Corporate news releases and the profitability of retail trades[*]

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Abstract: Combining a large archive of public corporate news events with retail trading records from NYSE, we examine whether and how news releases affect the informedness of individual investors. We find a significantly positive relationship between retail order imbalance on days with positive news sentiment and future stock returns. The predictive ability of retail order imbalance is more pronounced on both neutral news and positive news days during times of elevated market uncertainty and across a broad spectrum of corporate news categories such as corporate business activities, financial results and analysis, domestic politics, and international trade. We consider a multitude of explanations (e.g., news processing skills, news anticipation, liquidity provision, investor attention, changes in liquidity) and conclude that the argument that is most compatible with our findings is that individual investors in our sample are skilled at interpreting news.

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1. Introduction

Public news releases create significant profit opportunities for investors with superior information processing skills (Kandel and Pearson, 1995). Consistent with this idea, prior studies have shown that sophisticated investors such as short sellers and institutional investors benefit from public news releases and a substantial portion of these traders' informedness comes from their ability to analyze publicly available information (Engelberg et al., 2012; Hendershott et al., 2015). Recent studies provide strong empirical evidence that individual investors are not as naïve as is generally thought,[1] and, similar to short sellers and institutional investors, their trades contain significant information about future stock prices.[2] Given the importance of public news for other sophisticated investors, in this paper, we examine whether individual investors benefit from public news releases and explore how these benefits, if any, vary across news categories.

The predictions on how corporate public news releases affect individual investors' trading decisions and, in turn, the predictive ability of their trades for future stock returns are mixed ex-ante. Kandel and Pearson (1995) argue that different investors interpret public information differently as they employ distinct assumptions and models in interpreting various world phenomena. Kim and Verrecchia (1997) argue that investors might use public announcements to infer new private information. Thus, investors who possess the skills and resources to carefully analyze hard-to-interpret value-relevant information could obtain an informational advantage relative to other investors. Unlike short-sellers and institutional investors who have such skills and resources, individual traders cannot allocate vast amounts of

[1] Kyle (1985) and Black (1986) describe individual investors as uninformed noise traders. Subsequent studies provide arguments on how individual traders create noise and increase risk for rational arbitrageurs (e.g., Shleifer and Summers, 1990; DeLong, Shleifer, Summers, and Waldman, 1990a, 1990b; and Shleifer and Vishny, 1997). Moreover, the early evidence indicates that individual traders exhibit behavioral biases that decrease their performance (Odean, 1998; Barber and Odean, 2000; and Benartzi and Thaler, 2001).
[2] See, for example, Kaniel, Saar, and Titman, 2008; Kaniel, Liu, Saar, and Titman, 2012; Kelley and Tetlock, 2013; Barrot, Kaniel, Sraer, 2016; and Boehmer, Jones, and Zhang, 2016.

resources to periodically monitor and gather information about various firms prior to news events.[3] Therefore, public news releases could alleviate the search problem for potential buyers by increasing the visibility of a particular stock for individual investors (Barber and Odean, 2008), who, in turn, can limit their focus to these attention-grabbing stocks and process the information content of the news. If individual traders have information processing skills, then public news releases can create a relatively cheaper information advantage for individual investors and might enable them to place more profitable trades. Accordingly, the news interpretation channel provides a plausible explanation for how individual investors could obtain an informational advantage about future stock price performance.

On the other hand, the predictive ability of individual investors' trades for future stock returns could be lower on news days. This is because, the release of public news decreases the information asymmetry among market participants (Tetlock, 2010) and could result in informationally more efficient stock prices. This implies that there should be less profitable trading opportunities for informed investors, and, in turn, a muted relationship between net individual trading volume on news days and future stock returns. Further, several studies document that, unlike short sellers or institutional investors, individual investors often fail to use value-relevant information (e.g., Lee 1992; Hirshleifer et al. 2008; Maines & Hand 1996; Blankespoor et al. 2018) even if this information is disseminated through news releases and designed to reduce the awareness and acquisition costs of investors (Drake et al. 2017). Individual investors might disregard the information in public news releases if their integration cost – the cost of processing and incorporating the news into valuation models and trading

[3] Hendershott, Livdan, and Schurhoff (2015) argue that institutional traders have strong connections with various market players including sell side analysts, firm managers, and brokerage firms and can allocate large amounts of resources to interpret news.

decisions (Hodge et al. 2004) – exceeds their benefits from the news. Additionally, various behavioral biases (e.g., overconfidence) might result in individuals ignoring the information content of public news or overreacting to the news if it confirms their prior beliefs. Overall, these arguments predict a negative or zero effect of news releases on the association between individual investors' trades and future stock returns.

