive and negative surprises become much more symmetric. If a positive large surprise generated the same amount of attention than a negative large surprise, they have similar return implications. Hence, the asymmetric baseline results in Table 2 (stronger return effects for negative large surprises) might indeed be partly driven by the "negativity" bias, i.e. the idea that negative events generate more attention, e.g. because they are more frequently covered in the media.

Second, in Panel B, I report the results when using linear spline regressions instead of indicator variables. Therefore, I use decile ranks based on quarterly sorts by forecast error (FE). I then demean the decile ranks and allow for a potential kink at zero. Thus, I am estimating the following model:

$$BHAR[2,31]^{i,q}_{overnight} = \alpha + \beta_1 \min(FE_{dec,dem}, 0) + \beta_2 \max(0, FE_{dec,dem}) + Controls + \epsilon \quad (11)$$

Hence, the coefficient β_1 on $\min(FE_{dec,dem}, 0)$ refers to the slope estimate for the first five deciles, i.e. negative surprises. Correspondingly, the coefficient β_2 on $\min(FE_{dec,dem}, 0)$ refers to the slope estimate between the last five deciles, i.e. positive surprises. In general, the results when using linear spline regressions with decile ranks are consistent with the results when using indicator variables for negative and positive surprises separately. As an additional robustness test, I redo the linear spline analyses but use abnormal Wikipedia pageviews as proxy for retail investor attention. The results are even slightly stronger as when using abnormal Google search volume.

Taken together, there is striking evidence that both negative and positive earnings surprises are associated with following high positive overnight returns and corresponding negative intraday returns which is strong support for attention-induced buying pressure.

5.5 Overnight and Intraday Returns Within the Same Event

In this subsection, I analyze the 'tug of war' patterns between overnight and intraday returns within the event window of a given earnings surprise in more detail. Although I already use firm-fixed effects in the previous analyses, it might still be the case that for a given firm there are large positive overnight returns after one large earnings surprise and large negative intraday returns after another large earnings surprise. On average, this would look like a 'tug of war' behavior whereas in reality two distinct effects are at work. In order to test this, I use the interaction between overnight and intraday returns during the event window ($r^i_{overnight,\tau} \times r^i_{intraday,\tau}$) as the dependent variable. I then regress this interaction term on the indicator variable for large earnings surprises ($AbsFE10$) as well as the interaction with abnormal Google attention and all other control variables. I report the results in Table 11.

[Insert Table 11 about here]

All specifications show that large earnings surprises are associated with a more negative interaction term between overnight and intraday returns for that specific announcement. This effect is both statistically and economically highly significant. For instance, a large earnings surprise decreases the interaction term by -1.083% (t-stat: -13.43) in column (1). Large retail investor attention as measured with abnormal Google search volume further amplifies this negative relationship and strongly moderates the baseline effect. Thus, large earnings surprises that generate high retail investor attention seem to increase the 'tug of war' patterns between overnight and intraday returns. In Panel B, I report the results when using only observations for which the abnormal overnight return during the drift period [t-2, t+31] was actually positive. This addresses the concern that a negative interaction term might be driven not only by positive overnight and corresponding negative intraday returns but also by negative intraday and corresponding positive overnight returns. However, only the first scenario fits the overnight attention-induced buying pressure story. Thus, I further exclude the observations where abnormal intraday returns were negative. Consistent with the overnight price-pressure hypothesis, the economic size of the effect of large earnings surprises increases by about 50% in all specifications whereas the statistical significance remains similar (although the number of observations roughly is halved). Overall, this indicates that large earnings surprises increase the 'tug of war' between overnight and intraday returns within the same event window.

6 Trading Strategy

The previous results indicate that there are economically large positive overnight and negative intraday returns after large earnings surprises. One then might ask whether one can use this predictability in order to construct a profitable trading strategy. Although such a strategy is simple, it requires trading each position twice a day, namely at the open and the close, during the whole 'holding' period. Because of this, it is substantial to explore the economic size of the effect in order to estimate whether transaction costs would eliminate all profits. I construct a simple calendar-time trading strategy that takes a long position in a stock during the overnight period (i.e. buy at the close and sell at the next open) if an earnings announcement was among the largest 10% based of all other announcements during the previous quarter. Thus, for instance, the strategy indicates to buy at the close of day $t + 2$ and to sell at the open of day $t + 3$, then to buy again at the close of day $t + 3$ and to sell again at the open of day $t + 4$. This trading pattern is repeated up to day $t + 31$. Contrary, for the short leg, the strategy indicates to go short intraday (i.e. short-sell at the open and to close the position at the close of the same trading day) and to repeat this pattern up to day $t + 31$. I report the annualized DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted abnormal returns as well as raw returns that result from this strategy in Table 12.

[Insert Table 12 about here]

Overall, the economic size of the returns is large. Implementing only the long leg of the strategy already results in an annualized raw return of 39.84% (an alpha of 32.46%, t-statistic: 13.60). The long-short portfolio is even associated with an annualized alpha of 61.07%. In Panel B, I report the alphas from a strategy where I exclude all stocks that are in the bottom NYSE size quintile or in the most illiquid Amihud (2002) quintile. Lachance (2015) estimates that investing overnight is associated with daily costs between

1.5 and 3.1 basis points and the recent study of Frazzini et al. (2015) shows that especially institutional investors actually face lower trading costs than previously estimated. Using the upper limit of Lachance (2015) results in annualized costs of about 8.06%. Even when implementing only the long leg of the strategy without small and illiquid stocks, the estimated net return from a back of the envelope calculation (21.62% - 8.06% = 13.56%) are economically large. Of course, the scalability of this strategy in terms of total dollar volume invested might be an issue since it is not possible to spread orders over a longer time horizon in order to reduce a potential price impact.

7 Conclusion

In this paper, I dissect close-to-close returns into their overnight and intraday components and document strong positive abnormal overnight returns for several weeks after both large positive and negative earnings surprises. This is consistent with a price impact of buying pressure after attention-grabbing earnings surprises. In line with this, the effect is strongly mediated by direct measures of retail investor attention like Google search volume and Wikipedia pageviews and does only exist if retail investors are net buyers. Furthermore, the disposition effect seems to have a strong mediating role as well: Overnight returns are substantially reduced after large earnings surprises if existing investors on average hold the stock at a gain.

Corresponding intraday returns go in the opposite direction and are of similar magnitude. Thus, in most cases these systematic strong patterns in returns are not detectable when looking at standard close-to-close returns. Hence, contrary to the existing literature, these findings suggest that there is indeed a price impact of the attention-induced buying behavior of retail investors after large earnings surprises. However, markets seem to be relatively efficient (related to the concept of "efficiently inefficient" markets of Pedersen (2015)) and hence this price impact is corrected relatively short-term by more sophisticated investors during the next intraday period.

Overall, these findings suggest that there seems to be an important clientele effect after large earnings surprises. Apparently, overnight returns are affected heavily by trading behavior that is usually attributed to irrational traders like buying attention-grabbing stocks or the disposition effect whereas intraday returns seem to reflect rational corrections of this behavior. Thus, looking only at close-to-close returns can hide strong systematic patterns in stock returns. For this reason, my findings may have broader implications for analyzing the price impact of other types of trading patterns that are based on behavioral biases of investors like overconfidence (De Bondt and Thaler, 1985), mental-accounting (Thaler, 1999), or sentiment (Keynes, 1936) where the previous literature does not always find clear price impact patterns by looking at close-to-close returns only.