To examine whether and how public news events affect the predictive ability of individual investors' trades for future stock returns, we combine a large archive of corporate news events with retail trading records from the New York Stock Exchange (NYSE ReTrac). Confirming the findings in prior studies that use NYSE ReTrac (e.g., Kaniel, Saar, and Titman, 2008; Kaniel, Liu, Saar, and Titman, 2012), we find a strong positive relation between daily net trading by individual investors and subsequent monthly stock returns. More importantly, we find that the predictive ability of individual investors' trades increases significantly on days with a positive-sentiment public news event. To provide some perspective, positive news events occur on roughly 6% of the days in our sample; however, they account for 15% of the predictive ability of retail trades. The effect of positive news events on the profitability of retail trades is also economically meaningful. The relation between net retail trading volume on positive news days and future stock returns is twice as large as that on no-news days and even larger when there is high firm-level uncertainty.

News days with negative or neutral sentiment do not differ from no-news days with respect to the relationship between retail volume executed on these days and future stock returns. However, during times of high market uncertainty, we find that both neutral and positive news events result in a retail volume that has a more pronounced predictive ability with respect to future returns.[4] Finally, individual investors can execute more profitable trades on days with positive-sentiment news categories such as corporate financial results and analysis, corporate business activities, domestic politics, international trade, and short-term interest rate news, which constitute roughly 45% of the positive news events in our sample. Overall, our findings suggest that public news releases have a significant effect on the predictive ability of individual investors' trades for future stock returns.

Our sample is based on retail trades executed on NYSE over the sample period from April 2004 to December 2011. According to Battalio and Loughran (2008), retail brokers have incentives to route naïve orders away from NYSE and an average individual trade executed on the NYSE might be more informed compared to other individual trades. However, individual investors are also documented to be informed when trading at other exchanges (Tetlock and Kelley, 2013) and there is no obvious reason to believe that informed individual traders in other markets are systematically inferior to informed NYSE traders in processing information. Therefore, we believe that our results might very likely show the information processing skill of an average informed individual trader.

We consider several explanations for the effect of positive news events on the predictive ability of retail volume for future stock returns. Our findings are consistent with the argument that the group of informed individual traders we study in this paper possess superior information processing skills and news releases create trading opportunities for these investors. Two important implications of this argument are that individual investors should process the news following its release rather than anticipate it and news events should have a more pronounced impact on retail trades when there is more firm-specific and market-wide information

[4] Positive and neutral news events occur on only 25% of the days in our sample but account for roughly 46% of the predictive ability of individual investors' trades during times of elevated market uncertainty.

uncertainty. Consistent with the first implication, we find that individual investors do not seem to anticipate the content of public news announcements suggesting that they do not have the market timing ability to trade on the news before its announcement. With respect to the second implication, we find that individual investors benefit significantly more from public news during times of elevated market uncertainty and when trading stocks of firms with low analyst following (i.e., high firm-specific uncertainty). Importantly, most of the news processing occurs during times of higher market uncertainty when it is arguably harder to correctly interpret the news and value stocks.

Barber and Odean's (2008) finding that individual investors tend to buy attention-grabbing stocks could be an alternative explanation for our findings. Under this explanation, public news announcements increase the visibility of a stock and individual investors buy the stock simply because it catches their attention and not because they carefully process the information content of the news event. Therefore, it might be the price pressure from the demand shocks that underlies the positive relation between net retail trading volume and future returns rather than individual investors being able to successfully process the information in news releases. However, the price pressure due to investor attention cannot be justified by changes in firm fundamentals; therefore, the investor attention argument implies that over longer horizons, the stock price should revert to fundamentals and the return predictability should reverse. We test this implication by examining whether the relation between individual trading and future returns reverses over longer holding horizons. We find no evidence of a price reversal over up to 60-day holding periods following news events.[5]

[5] Hvidkjaer (2008) and Barber, Odean, and Zhu (2009) provide evidence of return reversals after buyer-initiated small trades—their proxy for retail trades—that suggests a horizon of 60 trading days is sufficient to detect reversal. Moreover, Bali, Bodnaruk, Scherbina, and Tang (2017) document that following unusual firm-level news flows, firms experience price reversal over the following six months.

Another implication of the investor attention argument is that the positive price pressure due to individual trading should be more relevant in stocks with higher short selling constraints. This is because, when short selling is restricted, short sellers would stay by the sidelines as they cannot short the stock and cannot prevent the price from diverging from fundamentals due to individual investors' excess demand. Using put option volume as our measure of short selling restrictions, we find that individual investors benefit similarly from news in stocks with low or high put option volume suggesting that short selling constraints do not play a role in explaining our findings.

Finally, according to the investor attention argument, our results should be more pronounced among stocks with a more persistent individual order imbalance, which may be subject to more price pressure. Following Kelley and Tetlock (2013), we test this argument by examining how the predictive ability of net retail trading volume following news events varies with firm-level persistence in retail trading and find no evidence of increased return predictability among firms with persistent retail trading. This finding casts further doubt that our results are driven by price pressure stemming from increased investor attention following public news. Hence, the increased investor attention argument around public news events does not explain our results.

Another potential explanation for our findings is that news days might cluster together, and their sentiment might be positively autocorrelated. For example, good news today might lead to good news in the future and if the market fails to adjust prices accordingly, individual investors might simply trade based on the persistence of signed news rather than a careful analysis of the content of the news. Accordingly, the significant increase in return predictability we document would be an artifact of news persistence. We address this concern in two ways.

First, we examine how the predictive ability of retail trading following news events varies with the persistence in news sentiment but find no evidence of a relationship. Second, we explicitly control for both lead and lagged news sentiment and continue to find a significant increase in the predictive ability of net retail trading following public news. Overall, we conclude that our results cannot be explained by persistency in news sentiment.

Next, we examine whether our results are driven by improved stock liquidity around news event days. In this view, to the extent that a news event decreases information asymmetry about a firm, it may lead to a reduction in transaction costs (Diamond and Verrecchia 1991). Hence, individual traders would find it optimal to trade on their information around news events. To explore this view, we follow Engelberg, Reed, and Ringgenberg (2012) and examine market liquidity, as measured by bid-ask spreads, around event dates. Our findings suggest no evidence of improvement in market liquidity on news days.

Finally, another alternative explanation for our findings is that risk-averse individuals provide liquidity to meet the demand for immediacy from other market participants such as institutions. For example, institutional traders can correctly anticipate the outcome of positive news and buy the stock before the news (Hendershott, Lidvan, and Schürhoff, 2015). Later, these institutional traders can sell their shares immediately after the news is revealed to profit from their pre-event trades.[6] In this view, when institutions with informational advantage reverse their orders after the news, the adjustment of prices to the information revealed at the announcement will be incomplete. Therefore, if individual investors also trade in the direction of the news

[6] This trading behavior is also in line with "buy the rumor and sell the fact (news)" strategy (see, e.g., Maiello, 2004) such that when an agent receives private positive information signal, she will buy the stock and then sell it after the information becomes public to take the advantage of being the first runner in trading on the information. Hirshleifer, Subrahmanyam, and Titman (1994) and Brunnermeier (2005) theoretically describe how investors possessing a short-lived informational advantage are expected to trade and Kadan, Michaely and Moulton (2016) present empirical evidence on such behavior.

sentiment after they observe the news event to benefit from the immediacy need of the institutional traders, then we would obtain similar results to our findings.