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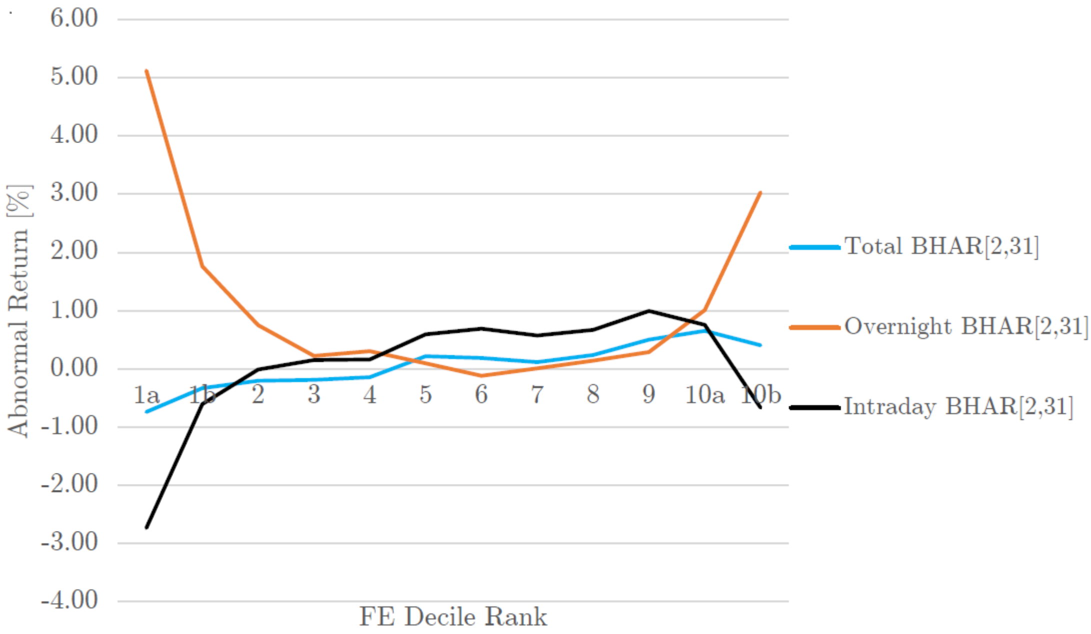
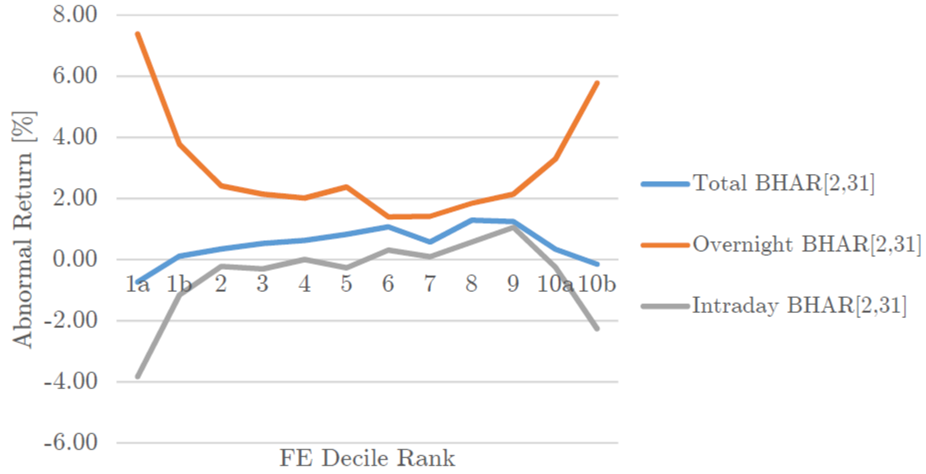
Figure 1: Mean BHAR by Earnings Surprise Rank



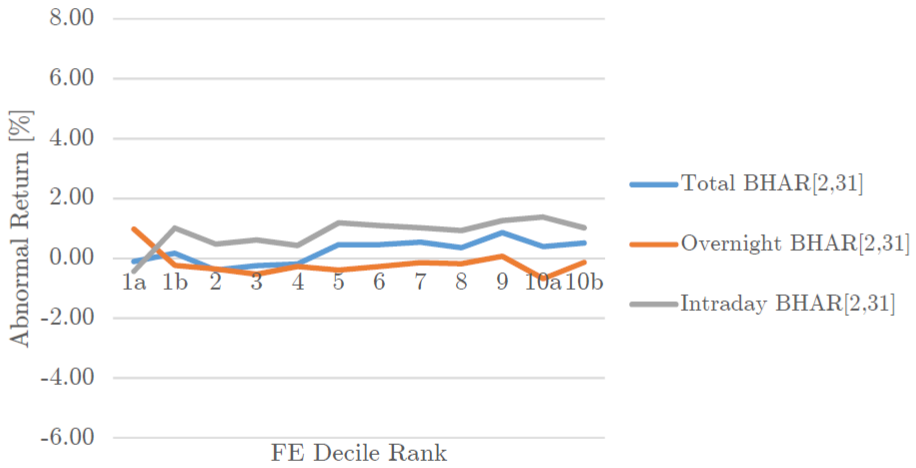
In this figure, I display the mean BHAR by earning surprise rank during the time period day $t+2$ to $t+31$ after an earnings announcement. Total (close-to-close), overnight and intraday returns are DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted. Earnings surprise decile ranks are based on quarterly sorts by the corresponding analyst forecast error (FE). I further split decile 1 (negative surprises) and decile 10 (positive surprises) into two vigintiles. The sample period is from June 1992 to December 2016 and there are 217,884 observations.

Figure 2: Independent Double Sorts by Earnings Surprise and Capital Gains

Panel A: Bottom CGO Quintile (On Average Hold at a Loss)



Panel B: Top CGO Quintile (On Average Hold at a Gain)



In this figure, I display the mean BHAR during the time period day $t+2$ to $t+31$ after an earnings announcement of independent double sorts by earning surprise and aggregate capital gains overhang (CGO). CGO is based on the capital gains overhang at the announcement date t. Panel A shows the results for earnings surprises in the bottom quintile of CGO (hold at a loss on average). Panel B shows the results for earnings surprises in the top quintile of CGO (hold at a gain on average). Total (close-to-close), overnight and intraday returns are DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted. Earnings surprise decile ranks are based on quarterly sorts by the corresponding analyst forecast error (FE). I further split decile 1 (negative surprises) and decile 10 (positive surprises) into two vigintiles. The sample period is from June 1992 to December 2016.

Table 1: Summary Statistics

Panel A: Univariate Distributions						
	Mean	Median	Std. Dev	p10	p90	N
Returns						
Total BHAR [2,31]	0.0007	-0.0040	0.1369	-0.1389	0.1397	217,887
Overnight BHAR [2,31]	0.0072	-0.0023	0.1170	-0.0850	0.0984	217,887
Intraday BHAR [2,31]	0.0022	-0.0008	0.1537	-0.1544	0.1565	217,887
Interaction ON/ID [2,31]	-0.0086	-0.0006	0.0509	-0.0198	0.0032	217,887
Earnings Surprises						
Forecast Error (FE)	-0.0003	0.0003	0.0120	-0.0042	0.0049	217,884
Direct Attention Proxies						
Abn. Google	0.1643	0.0706	0.5697	-0.4081	0.8705	58,498
Abn. Wiki	0.3770	0.3047	0.5550	-0.2231	1.0669	33,045
Abn. SEC Edgar	1.0395	1.0498	1.1360	-0.3070	2.4801	106,127
Other Variables						
Ln Mcap	6.8874	6.7598	1.7033	4.7940	9.1734	217,886
BTM	0.5353	0.4314	0.6128	0.1417	0.9799	217,887
Market Beta	1.0400	0.9886	0.5541	0.3804	1.7556	217,886
Idio. Vola	2.1656	1.7277	1.5604	0.7911	4.0400	217,886
Amihud Illiquidity	0.1037	0.0089	0.4521	0.0007	0.1571	217,886
Abn. Volume	0.5120	0.5479	0.8987	-0.5684	1.5752	217,586
Ln Num Analysts	1.9142	1.7918	0.6128	1.0986	2.7726	217,887
Analyst Dispersion	0.2096	0.0632	0.4697	0.0137	0.4703	217,887
CGO Raw	-0.1083	0.0059	0.4196	-0.5554	0.2333	217,884
Instit. Hold.	0.6452	0.6556	0.0574	0.5597	0.7140	186,469
Change Instit. Hold.	0.0019	0.0016	0.0216	-0.0206	0.0246	174,665

Panel B: Correlations

	Total BHAR [2,31]	ON BHAR [2,31]	ID BHAR [2,31]	Inter-action [2,31]	Forecast Error	Ln Mcap	BTM	Market Beta	Idio. Vola	Amihud Illiq.	Abn. Vol	Analyst Disp.	Num Analysts	CGO Raw	Abn. Google	Abn. Wiki	Abn. Edgar
Total BHAR [2,31]	1.000																
ON BHAR [2,31]	0.160	1.000															
ID BHAR [2,31]	0.740	-0.479	1.000														
Interaction [2,31]	0.098	-0.417	0.083	1.000													
Forecast Error	0.016	-0.062	0.038	0.073	1.000												
Ln Mcap	0.000	-0.064	-0.004	0.158	0.091	1.000											
BTM	0.003	-0.005	0.009	-0.008	-0.019	-0.160	1.000										
Market Beta	0.003	0.065	-0.049	0.004	0.017	0.105	-0.052	1.000									
Idio. Vola	0.000	0.169	-0.049	-0.235	-0.100	-0.433	-0.002	0.146	1.000								
Amihud Illiq.	-0.015	-0.001	0.014	-0.081	-0.035	-0.306	0.119	-0.229	0.136	1.000							
Abn. Volume	0.032	0.027	-0.012	0.060	0.040	0.190	-0.061	0.182	-0.082	-0.146	1.000						
Analyst Disp.	-0.004	0.032	-0.012	-0.049	-0.124	-0.158	0.079	0.068	0.168	0.018	-0.036	1.000					
Ln Num Analysts	0.008	-0.011	-0.014	0.088	0.055	0.701	-0.117	0.168	-0.171	-0.228	0.157	-0.058	1.000				
CGO Raw	-0.017	-0.187	0.046	0.242	0.178	0.284	-0.014	-0.058	-0.456	-0.056	0.099	-0.156	0.095	1.000			
Abn. Google	0.005	0.015	-0.005	-0.006	0.013	0.159	-0.070	0.028	0.016	-0.014	0.153	-0.012	0.164	0.005	1.000		
Abn. Wiki	-0.012	0.026	-0.034	0.007	-0.003	0.049	-0.010	0.049	-0.055	-0.005	0.178	-0.005	0.068	0.041	0.117	1.000	
Abn. Edgar	0.008	0.021	-0.003	-0.017	-0.017	-0.016	0.018	0.014	0.024	-0.004	0.110	0.015	-0.005	-0.054	0.037	0.133	1.000

In this table, I report summary statistics for my main variables. For a detailed description of the variables and their construction, see Table A1 in the Appendix. In Panel B, I additionally report pairwise Pearson correlation coefficients.