We examine this possibility by contrasting the sentiment in the news with the return over the news day. Since informed agents make profits from the price movements rather than the positive sentiment in the news story, if the above argument explains our findings, then institutions should sell the stock only if the positive news sentiment is accompanied by a positive return on the news day. Otherwise, even if the news sentiment is positive, institutions would not sell their shares if they do not observe a positive return. We find that net trading by individual investors on event days has a significantly positive association with future returns even if the positive sentiment is not accompanied by positive abnormal returns. Therefore, our results are not consistent with a liquidity provision explanation.[7]

Our paper builds upon a broadening base of empirical research that examines whether individual investors' trades contain information about future returns. While studies including Dorn, Huberman, and Sengmueller (2008), Hvidkjaer (2008), and Barber, Odean, and Zhu (2009) do not find evidence of informed individual trading using samples before 2000s, recent studies including Kaniel et al. (2008), Kaniel et al. (2012), and Kelley and Tetlock (2013) show

[7] An alternative argument holds that, some buyers could be making systematic mistakes when trading before news events and, therefore, need immediacy to cover their wrong positions after the news is revealed to the market. Hence, if individual investors take the opposite sides of these trades, then retail volume could reflect other investors' systematic mistakes rather than individual investors' information processing skills. For example, if some institutions buy a stock prior to bad news with the expectation that the news will be positive, then they might rush to sell the stock after the bad news is revealed. In this case, individual investors would purchase the stock and take the counterpart of the trade to provide liquidity to these institutions. If the selling pressure pushes prices even below fundamentals, then the subsequent reversal would explain the positive relation between individual purchases and future returns. However, in this scenario, the news sentiment and the trades of individuals should be in the opposite direction: i.e., negative sentiment followed by individual purchases, which are subsequently followed by return reversals (i.e., positive stock returns) but we find that individual investors sell significantly more after negative news events. Similarly, in the case of positive news preceded by sales by other investors, the above argument predicts that individual investors should be selling after positive news events, but our results suggest otherwise (i.e., individual order imbalance is significantly larger after positive news events).

that individual investors' trades are informative about future stock returns. Our paper contributes to this literature by documenting that, like well-established informed traders such as short sellers, individual investors significantly benefit from public news and retail volume on news days is more strongly associated with future stock returns than on non-news days.

Our findings also complement the strand of literature that explores the sources of individual traders' informational advantage.[8] There is an emerging consensus that informed trading and liquidity provision both contribute to the observed return predictability based on retail volume. Our findings suggest that a significant portion of individuals' informed trading occurs during news days and the news interpretation ability is an additional important source of individual investors' informational advantage.

2. Sample and Descriptive Statistics

Trading records of individual investors come from NYSE's historical end of day Retail Execution Reports (ReTrac) for a large cross-section of NYSE stocks for the period April 1, 2004 to December 31, 2011.[9] The data set contains all retail orders that execute on the exchange. Upon the execution of each retail trade, NYSE sends to ReTrac subscribers a real-time data feed on the ticker symbol, volume, and time of each retail execution. Around 8PM each day, NYSE makes available a summary of the NYSE ReTrac activity during the day for each stock and provides the aggregate retail buy and sell orders executed in separate quantities. Since classification of daily NYSE retail volume into buy and sell volumes is exact (Kaniel et al.,

[8]Among others, see Dorn et al. (2008), Kaniel, Saar, and Titman (2008), Hvidkjaer (2008), Barber, Odean, and Zhu (2009), Seru, Shumway, and Stoffman (2010), Linnainmaa (2010), Grinblatt, Keloharju, and Linainnmaa (2011), Kaniel, Liu, Saar, and Titman (2012), Kelley and Tetlock, (2013), Barrot, Kaniel, and Sraer (2013), Barber, Lee, Liu, and Odean (2014),Gamble and Xu (2017), and Kelley and Tetlock (2017).

[9] The NYSE retail trading data set contains all common domestic stocks that were traded on the NYSE. Kaniel, Saar, and Titman (2008) and Kaniel, Liu, Saar, and Titman (2012) use a similar data set covering the period from January 1, 2000 to December 31, 2003 and provide details on the scope of the data.

2008; Kaniel et al., 2012), we do not have to use the Lee and Ready (1991) volume classification algorithm.