Table 2: Main Result: Mean BHAR and Earnings Surprise Ranks

Panel A: Mean BHAR by FE Rank: Decile Ranks

FE Decile Rank	1	2	3	4	5	6	7	8	9	10
Total BHAR[2,31]	-0.54	-0.21	-0.19	-0.14	0.21	0.18	0.11	0.24	0.50	0.53
ON BHAR[2,31]	3.45	0.75	0.22	0.30	0.09	-0.12	0.01	0.14	0.29	2.02
ID BHAR[2,31]	-1.67	-0.01	0.15	0.16	0.59	0.69	0.57	0.67	0.99	0.04
Interaction[2,31]	-2.30	-0.94	-0.56	-0.59	-0.47	-0.38	-0.47	-0.57	-0.79	-1.52

Panel B: Mean BHAR by FE Rank: Extreme Ranks

FE Rank	Bottom 1%	Bottom 5%	Top 5%	Top 1%
Total BHAR[2,31]	-1.24	-0.74	0.41	-0.69
ON BHAR[2,31]	7.85	5.12	3.03	4.17
ID BHAR[2,31]	-5.13	-2.74	-0.67	-2.46
Interaction[2,31]	-3.95	-3.13	-1.93	-2.36

Panel C: Regression Analysis: Large and Extreme Absolute Earnings Surprises

	(1) Overnight BHAR[2,31]	(2) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]	(5) Overnight BHAR[2,31]	(6) Intraday BHAR[2,31]	(5) Overnight BHAR[2,31]	(6) Intraday BHAR[2,31]
Abs. FE 10	2.095***	-1.684***	1.153***	-0.490**				
	(13.40)	(-9.20)	(6.98)	(-2.45)				
Abs. FE 5					1.951***	-1.453***		
					(7.45)	(-4.92)		
Abs. FE 1							2.953***	-3.231***
							(4.99)	(-5.06)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	NO	NO	YES	YES	YES	YES	YES	YES
Observations	217,306	217,306	216,714	216,714	216,714	216,714	216,714	216,714

Panel D: Regression Analysis: Long-Term Effect

	(1) Overnight BHAR[32,61]	(2) Intraday BHAR[32,61]	(3) Overnight BHAR[62,91]	(4) Intraday BHAR[62,91]	(5) Overnight BHAR[62,91]	(6) Intraday BHAR[62,91]
Abs. FE 10	1.245***	-0.353*	0.595***	-0.222	0.242	0.097
	(6.82)	(-1.71)	(3.19)	(-1.12)	(1.34)	(0.49)
F1 Abs. FE 10					1.510***	-1.458***
					(8.32)	(-6.73)
Controls	YES	YES	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES
Observations	215,021	215,021	211,760	211,760	207,789	207,789

In this table, I report the buy-and-hold DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted total (close-to-close), intraday and overnight abnormal returns as well as the interaction between intraday and overnight abnormal returns for the event time period $t+2$ up to $t+31$ after an earnings announcement. In Panels A and B, I report univariate sorts by earnings surprise quantiles. Earnings surprise deciles are formed based on a quarterly sort of earnings announcements by the respective analyst forecast error (FE). In Panel A, I report univariate sorts by forecast error deciles ($FE\ Decile$). In Panel B, I report univariate sorts by extreme forecast error vingtiles (top and bottom 5%) and extreme percentiles (top and bottom 1%). In Panel C, I report results from OLS regressions of overnight and intraday BHARs on an indicator variable for the top absolute earnings surprise decile rank ($Abs\ FE$ 10) respectively top absolute earnings surprise quintile rank ($Abs\ FE$ 5) or percentile rank ($Abs\ FE$ 1). Absolute earnings surprise ranks are formed based on a quarterly sort of quarterly earnings announcements by the absolute value of the corresponding analyst forecast error (FE). In Panel D, I report results from OLS regressions of overnight and intraday BHARs on an indicator variable for the top absolute earnings surprise decile rank ($Abs\ FE$ 10) for more long-term horizons and additionally control for an indicator variable for the top absolute earnings surprise decile rank during the next quarter's earnings announcement ($F1\ Abs\ FE$ 10) Control variables are the logarithm of market capitalization ($Mcap$), logarithm of book-to-market ratio (BTM), market beta ($BetaMkt$), idiosyncratic volatility ($IVOLA$), Amihud (2002) illiquidity ratio ($Illiq$), abnormal trading volume at the announcement ($Abn\ Vol$), the logarithm of one plus the number of analysts ($NumAnalyst$), analyst forecast dispersion ($AnalystDisp$) as well as aggregated capital gains overhang quintile ranks (CGO^Q). The sample period is from June 1992 to December 2016. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 3: Announcement Date Impact and Alternative Horizons

Panel A: Announcement Date Impact and First Days

	(1) Overnight BHAR[0,0]	(2) Intraday BHAR[0,0]	(3) Overnight BHAR[1,1]	(4) Intraday BHAR[1,1]	(5) Overnight BHAR[2,2]	(6) Intraday BHAR[2,2]	(7) Overnight BHAR[2,3]	(8) Intraday BHAR[2,3]
Abs FE 10	-0.1638**	-0.4393***	-0.0563*	-0.1373***	0.0568**	-0.0439	0.1453***	-0.1330**
	(-3.04)	(-8.06)	(-1.99)	(-3.59)	(3.24)	(-1.36)	(5.76)	(-3.02)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Additional Horizons

	(1) Overnight BHAR[2,11]	(2) Intraday BHAR[2,11]	(3) Overnight BHAR[2,21]	(4) Intraday BHAR[2,21]	(5) Overnight BHAR[3,31]	(6) Intraday BHAR[3,31]	(7) Overnight BHAR[10,31]	(8) Intraday BHAR[10,31]
Abs FE 10	0.7048***	-0.6544***	1.5066***	-1.1639***	2.0513***	-1.6618***	1.4447***	-1.2408***
	(10.12)	(-6.60)	(12.18)	(-8.12)	(12.60)	(-9.23)	(11.45)	(-8.34)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES	YES	YES	YES	YES

In this table, I report results from OLS regressions of overnight and intraday BHARs on an indicator variable for the top absolute earnings surprise decile rank ($Abs\ FE$ 10) for alternative event window horizons. Absolute earnings surprise ranks are formed based on a quarterly sort of quarterly earnings announcements by the absolute value of the corresponding analyst forecast error (FE). In Panel A, I report the results when using BHARs of the announcement date (columns (1) and (2)) or the first few trading days immediately after the announcement (columns (3) to (8) as the dependent variable. In Panel B, I report the results when using BHARs for various subperiods of the initial baseline event window [t+2, t+31] as the dependent variable. Control variables are the logarithm of market capitalization at the end of the previous fiscal quarter ($Mcap$), logarithm of book-to-market ratio (BTM), market beta ($BetaMkt$), idiosyncratic volatility ($IVOLA$), Amihud (2002) illiquidity ratio ($Illiq$), abnormal trading volume at the announcement ($Abn\ Vol$), the logarithm of one plus the number of analysts ($NumAnalyst$), analyst forecast dispersion ($AnalystDisp$) as well as aggregated capital gains overhang quintile ranks (CGO^Q). For the announcement date regression (Panel A, columns (1) and (2)), I use CGO lagged by one day. The sample period is from June 1992 to December 2016. Each regression model includes day fixed effects and some models additionally include firm fixed effects. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 4: Examining the Role of Retail Investor Buying

Panel A: Interaction

	(1) Overnight BHAR[2,31]	(2) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]
Abs. FE 10	0.220	-0.017	-0.791***	1.269***
	(0.94)	(-0.05)	(-3.15)	(3.85)
Retail Buy [2,31]	1.335***	-1.650***	1.175***	-1.445***
	(22.21)	(-19.10)	(19.41)	(-16.44)
Abs. FE 10 × Retail Buy [2,31]	2.447***	-2.527***	2.216***	-2.364***
	(6.68)	(-5.68)	(6.09)	(-5.38)
Controls	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES
Firm FEs	NO	NO	YES	YES
Observations	83210	83210	82956	82956

Panel B: Scaled Retail Buy-Sell Imbalances after Earnings Announcements

	(1) Abs. FE 10 = 0	(2) Abs. FE 10 = 1	(3) Scaled Retail BSI [2,31] > 0	(4) Scaled Retail BSI [2,31] > 0 & Abs. FE 10 = 1
Scaled Retail BSI [2,31]	-0.12***	0.28***	1.65***	2.71***
	(-9.13)	(5.93)	(67.22)	(42.07)
Observations	75,040	8,326	36,587	4,028