Table 1 reports descriptive information on the retail trading data that we use in our analyses.[10] The sample includes around $1.3 trillion in trading volume across 1,659 NYSE stocks. The table depicts a marked decrease in NYSE retail trading activity (both in dollar and shares traded as well as number of orders) over our sample period. For example, the yearly aggregate NYSE retail dollar volume has declined monotonically over our sample period from $278.94 billion in 2005 to $54.49 billion in 2011. [11] Further, the average order size (both in dollars and shares) has decreased over time. The mean order size in our sample is $11,676 (354 shares) and ranges between $6,832 (287 shares) in 2009 and $14,214 (395 shares) in 2006. The average order sizes in the earlier years in our sample are comparable to the $15,822 average order size reported by Kaniel et al. (2008).

We obtain news data from Thomson Reuters News Analytics (TRNA). TRNA reports for each security a time stamped news item identifier, relevance of the news item to the security, and a sentiment score generated via a neural-network (see Sinha (2016), Infoic (2008), and Hendershott et al. (2015) for further details on TRNA's text processing).[12]

[10] We report descriptive information for the NYSE sample after merging it with news data from Thomson Reuters and return data from the Center for Research in Securities Prices (CRSP). The full NYSE sample includes roughly $1.93 trillion in trading volume on 3,697 unique stocks over the April 2004-December 2011. The average order sizes in the full NYSE sample (both in USD and stock shares) are similar to those reported in Table 1.

[11] In comparison, for the January 2000-December 2003 period, Kaniel et al. (2008) and Kaniel et al. (2012) report a total retail dollar volume of $1.55 trillion in 2034 NYSE stocks, representing an average of $350 billion annual volume over that period.

[12] To examine whether the sentiment score generated via a neural-network captures the news content it is supposed to measure, we examine the average daily returns by positive, negative, and neutral sentiment groups. We find that the average daily returns are 0.26% (t-stat= 7.31), -0.31% (t-stat= -7.50), and 0.07% (t-stat= 2.01) for positive, negative, and neutral news, respectively. These results suggest that the market reaction to news and the sentiment score are aligned.

Following Hendershott et al. (2015) we create a firm-day level sentiment score by averaging sentiment scores across all news items in a news story and subsequently constructing a relevance weighted sentiment score using each news story's relevance measure as weight. The TRNA sentiment scores vary between 1 and -1, with the former suggesting a positive news story and the latter a negative news story. For news items appearing after 4PM EST, we use the subsequent trading date as the story date in order to align the story date with price and individual trading (Hendershott et al., 2015).

We merge the NYSE ReTrac and TRNA databases with price data from the Center for Research in Security Prices (CRSP). We eliminate firms with stock prices less than $2 on a given day and CRSP share codes other than 10 and 11 (ordinary common shares). Our final sample includes 2,468,228 firm-day observations for 1,659 unique NYSE-listed stocks from April 1, 2004 to December 31, 2011 (1,953 trading days).

Table 2 presents summary statistics. In Panel A of Table 1, we report time series averages of daily cross-sectional summary statistics for the variables we use in our analyses. The average daily individual order imbalance for a given firm i on day t, OIB_{it}, defined as the total number of shares bought minus sold by all individual investors and divided by total CRSP volume, is -0.29% suggesting that individual investors in our sample are net sellers during our sample period. On average, total daily individual trading volume in a given security is 1.77% of total daily CRSP volume in that security. In addition, the mean number of news stories per firm-day is 1.44 and the mean sentiment score for news is 0.05. The mean (median) firm size is $7858 (1906) Million and suggests that our sample contains relatively bigger firms.

Table 2, Panel B presents summary statistics on firm-level news event frequencies. The sample includes 1,659 unique firms and a typical firm has news stories on 26.75% of the days in its life span in our sample period. We classify news events as positive, negative, and neutral if the relevance weighted sentiment score is larger than 0.5, less than -0.5, and between -0.5 and 0.5, respectively. We find that the average firm has positive news events 5.93% of the time, negative news events 1.81% of the time, and neutral news events 19.01% of the time.

Finally, in Panel C of Table 2, we present summary statistics on the number of firms, news events, and firms with various types of news events for an average day. On average there are 1,356 firms on a given day and 373 of these firms have a news event. Of these 373 firms, 82 have a positive news event, 25 a negative news event, and 266 a neutral news event.

3. Empirical Analyses and Results

3.1. Individual investor trading and future returns

We begin our empirical analysis by examining the association between net individual trading and future returns. If the individual investors in our NYSE sample are informed, then, in line with the existing literature, we expect to find that the net individual trading order imbalance should predict future returns.

We explore the predictive power of individual investors' trades, by sorting stocks into terciles in each day t based on the daily net individual order imbalance, OIB_{it}, computed as a percentage of total daily CRSP volume as follows:

$$OIB_{it} = \frac{\sum_{j=1}^{j=N} Buy\ Volume_{ijt} - \sum_{k=1}^{k=N} Sell\ Volume_{ikt}}{CRSP\ Total\ Volume_{it}}$$

where $Buy\ Volume_{it}$ and $Sell\ Volume_{it}$ denote the NYSE retail buy and sell volumes on day i for stock t, respectively and N is the number of individual investors on a given day.[13] Buy

[13] Note that we employ daily Fama-MacBeth regressions which rely on cross-sectional variation in OIB in explaining future returns and dividing the daily net NYSE retail volume by contemporaneous CRSP volume ensures that our results are not driven by retail investors chasing overall trading volume in a given stock. However, as indicated in section 2, the NYSE retail volume has declined monotonically over our sample period with the largest

and sell volumes are measured in numbers of shares ordered. Since total trading volume on news days is documented to contain information about post-news returns and retail trading volume is correlated with the total trading activity (Tetlock , 2010), dividing the net retail trading by daily total CRSP volume ensures that the information in retail trading activity on news days is not simply due to an increase in total trading activity. All stocks are held for 20 days after portfolio formation. Daily portfolio returns are calculated as equally-weighted averages of the returns of all stocks in the portfolio. In Table 3, we present the time series averages of order imbalances and stock returns for each OIB tercile. Column 1 suggests that individual investors are net sellers in the smallest OIB tercile, T1, (mean OIB=-0.0157, t-stat=-12.75) and net buyers in the largest OIB tercile, T3, (mean OIB=0.007, t-stat=14.33).

In columns 2 and 3, we examine future buy and hold raw and abnormal returns over the [t+1, t+20] for OIB terciles formed on day t.[14] The average monthly raw return is 65 basis points for the lowest OIB tercile and increases to 98 basis points for the highest OIB tercile. The difference in average monthly returns between the highest and lowest OIB terciles (T3-T1) is 33 basis points and is significant with a t-statistic of 6.63.[15] In column 3, we present the average monthly buy and hold abnormal returns, defined as the compounded raw return over the [1,20] window minus the compounded CRSP value-weighted index return over the same window. The average abnormal return is 13 basis points for the lowest OIB tercile (T1) and increases to 46 basis points for the highest OIB tercile (T3). The difference in buy-and-hold raw returns between the highest and lowest OIB terciles (T3-T1) is 33 basis points and is significant with a Newey-

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drop in 2009, after which the NYSE retail trading volume has remained relatively stable. We obtain similar results when we conduct our analyses by limiting the sample to the period from January 1, 2009 to December 31, 2011.

[14] To assess the robustness of our findings, we also repeat our analysis using Fama and French 3 and 4 factor alphas and obtain similar results. In addition, our results are robust if we apply DGTW adjustment to our returns.

[15] All t-statistics are based on Newey-West (1987) standard errors corrected for serial correlation up to 20 lags.

West t-statistic of 6.51. The abnormal return analysis in column 3 also suggests that while the individual investors are informed when they are net buyers, they do not significantly outperform the benchmark when they are net sellers. For example, the future abnormal return in tercile T1 is not significant at conventional statistical levels (t-statistic= 0.86) while the abnormal return in tercile T3 is significant with a Newey-West t-statistic of 2.68. This finding confirms the results documented in the literature that individual investors are mainly informed when they are net buyers. Finally, the average raw returns on day *t* suggest that individual investors are contrarians with respect to same day stock price changes consistent with prior evidence that individual investors tend to be return contrarian in the short term (e.g., Choe, Kho, and Stulz, 1999; Grinblatt and Keloharju (2000, 2001); Kaniel et al. 2008).

Overall, the findings in Table 3 suggest that net retail trading in our sample predicts future returns up to 20 days following portfolio formation and the average individual trading is informative about future returns.