In this table, I report the results from examining the role of retail investor trading. In Panel A, I report results from OLS regressions of buy-and-hold DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted overnight and intraday abnormal returns on an indicator variable for the top absolute earnings surprise decile rank ($Abs\ FE$ 10) while including interaction terms between $Abs\ FE$ 10 and and indicator variable for net buying of retail investors during event time day $t+2$ and $t+31$ ($RetailBuy[2,31]$). The retail trading measure is based on the sub-penny trade classification of Boehmer et al. (2019). Control variables are the logarithm of market capitalization at the end of the previous fiscal quarter ($Mcap$), logarithm of book-to-market ratio (BTM), market beta ($BetaMkt$), idiosyncratic volatility ($IVOLA$), Amihud (2002) illiquidity ratio ($Illiq$), abnormal trading volume at the announcement ($Abn\ Vol$), the logarithm of one plus the number of analysts ($NumAnalyst$), analyst forecast dispersion ($AnalystDisp$) as well as aggregated capital gains overhang quintile ranks (CGO^Q). In columns (3) and (4), I additionally control for firm-fixed effects. In Panel B, I report the results from analyzing buy-sell imbalances after earnings announcements. Columns (1) and (2) show the average retail buy-sell imbalances after earnings announcements for large ($Abs.FE10 = 1$) and small earnings surprises ($Abs.FE10 = 0$). In column (3), I show the average retail buy-sell imbalance if the retail buy-sell imbalance was positive. In column (4), I show the average retail buy-sell imbalance if the retail buy-sell imbalance was positive and there was a large earnings surprise. Retail buy sell-imbalances are scaled by the total number of shares outstanding to make the measure comparable across stocks and are winsorized at the 1% level. The sample period is from January 2007 to December 2016. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 5: Changes in Institutional Holdings after Large Earnings Surprises

	Change in Institutional Ownership (percentage points)							
	Baseline Analysis						**Exclude Extreme Values**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abs. FE 10	-0.443***	-0.243***					-0.293***	-0.150***
	(-17.44)	(-10.01)					(-14.10)	(-7.65)
Abs. FE 5			-0.600***	-0.361***				
			(-16.81)	(-10.58)				
Abs. FE 1					-0.838***	-0.566***		
					(-10.61)	(-7.47)		
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Day FEs	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES
Observations	173,797	173,487	173,797	173,487	173,797	173,487	166,597	166,295

In this table, I report results from OLS regressions of the change in institutional holdings from event time quarter t-1 to quarter t+1 (in percentage points) on an indicator variable for the top absolute earnings surprise quantile rank. The change in institutional holdings variable is winsorized at the 1% level. Absolute earnings surprise ranks are formed based on a quarterly sort of quarterly earnings announcements by the absolute value of the corresponding analyst forecast error (FE). In columns (1) and (2), I report the results when using an indicator variable for the top absolute earnings surprise decile rank (*Abs* FE 10) as main independent variable. In columns (3) and (4), I report the results when using an indicator variable for the top absolute earnings surprise vigintile rank (*Abs* FE 5). In columns (5) and (6), I report the results when using an indicator variable for the top absolute earnings surprise percentile rank (*Abs* FE 1). In columns (7) and (8), I exclude all observations where the change in institutional ownership is in the top or bottom 1% of all values. Control variables are the logarithm of market capitalization at the end of the previous fiscal quarter ($Mcap$), logarithm of book-to-market ratio (BTM), market beta (*BetaMkt*), idiosyncratic volatility ($IVOLA$), Amihud (2002) illiquidity ratio (*Illiq*), abnormal trading volume at the announcement (*Abn* Vol), the logarithm of one plus the number of analysts ($NumAnalyst$), analyst forecast dispersion (*AnalystDisp*) as well as aggregated capital gains overhang quintile ranks (CGO^Q). Each regression model includes day and firm fixed effects. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 6: Large Earnings Surprises During High Sentiment Periods

	Baseline Bottom 80%		**High Sentiment Top 20%**		**Very High Sentiment Top 10%**	
	(1) Overnight BHAR[2,31]	(2) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]
Abs. FE 10	1.795***	-1.325***	3.213***	-3.338***	5.059***	-5.749***
	(11.57)	(-7.06)	(7.55)	(-7.28)	(6.92)	(-7.59)
Controls	YES	YES	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES	YES	YES
Observations	187,726	187,726	40,887	40,887	19,453	19,453

In this table, I report results from OLS regressions of buy-and-hold DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted overnight and intraday abnormal returns on an indicator variable for the top absolute earnings surprise decile rank (*Abs FE* 10) conditional on investor sentiment. Therefore, I divide the total sample into sub-samples based on the monthly Baker and Wurgler (2006) sentiment index. Absolute earnings surprise ranks are formed based on a quarterly sort of quarterly earnings announcements by the absolute value of the corresponding analyst forecast error (FE).In columns (1) and (2), I report the results when using only earnings announcements whose announcement date was on a not-high sentiment day (bottom 80% of the sentiment index values). In columns (3) and (4), I report the results of announcements during the top quintile (20%) of the sentiment index and in columns (5) and (6), I report the results for announcements during the top decile (10%) of the sentiment index. Control variables are the logarithm of market capitalization at the end of the previous fiscal quarter ($Mcap$), logarithm of book-to-market ratio (BTM), market beta ($BetaMkt$), idiosyncratic volatility ($IVOLA$), Amihud (2002) illiquidity ratio ($Illiq$), abnormal trading volume at the announcement ($Abn\ Vol$), the logarithm of one plus the number of analysts ($NumAnalyst$), analyst forecast dispersion ($AnalystDisp$) as well as aggregated capital gains overhang quintile ranks (CGO^Q). The sample period is from June 1992 to December 2016. Each regression model includes day fixed effects. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 7: Examining the Role of Limits to Arbitrage

	Baseline		Instit. Holdings	
	(1) Overnight BHAR[2,31]	(2) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]
Abs. FE 10	1.195***	-1.538***	1.316***	-1.632***
	(5.19)	(-5.91)	(5.29)	(-5.83)
Abs. FE 10 × Size^{Q}	-1.300***	0.821***	-1.270***	0.854***
	(-6.25)	(3.73)	(-5.39)	(3.50)
Abs. FE 10 × BTM^{Q}	-0.639***	0.779***	-0.578***	0.682***
	(-5.88)	(6.58)	(-4.85)	(5.40)
Abs. FE 10 × IVOLA^{Q}	1.087***	-0.357**	1.121***	-0.431**
	(8.68)	(-2.43)	(8.18)	(-2.71)
Abs. FE 10 × NumAnalyst^{Q}	0.374**	-0.309*	0.567***	-0.599***
	(2.40)	(-1.84)	(3.20)	(-3.25)
Abs. FE 10 × Abn Vol^{Q}	0.396***	-0.008	0.427***	-0.019
	(3.93)	(-0.08)	(3.80)	(-0.16)
Abs. FE 10 × Illiq^{Q}	-0.579**	0.606**	-0.377	0.375
	(-3.09)	(3.15)	(-1.78)	(1.73)
Abs. FE 10 × AnalystDisp ^{Q}	-0.303**	0.169	-0.348**	0.181
	(-2.40)	(1.20)	(-2.53)	(1.20)
Abs. FE 10 × BetaMkt^{Q}	0.134	-0.227	0.120	-0.244*
	(1.20)	(-1.82)	(0.98)	(-1.82)
Abs. FE 10 × ResInstHold^{Q}			-0.258**	0.437***
			(-2.08)	(3.26)
Baseline Controls	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES
Observations	217,312	217,312	183,955	183,955

In this table, I report results from OLS regressions of buy-and-hold DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted overnight and intraday abnormal returns on an indicator variable for the top absolute earnings surprise decile rank (*Abs FE* 10) while including interaction terms between (*Abs FE* 10) and quintile ranks of various firm and event characteristics. The quintile ranks are based on quarterly sorts by the respective characteristics. All quintile ranks are demeaned in order to make the interpretation of the baseline coefficient on (*Abs FE* 10) meaningful (Jaccard, 2003). Thus, a demeaned quintile rank of zero corresponds to firms in the median quintile of that particular firm characteristic. The superscript Q indicates that the variable is constructed in this way. Absolute earnings surprise ranks are formed based on a quarterly sort of quarterly earnings announcements by the absolute value of the corresponding analyst forecast error (FE). The set of event and firm characteristics includes NYSE size quintile ranks (based on the equity market capitalization at the end of the previous fiscal quarter($Size$)), logarithm of book-to-market ratio (BTM), market beta ($BetaMkt$), idiosyncratic volatility ($IVOLA$), Amihud (2002) illiquidity ratio ($Illiq$), abnormal trading volume at the announcement ($Abn\ Vol$), the logarithm of one plus the number of analysts ($NumAnalyst$), analyst forecast dispersion ($AnalystDisp$), residual institutional ownership ($ResInstHold$). The sample period is from June 1992 to December 2016. Each regression model includes day fixed effects and some models additionally include firm fixed effects. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 8: Examining the Role of the Disposition Effect

Panel A: Independent Double Sorts on FE and Aggregate Capital Gains Overhang

	Bottom Gains Quintile		**Top Gains Quintile**	
FE Decile Rank	1	10	1	10
Total BHAR[2,31]	-0.39	0.03	0.06	1.59
ON BHAR[2,31]	5.94	4.83	0.26	0.75
ID BHAR[2,31]	-2.75	-1.49	0.42	1.40
Interaction[2,31]	-3.56	-3.28	-0.62	-0.54

Panel B: Regression: Including Aggregate Capital Gains Overhang

	(1) Overnight BHAR[2,31]	(2) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]
Abs. FE 10	1.288***	-1.021***	0.588***	-1.265***
	(9.71)	(-5.78)	(3.57)	(-6.15)
CGO^{Q}	-0.323***	0.176***	-0.368***	0.197***
	(-13.61)	(5.04)	(-15.64)	(5.61)
Abs. FE 10 × CGO^{Q}	-1.038***	0.852***	-0.671***	0.770***
	(-11.37)	(7.74)	(-7.80)	(6.95)
Controls	YES	YES	YES	YES
Controls x Surprise 10	NO	NO	YES	YES
Day FEs	YES	YES	YES	YES
Observations	217306	217306	217306	217306

In this table, I examine the role of the disposition effect on overnight and intraday returns as well as the interaction between the disposition effect and attention-grabbing large absolute earnings surprises. In Panel A, I report multivariate independent sorts by forecast error deciles and capital gains overhang (CGO) bottom and top quintile ranks. In Panel B, I report results from OLS regressions of buy-and-hold DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted overnight and intraday abnormal returns on an indicator variable for the top absolute earnings surprise decile rank ($Abs\ FE$ 10) while including interaction terms between $Abs\ FE$ 10 and aggregated capital gains overhang quintile ranks (CGO^Q).The quintile ranks are based on quarterly. Quintile ranks are demeaned in order to make the interpretation of the baseline coefficient on ($Abs\ FE$ 10) meaningful (Jaccard, 2003). Thus, a demeaned quintile rank of zero corresponds to firms in the median quintile of CGO. The superscript Q indicates that the variable is constructed in this way. Absolute earnings surprise ranks are formed based on a quarterly sort of quarterly earnings announcements by the absolute value of the corresponding analyst forecast error (FE). Control variables are the logarithm of market capitalization at the end of the previous fiscal quarter ($Mcap$), logarithm of book-to-market ratio (BTM), market beta ($BetaMkt$), idiosyncratic volatility ($IVOLA$), Amihud (2002) illiquidity ratio ($Illiq$), abnormal trading volume at the announcement ($Abn\ Vol$), the logarithm of one plus the number of analysts ($NumAnalyst$) as well as analyst forecast dispersion ($AnalystDisp$). The sample period is from June 1992 to December 2016. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 9: Examining the Role of Retail Investor Attention

Panel A: Google Attention - Basic Analysis

	(1) Overnight BHAR[2,31]	(2) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]	(5) Overnight BHAR[2,31]	(6) Intraday BHAR[2,31]
Surprise 10%	1.520***	-1.188***	0.892***	-1.288***	0.026	-0.158
	(6.55)	(-4.11)	(3.41)	(-3.68)	(0.09)	(-0.40)
Abn Google	-0.007	0.117**	0.006	0.110*	0.080*	-0.046
	(-0.19)	(2.07)	(0.17)	(1.95)	(1.91)	(-0.75)
Surprise 10 × Abn Google	0.964***	-1.027***	0.836***	-0.957***	0.583**	-0.609**
	(3.25)	(-3.73)	(2.90)	(-3.46)	(2.03)	(-2.21)
Controls	YES	YES	YES	YES	YES	YES
Controls x Surprise 10	NO	NO	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES	YES	YES
Firm FEs	NO	NO	NO	NO	YES	YES
Observations	58,219	58,219	58,219	58,219	58,059	58,059

Panel B: Including Institutional Investor Attention

	(1) Overnight BHAR[2,31]	(2) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]
Surprise 10	0.901***	-1.281***	0.027	-0.159
	(3.44)	(-3.65)	(0.09)	(-0.40)
Abn Google	0.004	0.111*	0.077*	-0.046
	(0.12)	(1.96)	(1.83)	(-0.76)
Surprise 10 × Abn Google	0.829***	-0.961***	0.574**	-0.608**
	(2.88)	(-3.47)	(2.00)	(-2.20)
Abn Edgar	0.120**	-0.038	0.092**	0.036
	(2.52)	(-0.55)	(1.99)	(0.52)
Abs. FE 10 × Abn Edgar	0.301	0.153	0.384	-0.026
	(1.20)	(0.53)	(1.49)	(-0.09)
Controls	YES	YES	YES	YES
Controls x Surprise 10	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES
Firm FEs	NO	NO	YES	YES
Observations	58219	58219	58059	58059

In this table, I report results from OLS regressions of buy-and-hold DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted overnight and intraday abnormal returns on an indicator variable for the top absolute earnings surprise decile rank (*Abs* FE 10) while including interaction terms between *Abs* FE 10 and abnormal Google search volume for stock tickers (*AbnGoogle*) at event time day t and $t+1$ as a direct measure of retail investor attention. Absolute earnings surprise ranks are formed based on a quarterly sort of quarterly earnings announcements by the absolute value of the corresponding analyst forecast error (FE). *AbnGoogle* is demeaned and standardized such that it has a mean of zero and a standard deviation of one, and winsorized at the 1% level. In Panel A, I report the baseline results for the event window up to 31 days. In columns (3) and (4) I additionally control for all interaction terms between *Abs* FE 10 and other control variables, including indirect measures of attention like abnormal trading volume. In columns (5) and (6), I additionally control for firm-fixed effects. In Panel B, I report the results when including abnormal SEC Edgar filing downloads (*AbnEdgar*) as a proxy for institutional investor attention. Control variables are the logarithm of market capitalization at the end of the previous fiscal quarter ($Mcap$), logarithm of book-to-market ratio (BTM), market beta ($BetaMkt$), idiosyncratic volatility ($IVOLA$), Amihud (2002) illiquidity ratio (*Illiq*), abnormal trading volume at the announcement (*Abn* Vol), the logarithm of one plus the number of analysts ($NumAnalyst$), analyst forecast dispersion (*AnalystDisp*) as well as aggregated capital gains overhang quintile ranks (CGO^Q).
The sample period is from March 2004 to December 2016. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 10: Examining Negative and Positive Surprises Separately

Panel A: Negative and Positive Surprise Indicators

	(1) Overnight BHAR[2,31]	(2) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]	(5) Overnight BHAR[2,31]	(6) Intraday BHAR[2,31]	(7) Overnight BHAR[2,31]	(8) Intraday BHAR[2,31]
FE 1	1.762***	-1.662***	1.161***	-1.311***	1.077***	-1.233***	0.726***	-1.037***
	(12.39)	(-9.54)	(5.17)	(-4.75)	(5.17)	(-4.82)	(2.77)	(-2.99)
FE 10	0.751***	-0.134	0.998***	-0.039	0.882***	-0.075	1.359***	-0.554*
	(6.10)	(-0.86)	(5.51)	(-0.17)	(5.43)	(-0.35)	(5.01)	(-1.75)
Abn Google			-0.011	0.160***	-0.035	0.162***	0.002	0.154***
			(-0.31)	(2.83)	(-0.98)	(2.86)	(0.07)	(2.72)
FE 1 × Abn Google			0.565**	-0.761***	0.634**	-0.781***	0.372	-0.661**
			(2.17)	(-2.97)	(2.45)	(-3.06)	(1.46)	(-2.55)
FE 10 × Abn Google			0.459**	-0.781***	0.557***	-0.771***	0.457**	-0.770***
			(2.43)	(-3.52)	(2.99)	(-3.43)	(2.43)	(-3.34)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Ln Mcap x FE 1/10	NO	NO	NO	NO	YES	YES	YES	YES
Controls x FE 1/10	NO	NO	NO	NO	NO	NO	YES	YES
Day FEs	YES	YES	YES	YES	YES	YES	YES	YES
Observations	217,306	217,306	58,219	58,219	58,219	58,219	58,219	58,219