3.2. Individual investor trading around public news

One potential channel through which individual investors can obtain a trading advantage is through successful timing of the news events. in this section, we examine individual investors' trading behavior shortly before and after public news events and investigate whether they can time the news. As a precursor to our main analysis, in Figure 1 we plot daily excess individual order imbalance from trading day -5 to day +5 around positive (Panel A), neutral (Panel B), and negative (Panel C) news events. For a given stock *i*, excess order imbalance on day *t* is calculated as follows:

$$Excess\ OIB_{it} = \frac{Net\ Volume_{it} - (\sum_{\tau=-30}^{\tau=-11} Net\ Volume\ i\tau)/20}{|(\sum_{\tau=-30}^{\tau=-11} Net\ Volume\ i\tau)/20|}$$

where $Net\ Volume_{it} = \sum_{j=1}^{j=N} Buy\ Volume_{ijt} - \sum_{k=1}^{k=N} Sell\ Volume_{ikt}$ and N denotes the number of individual investors in the sample. $Buy\ Volume_{ijt}$ ($Sell\ Volume_{ijt}$) is the total number of shares of stock *i* bought (sold) by investor *j* on day *t*. That is, we subtract from the order imbalance on a given day the average daily order imbalance over the [-30, -11] window and divide by the absolute value of the order imbalance over the [-30, -11] window. Plots of excess order imbalance around positive, neutral, and negative news events are presented in Panels A, B, and C of Figure 1, respectively. These plots suggest that individual investors buy more on positive news days, sell on the negative news days, and moderately sell on neutral news days. However, we do not observe any significant increase (decrease) in excess retail order imbalance prior to positive (negative) news events. Rather, individual investors seem to trade based on the news content mainly on the news day and increase (decrease) their positions on days with positive (negative) news. This finding is in line with the idea that, on average, individual traders are not informed about the news before its public release and trade on the news only after it becomes public.

Next, we turn to our formal analysis on the news timing ability of individual investors. In a similar spirit to Engelberg, Reed, and Ringgenberg (2012), we run the following panel regression separately for positive, negative, and neutral news events:

$$OIB_{i\tau} = \beta x News\ Event_{it} + a_1 Return_{i\tau-1} + a_2 Return_{i\tau-2} + Firm\ Fixed\ Effects$$
$$+ Year\ and\ Month\ Fixed\ Effects + \varepsilon_{i\tau}$$

where $OIB_{i\tau}$ is individual order imbalance in stock *i* on day τ. A news event is classified as positive, negative, or neutral if the TRNA relevance-weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively. The timing of the dependent variable, τ, varies between *t*-2 and *t*+2. $Return_{i\tau-1}$ and $Return_{i\tau-2}$ are daily raw stock returns one and two days before the day the dependent variable is measured, respectively. We present the results in Panels A to C of Table 4 for positive, negative, and neutral news, respectively.[16]

According to the results in Panels A and B of Table 4, retail order imbalances prior to both positive and negative news events are not significantly different from zero on both day t-2 and day t-1. In both panels, individual investors react to the news in a manner consistent with the sign of the news (i.e., buy on positive news days and sell on negative news days). Consistent with our inference from Figure 1, individual investors do not seem to anticipate positive or negative news events; rather, they trade on the day the news becomes public. On the other hand, an interesting pattern of individual order imbalance emerges prior to days with neutral news events. According to the results in Panel C of Table 4, individual investors seem to buy significantly one day before the neutral news and sell significantly on days following the news day. Collectively, however, the results in neither panel of Table 4 provide any evidence in support of the idea that individual investors are informed about the upcoming news. Rather, our evidence is consistent with individual investors trading mainly on the day the news becomes public.

3.3. Profitability of Individual Trading on the News Days

Our analysis thus far suggests that individual investors are informed traders, but they do not have the skill to predict the content of the news events before they become public. On the other hand, we do find that individual investors significantly trade in the direction of the news on the news days. In this section, we examine whether the return predictability of individual

[16] It is important to note that we use the same sample in all three panels and only the dummy variable for each news category differs in the panels. Also, since the number of negative and positive news days are smaller compared to the no-news days, we obtain similar adjusted R^2 's up to two decimal points.

investors' trading on the news days is different than trading on no news days. If individual investors have information processing skills, then as proposed by Kandel and Pearson (1995), public news releases might be an opportunity for them to use this skill and benefit from public news releases. Accordingly, we expect retail investors trades to have a stronger association with future returns when they trade on news days.