Panel B: Linear Splines - Forecast Error Deciles

	(1) Overnight BHAR[2,31]	(2) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]	(5) Overnight BHAR[2,31]	(6) Intraday BHAR[2,31]	(7) Overnight BHAR[2,31]	(8) Intraday BHAR[2,31]
FE Decile Neg Spline	-0.308***	0.337***	-0.218***	0.194***	-0.292***	0.198***	-0.285***	0.155**
	(-11.69)	(10.06)	(-5.88)	(3.90)	(-6.83)	(3.51)	(-4.61)	(1.99)
FE Decile Pos Spline	0.159***	-0.041	0.175***	-0.007	0.255***	-0.004	0.341***	-0.029
	(6.34)	(-1.19)	(5.31)	(-0.15)	(6.30)	(-0.08)	(5.10)	(-0.36)
Abn Google			-0.166**	0.459***	-0.251***	0.464***	-0.131*	0.431***
			(-2.17)	(4.81)	(-3.32)	(4.78)	(-1.77)	(4.40)
FE Decile Neg Spline × Abn Google			-0.110**	0.201***	-0.138***	0.206***	-0.080*	0.187***
			(-2.34)	(4.03)	(-2.93)	(4.11)	(-1.75)	(3.68)
FE Decile Pos Spline × Abn Google			0.103***	-0.174***	0.136***	-0.171***	0.104***	-0.164***
			(2.80)	(-3.97)	(3.73)	(-3.81)	(2.85)	(-3.57)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Ln Mcap x FE Decile Neg/Pos Spline	NO	NO	NO	NO	YES	YES	YES	YES
Controls x FE Decile Neg/Pos Spline	NO	NO	NO	NO	NO	NO	YES	YES
Day FEs	YES	YES	YES	YES	YES	YES	YES	YES
Observations	217,306	217,306	58,219	58,219	58,219	58,219	58,219	58,219

Panel C: Wikipedia Attention						
	(1) Overnight BHAR[2,31]	(2) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]	(5) Overnight BHAR[2,31]	(6) Intraday BHAR[2,31]
FE Decile Neg Spline	-0.270***	0.154**	-0.428***	0.111	-0.543***	-0.008
	(-5.54)	(2.38)	(-5.33)	(1.17)	(-4.77)	(-0.06)
FE Decile Pos Spline	0.079*	-0.032	0.176**	0.039	0.347***	0.066
	(1.77)	(-0.57)	(2.53)	(0.46)	(3.24)	(0.50)
Abn Wiki	-0.095	0.167	-0.109	0.161	-0.254***	0.156
	(-1.10)	(1.44)	(-1.27)	(1.39)	(-2.68)	(1.27)
FE Decile Neg Spline × Abn Wiki	-0.124**	0.216***	-0.131**	0.214***	-0.194***	0.201***
	(-1.96)	(3.07)	(-2.07)	(3.04)	(-2.85)	(2.78)
FE Decile Pos Spline × Abn Wiki	0.129***	-0.181***	0.131***	-0.177***	0.174***	-0.169***
	(2.79)	(-3.12)	(2.83)	(-3.05)	(3.42)	(-2.76)
Controls	YES	YES	YES	YES	YES	YES
Ln Mcap x FE Decile Neg/Pos Spline	NO	NO	YES	YES	YES	YES
Controls x FE Decile Neg/Pos Spline	NO	NO	NO	NO	YES	YES
Day FEs	YES	YES	YES	YES	YES	YES
Observations	32,854	32,854	32,854	32,854	32,854	32,854

In this table, I report results from OLS regressions of buy-and-hold DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted overnight and intraday abnormal returns on large earnings surprises where the effects of positive and negative surprises are separately tested. In Panel A, I report the results when using indicator variables for negative (bottom 10%, $FE1$) and positive (top 10%, $FE10$) surprises based on quarterly sorts on the forecast error. In columns (3) to (8), I include interaction terms between FE 1, FE 10 and abnormal Google search volume. In columns (5) and (6), I additionally include interaction terms between FE 1, FE 10 and firm size. In columns (7)9 and (8), I include interaction terms between FE 1, FE 10 and all control variables. In Panel B, I report the results from linear spline regressions. I use decile ranks based on quarterly sorts by forecast error (FE). I demean the decile ranks and allow for a potential kink at zero. Thus, the coefficient on *FE Decile Neg Spline* shows the slope estimate for earnings surprises that are below the median surprise whereas the coefficient on *FE Decile Pos Spline* shows the slope estimate for earnings surprises above the median surprise. In Panel C, I report the results from linear spline regressions using the same methodology as the one reported in Panel B, but using abnormal Wikipedia page views as an alternative measure of retail investor attention instead of abnormal Google search volume. *Abn Google* as well as *Abn Wikipedia* is demeaned and standardized such that they have a mean of zero and a standard deviation of one, and winsorized at the 1% level. Control variables are the logarithm of market capitalization at the end of the previous fiscal quarter ($Mcap$), logarithm of book-to-market ratio (BTM), market beta ($BetaMkt$), idiosyncratic volatility ($IVOLA$), Amihud (2002) illiquidity ratio ($Illiq$), abnormal trading volume at the announcement ($Abn\ Vol$), the logarithm of one plus the number of analysts ($NumAnalyst$), analyst forecast dispersion ($AnalystDisp$) as well as aggregated capital gains overhang quintile ranks (CGO^Q).
Each regression model includes day fixed effects. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 11: The Interaction of Overnight and Intraday Returns Within an Event

Panel A: Baseline

	(1) Interaction ON/ID F2F31 (%)	(2) Interaction ON/ID F2F31 (%)	(3) Interaction ON/ID F2F31 (%)	(4) Interaction ON/ID F2F31 (%)
Abs. FE 10	-1.083***	-0.711***	-0.336***	-0.136
	(-13.43)	(-8.75)	(-3.47)	(-1.21)
Google			-0.012	-0.006
			(-0.77)	(-0.31)
Abs. FE 10 × Google			-0.357**	-0.344**
			(-2.43)	(-2.31)
Controls	YES	YES	YES	YES
Controls x Abs FE 10	NO	NO	YES	YES
Day FEs	YES	YES	YES	YES
Firm FEs	NO	YES	NO	YES
Observations	217,312	216,720	58,219	58,059

Panel B: Only if Overnight Returns are Positive

	(1) Interaction ON/ID (%)	(2) Interaction ON/ID (%)	(3) Interaction ON/ID (%)	(4) Interaction ON/ID (%)
Abs. FE 10	-1.570***	-0.905***	-0.296*	-0.092
	(-12.38)	(-6.98)	(-1.86)	(-0.49)
Google			-0.007	0.009
			(-0.24)	(0.21)
Abs. FE 10 × Google			-0.574**	-0.546**
			(-2.42)	(-2.49)
Controls	YES	YES	YES	YES
Controls x Abs FE 10	NO	NO	YES	YES
Day FEs	YES	YES	YES	YES
Firm FEs	NO	YES	NO	YES
Observations	104,499	103,602	27,237	26,993

In this table, I report results from OLS regressions of the interaction term between buy-and-hold DGTW (Daniel et al. (1997) and Wermers (2003)) overnight and intraday abnormal returns within an event ($r^i_{overnight,\tau} \times r^i_{intraday,\tau}$) on an indicator variable for the top absolute earnings surprise decile rank ($Abs\ FE$ 10). Absolute earnings surprise ranks are formed based on a quarterly sort of quarterly earnings announcements by the absolute value of the corresponding analyst forecast error (FE). In Panel A, I report the results when using all observations. In Panel B, I report the results when using only observations where the average overnight abnormal return during the event window (F2F31) was positive. In Columns (3) and (4), I additionally report the results when including interaction terms between $Abs\ FE$ 10 and abnormal Google search volume for stock tickers (*AbnGoogle*) at event time day t and $t+1$ as a direct measure of retail investor attention. I additionally control for all interaction terms between $Abs\ FE$ 10 and other control variables, including indirect measures of attention like abnormal trading volume. In columns (2) and (4), I additionally control for firm-fixed effects. Control variables are the logarithm of market capitalization at the end of the previous fiscal quarter ($Mcap$), logarithm of book-to-market ratio (BTM), market beta ($BetaMkt$), idiosyncratic volatility ($IVOLA$), Amihud (2002) illiquidity ratio (*Illiq*), abnormal trading volume at the announcement ($Abn\ Vol$), the logarithm of one plus the number of analysts ($NumAnalyst$), analyst forecast dispersion ($AnalystDisp$) as well as aggregated capital gains overhang quintile ranks (CGO^Q). Each regression model includes day fixed effects. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 12: Trading Strategy

	(1) Long Overnight [2,31]	(2) Short Intraday [2,31]	(3) Long minus Short [2,31]	(4) Average No of Stocks in Portfolio	(5) Number Trading Days
Panel A: DGTW Returns					
Largest 10% Surprises	32.456***	-17.793***	61.065***	106	6,167
	(13.30)	(-5.79)	(10.06)		
Largest 5% Surprises	46.396***	-25.208***	95.584***	53	6,156
	(14.60)	(-6.78)	(11.43)		
Panel B: DGTW Returns without Illiquid and Small Stocks (NYSE Bottom Quintile)					
Largest 10% Surprises	21.616***	-17.162*	46.769***	38	6,167
	(9.34)	(-5.37)	(8.20)		
Largest 5% Surprises	33.552***	-22.176***	71.516***	17	6,156
	(14.60)	(-6.78)	(11.43)		
Panel C: Raw Returns					
Largest 10% Surprises	39.846***	-11.014*	57.121***	106	6,167
	(12.52)	(-1.81)	(6.14)		
Largest 5% Surprises	55.064***	-19.765***	93.150***	53	6,156
	(14.27)	(-3.06)	(7.92)		

In this table, I report the annualized returns from a calendar-time trading strategy based on a large absolute earnings surprise signal. For the long-leg returns that I report in column (1), the strategy goes long overnight (i.e. buy at the close and sell at the next open) if an earnings announcement was among the largest based of all other announcements during the previous quarter. The positions are opened two days after the announcement at $t+2$ to ensure implementability and the trading period is up to trading day $t+31$. Thus, for instance the strategy buys at the close of day $t+2$ and sells at the open of day $t+3$, then buys again at the close of day $t+3$ and sells again at the open of day $t+4$. This trading pattern is repeated up to day $t+31$. Contrary, for the short leg returns that I report in column (2), the strategy goes short intraday (i.e. short-sell at the open and close the position at the close) and repeats this pattern up to day $t+31$. In the first row of each panel, I show the resulting abnormal returns when trading all stocks of the top absolute earnings surprise decile ($Abs\ FE$ 10). In the second row of each panel, I report the abnormal returns when trading all stocks in the top absolute earnings surprise vigintile ($Abs\ FE$ 5). In Panel A, I report annualized DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted abnormal returns from a strategy that trades all stocks that are traded on NYSE/Nasdaq/Amex with a stock price of larger than 1 USD at the end of the previous fiscal quarter before the announcement. In Panel B, the strategy does not trade stocks that are in the bottom NYSE size quintile or in the bottom quintile based on the Amihud (2002) illiquidity ratio. In Panel C, I report raw annualized returns that are not adjusted for systematic risk factors. All standard errors are Newey and West (1987) adjusted with 30 lags.

Table A1: Description of Variables

The following table briefly defines the main variables used in my empirical analysis. A superscript "Q" following the variable name indicates that the variable has been transformed into quintile ranks (NYSE size quintile ranks for Size) based on quarterly sorts by the respective variable.

Variable Name	Description
Returns	
Total BHAR (C2C)	The close-to-close abnormal buy-and-hold-return during a specific time period. Returns are DGTW-adjusted (Daniel et al. (1997) and Wermers (2003)). Winsorized at the 0.01% level.
Overnight BHAR (ON)	The overnight abnormal buy-and-hold-return during a specific time period. Returns are DGTW-adjusted (Daniel et al. (1997) and Wermers (2003)). Open prices are the first transaction price from CRSP or the transaction-based volume-weighted open price (VWAP) during the first half trading hour from Algoseek. Winsorized at the 0.01% level.
Intraday BHAR (ID)	The intraday abnormal buy-and-hold-return during a specific time period. Returns are DGTW-adjusted (Daniel et al. (1997) and Wermers (2003)). Open prices are the first transaction price from CRSP or the transaction-based volume-weighted open price (VWAP) during the first half trading hour from Algoseek. Winsorized at the 0.01% level.
Interaction ON/ID	The interaction between intraday and overnight returns, that is Overnight BHAR $\times$ Intraday BHAR.
Earnings Surprises	
FE	The forecast error is defined as the difference between the actual announced earnings recorded in I/B/E/S ($E_{i,q}$) and the analyst consensus earnings forecast ($F_{i,q}$) as the estimate of the earnings surprise (analyst-based earnings surprise). The consensus forecast is defined as the median forecast among all analysts. This difference is then normalized by the share price at the end of the previous corresponding fiscal quarter ($P_{i,q}$)
FE Decile	Decile ranks, based on quarterly sorts on FE at the end of the previous fiscal quarter.
Abs FE	The absolute value of FE. Winsorized at the 1% level.
Abs FE 10	An indicator variable that is one if an earnings announcement is in the top decile (largest 10% of earnings surprises), based on quarterly sorts on the absolute value of FE at the end of the previous fiscal quarter.
Abs FE 5	An indicator variable that is one if an earnings announcement is in the top vigintile (largest 5% of earnings surprises), based on quarterly sorts on the absolute value of FE ($AbsFE$) at the end of the previous fiscal quarter.
Abs FE 1	An indicator variable that is one if an earnings announcement is in the top percentile (largest 1% of earnings surprises), based on quarterly sorts on the absolute value of FE at the end of the previous fiscal quarter.
Abs FE Dec	Decile ranks, based on quarterly sorts on the absolute value of FE at the end of the previous fiscal quarter.
Abs FE Sq	The squared value of $AbsFE$.
Attention Proxies	
SVI	The value of the Google search volume index for a specific firm ticker as provided by Google trends (accessible at trends.google.com).
Abn Google	The log of one plus the difference between the Google search volume index ($SVI_{i,t}$) and the median search volume index value of the same day-of-the-week over the previous 10 weeks, normalized by the median search volume index value of the same day-of-the-week over the previous 10 week volume as in Drake et al. (2012). Winsorized at the 1% level.
Wiki	The number of Wikipedia pageviews (counts) for Wikipedia pages of firms.
Abn Wiki	The log of one plus the difference between Wikipedia pageviews ($Wiki_{i,t}$) and the median Wikipedia pageviews of the same day-of-the-week over the previous 10 weeks, normalized by the median pageviews of the same day-of-the-week over the previous 10 week as in Drake et al. (2012). Winsorized at the 1% level.

Variable Name	Description
Attention Proxies	
EDGAR	The number of requests for firm filings on the SEC EDGAR server. I use the data provided by James Ryans (accessible at www.jamesryans.com) that is cleaned for non-human views.
Abn EDGAR	The log of one plus the difference between EDGAR requests ($EDGAR_{i,t}$) and the median EDGAR requests of the same day-of-the-week over the previous 10 weeks, normalized by the median number of requests of the same day-of-the-week over the previous 10 week as in Drake et al. (2012). Winsorized at the 1% level.
Other Variables	
Ln Mcap	The logarithm of the equity market capitalization at the end of the previous fiscal quarter.
Size	Size quintiles according to the market capitalization at the end of the respective previous fiscal quarter, based on NYSE breakpoints.
Ln BTM	Following Fama and French (1992), I use the logarithm of the firm's book-to-market ratio rebalanced every June.
BetaMkt	The coefficient of the value-weighted market return from CRSP in a regression of last year's daily returns on market returns. Winsorized at the 0.1% level.
Idio Vola	The standard-deviation of residuals from the Fama and French (1993) three factor model, estimated with last month's daily returns and lagged by one week. Winsorized at the 0.1% level.
Illiq	The Amihud illiquidity ratio as defined in citetAmihud2002, i.e. the average daily ratio of absolute stock return to dollar volume during the previous year. Winsorized at the 0.1% level.
Abn. Vol	The ratio of a stock's trading volume at the announcement date ($Vol_{i,t}$) to its average trading volume over the previous 252 trading days. Winsorized at the 0.1% level.
Ln Num Analysts	The logarithm of one plus the number of distinct analysts that have made a forecast for a given earnings announcements. Winsorized at the 0.1% level.
CGO	The daily aggregate unrealized capital gains overhang for a stock according to Grinblatt and Han (2005). Winsorized at the 1% level.
Inst Hold	The fraction of institutional ownership from 13f filings.
Inst Hold Change	The difference between Inst Hold at the end of quarter $t+1$ and Inst Hold at the end of quarter $t-1$. Winsorized at the 1% level.
ResInstHold	Similar as in Nagel (2005) and Kumar et al. (2016), I use the residuals from cross-sectional regressions of the logit transformation of institutional ownership ($InstHold$) on the logarithm of market cap, the logarithm of market cap squared and the Amihud (2002) illiquidity ratio.
Analyst Disp	Similar as in Avramov et al. (2009), I calculate analyst dispersion as the standard devition across analysts' forecasts for an earnings announcement of firm i in quarter q divided by the absolute value of the median forecas for that announcement as a measure of disagreement. I replace Analyst Disp with the median value if the median forecast is zero in order to not drop the respective observation. Winsorized at the 1% level.
Ln Rep Lag	The logarithm of the number of days between the fiscal quarter end and the actual announcement date of the earnings announcement. Winsorized at the 0.1% level.
Cum. Ret [-5,-1]	The cumulative raw return during the trading days before the earnings announcement date. Winsorized at the 0.1% level.
Turnover [-5,-1]	The mean turnover during the five trading days before the earnings announcement date. Winsorized at the 0.1% level.
Scaled Retail BSI [2,31]	The number of shares that are classified as retail buys minus the number of shares that are classified as retail sells. The classification is based on subpenny-price improved trades as proposed by Boehmer et al. (2019). The BSI is scaled by the number of shares outstanding, summed up over even time day $t+2$ to $t+31$, and winsorized at the 1
Retail Buy [2,31]	An indicator value that takes the value one if Scaled Retail BSI [2,31] is larger than zero.

Table A2: Baseline Regression - Robustness Tests

	Overnight BHAR[2,31]	Intraday BHAR[2,31]	Overnight BHAR[2,31]	Intraday BHAR[2,31]
	Panel A: Excl. Bottom NYSE Size Quintile, Only Price > 10 USD		**Panel B: Excl.Extreme Surprises (1%) and Extreme Returns (0.1%)**	
Abs. FE 10	0.3366***	-0.4558***	1.2623***	-1.1776***
	(3.73)	(-3.39)	(11.08)	(-7.80)
Controls	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES
Observations	147,317	147,317	212,042	212,042
	Panel C: Log-Returns		**Panel D: Raw Returns**	
Abs. FE 10	1.5259***	-2.4498***	2.4512***	-1.9240***
	(11.34)	(-12.33)	(13.53)	(-10.04)
Controls	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES
Observations	148,891	148,891	225,567	225,567
	Panel E: Algoseek Volume-weighted Open Prices		**Panel F: No Daily Winners or Losers**	
Abs. FE 10	0.8405***	-0.9165***	2.3558***	-1.9705***
	(4.45)	(-5.18)	(11.74)	(-8.80)
Controls	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES
Observations	80,969	80,969	153,695	153,695
	Panel G: Only Bottom L0F1 Abs Ret Tercile		**Panel H: Control for Past Returns and Past Surprise**	
Abs. FE 10	1.2801***	-1.3953***	1.5619***	-1.1231***
	(4.90)	(-4.35)	(10.54)	(-5.97)
Controls	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES
Observations	64,372	64,372	208,387	208,387
	Panel I: Additional Controls		**Panel J: Raw Absolute FE**	
Abs. FE	2.0748***	-1.8474***	54.4272***	-47.9503***
	(13.26)	(-10.03)	(12.76)	(-10.98)
Controls	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES
Observations	217,306	217,306	217,306	217,306
	Panel K: Squared Absolute FE		**Panel L: Absolute FE Decile**	
Abs FE Sq/Dec	474.5958***	-447.0648***	0.1169***	-0.0696***
	(10.54)	(-9.86)	(9.90)	(-4.46)
Controls	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES
Observations	217,306	217,306	217,306	217,306
	Panel M: Sample Period Splits			
	1992 - 2004		**2005 - 2016**	
Abs. FE 10	2.7208***	-2.1585***	1.4145***	-1.2436***
	(10.88)	(-7.73)	(8.53)	(-5.40)
Controls	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES
Observations	115,445	115,445	101,859	101,859

	Panel N: Overnight Risk Control		Panel O: Only NYSE	
Abs. FE 10	1.3228***	-1.2516***	0.9542***	-0.6207***
	(9.02)	(-6.93)	(5.27)	(-2.62)
Controls	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES
Observations	217263	217263	104944	104944

In this table, I report results from additional robustness tests of the main findings in Table 2, Panel C. I show results from OLS regressions of buy-and-hold DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted overnight and intraday abnormal returns on a variable that captures large absolute earnings surprise using different sample restrictions or different variable definitions. Absolute earnings surprise deciles are formed based on a quarterly sort of quarterly earnings announcements by the absolute value of the corresponding analyst forecast (FE) error. In Panel A, I exclude all stocks that are ranked in the bottom NYSE size quintile at the end of the previous fiscal quarter as well as all stocks with a share price smaller or equal than 10 USD at the end of the previous fiscal quarter. In Panel B, I exclude all stocks with the largest and smallest 1% value of forecast error FE as well as the 0.1% smallest and largest BHARs, based on rankings during the whole sample period. In Panel C, I use log returns to calculate BHARs. Thus, there exists no interaction term between overnight and intraday returns by construction when analyzing cross-sectional expected (e.g. mean) returns. In Panel D, I use raw returns that are not adjusted for systematic risk factors. In Panel E, I use the volume-weighted open price during the first half hour of a trading day from Algoseek as an alternative open price. In Panel F, I exclude all stocks that are ranked within the bottom (daily losers) or top 100 (daily winners) across all NYSE/NASDAQ/Amex stocks at the earnings announcement date based on their event time day t raw return. In Panel G, I only include observations where the initial announcement absolute return reaction at event time day t and $t+1$ was in the bottom tercile. Thus, I exclude all announcements that are associated with a large absolute return at the announcement. In Panel H, I additionally control for past buy-and-hold DGTW adjusted intraday and overnight returns during the event time period $t-31$ to $t-2$ as well as for the lagged indicator variable of a large earnings surprises ($L1$ *Abs FE* 10) that indicates whether the previous earnings announcement was also a large absolute surprise. In Panel I, I additionally control for XXX In Panel J, I use a raw absolute FE measure instead of the dummy variable $Abs.FE10$ as the main independent variable. In Panel K, I use the squared absolute FE instead of the dummy variable $Abs.FE10$ as the main independent variable. In Panel L, I use decile ranks of absolute FE instead of the dummy variable $Abs.FE10$ as the main independent variable. In Panel M, I divide my sample into two subsamples. Columns (1) and (2) report the results for the subperiod 1992 - 2004 and columns (3) and (4) for the subperiod 2005 - 2016. In Panel N, I additionally control for the volatility of overnight returns during event time $t-32$ to $t-2$ as well as during event time $t+1$ to $t+31$ as a proxy for overnight risk. In Panel O, I only use stocks that are traded on NYSE. Control variables include NYSE size quintile ranks (based on market capitalization at the end of the previous fiscal quarter), number of analysts (*Ln Num Analysts*), analyst dispersion (F-$Vola$), reporting lag (*Ln Rep Lag*), cumulative raw return (*Cum Ret*$[-5,1]$) and mean turnover ($Turnover[-5,1]$) during the previous trading week as well as day-of-the week dummies. The sample period is from June 1992 to December 2016. Each regression model includes quarter fixed effects. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table A3: Wikipedia Attention

	(1) Overnight BHAR[2,31]	(2) Intraday BHAR[2,31]	(3) Overnight BHAR[2,31]	(4) Intraday BHAR[2,31]	(5) Overnight BHAR[2,31]	(6) Intraday BHAR[2,31]	(7) Overnight BHAR[2,31]	(8) Intraday BHAR[2,31]
Wiki	0.1254***	-0.1975***	0.1185**	-0.1573**	0.2194***	-0.3112***	0.2082***	-0.2655***
	(2.61)	(-3.04)	(2.38)	(-2.43)	(3.52)	(-3.85)	(3.31)	(-3.35)
Abs. FE 10	0.5810	0.2185	0.2564	1.4292**				
	(1.01)	(0.33)	(0.42)	(1.97)				
Abs. FE 10 × Wiki	1.0234**	-1.2852**	0.8306**	-1.0572**				
	(2.32)	(-2.53)	(1.96)	(-2.09)				
Abs. FE Decile					0.2420***	-0.0204	0.2647***	-0.0056
					(3.66)	(-0.29)	(3.11)	(-0.07)
Abs. FE Decile × Wiki					0.0981***	-0.0828***	0.0878***	-0.0828***
					(3.70)	(-2.66)	(3.39)	(-2.70)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Controls x Abs FE 10	YES	YES	YES	YES	NO	NO	NO	NO
Controls x Abs. FE Decile	NO	NO	NO	NO	YES	YES	YES	YES
Day FEs	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	NO	NO	YES	YES	NO	NO	YES	YES
Observations	32,854	32,854	32,851	32,851	32,854	32,854	32,851	32,851

In this table, I report results from OLS regressions of buy-and-hold DGTW (Daniel et al. (1997) and Wermers (2003)) adjusted overnight and intraday abnormal returns on different measures of large absolute earnings surprises while including interaction terms between the large earnings surprise measure and abnormal Wikipedia page views for firm pages ($AbnWiki$) at event time day t and $t+1$ as an alternative direct measure of retail investor attention. Absolute earnings surprise ranks are formed based on a quarterly sort of quarterly earnings announcements by the absolute value of the corresponding analyst forecast error (FE). $AbnWiki$ is demeaned and standardized such that it has a mean of zero and a standard deviation of one, and winsorized at the 1% level. In columns (1) to (4), I report the results when using an indicator variable for the top absolute earnings surprise decile rank ($Abs\ FE$ 10). In columns (5) to (8), I report the results when using absolute earnings surprise decile ranks ($AbsFEDecile$). Control variables are the logarithm of market capitalization at the end of the previous fiscal quarter ($Mcap$), logarithm of book-to-market ratio (BTM), market beta ($BetaMkt$), idiosyncratic volatility ($IVOLA$), Amihud (2002) illiquidity ratio ($Illiq$), abnormal trading volume at the announcement ($Abn\ Vol$), the logarithm of one plus the number of analysts ($NumAnalyst$), analyst forecast dispersion ($AnalystDisp$) as well as aggregated capital gains overhang quintile ranks (CGO^Q). The sample period is from March 2008 to December 2015. Each regression model includes day fixed effects and some specifications additionally include firm fixed effects. T-statistics are based on firm- and day-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.