To examine this question, we run daily Fama-MacBeth regressions of the following form:

$$Return_{i;t+1,t+20} = \beta_0 + \beta_1 OIB_{i,t} + \beta_2 News\ Event_{it} + \beta_3 OIB_{it} x News\ Event_{it} + \gamma \boldsymbol{X} + \varepsilon_{it}$$

where $Return_{i;\, t+1,\, t+20}$ is buy and hold raw or abnormal stock returns over trading days t+1 through t+20. *OIB* is individual investor order imbalance and defined as the total number of stock *i* shares bought minus sold on day *t*, divided by the total CRSP volume in stock *i* on day *t*. $News\ Event_{it}$ is a dummy variable that equals one if there is a news story covering stock i on day t and zero otherwise. News events are classified as positive (159,822 firm-day observations), negative (48,010 observations) or neutral (519,718 firm-day observations) if the relevance weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively. *X* is a vector of control variables and includes $Ln(MV)_{t-1}$ (the natural logarithm of one day lagged market value of equity), *Momentum* (cumulative raw stock returns over trading days *t*-63 through *t*-3), $Return_t$, $Return_{t-1}$, and $Return_{t-2}$ (daily raw stock returns on days *t*, *t*-1, and *t*-2, respectively). All continuous variables are standardized to have mean zero and variance one in order to ease their interpretations. We run 1,953 separate daily cross-sectional regressions and report time series means for each coefficient. We calculate t-statistics using standard errors corrected for serial correlation via the Newey-West (1987) procedure with 20 lags.

The results are reported in Table 5. In Panel A, the dependent variable is buy and hold raw returns over trading days t+1 through t+20. and in Panel B the dependent variable is abnormal returns over trading days t+1 through t+20. The results in column (1) in both panels support our earlier portfolio results reported in Table 3. Specifically, we continue to find a statistically significantly positive relation between future stock returns and net order imbalance on a given day even after controlling for lagged returns, order imbalance, stock returns, and firm size. In column (2), we interact the *News Event* indicator with *OIB* to examine whether individual investors better predict future returns on news days regardless of the sentiment of the news. The coefficients on the interaction terms in both panels are not significant suggesting that the mere presence of public news does not increase the informativeness of individual investors' trades about future returns.

In column (3), we include separate dummies for each type of news event and find a significant post-event drift only for negative news events. The coefficient on *Positive News Event* is positive but insignificant while the coefficient on neutral news event is negative but insignificant.

Since the individual investors we analyze in our sample are more informed when they buy a stock, these investors might be more interested in processing positive news and devote their time and energy to analyzing such news. In other words, the sentiment of a news event might affect individual investors' ability and effort to profit from the news. In this case, the informedness of individual investors would depend on the sentiment of the news rather than the mere existence of the news. In order to examine this issue, in column (4), we separate news events into three categories, negative news, neutral news, and positive news, based on the sentiment score provided by Thomson Reuters as described before. In these specifications, we include three news event indicators and three interaction variables between *OIB* and these three news type indicators. The benchmark group in these regressions is firm-day observations without any news event.

In both panels, the interaction between *Positive News Event* and *OIB* has a significantly positive coefficient while the coefficients on the other two interaction terms are both insignificant. Positive news events seem to have an economically meaningful impact on the relation between net trading by individual investors and future returns. Specifically, from Panel A, the coefficient on the interaction of *OIB* with *Positive News Event* in column (4) is 0.111 (t-stat=3.71). In comparison, the coefficient on OIB on no news days is 0.095, indicating that the relation between OIB and future returns doubles on positive news days. The effect of positive news on the predictive ability of retail volume is economically meaningful. Specifically, a one standard deviation increase in *OIB* on positive news days is associated with an increase of roughly 20 basis points in future returns. [17]

Therefore, individual investors are significantly more informed when they trade stocks that have positive news events suggesting that these investors are good at processing information released at positive news events. On the other hand, for neither negative nor neutral news do we find a significant effect on the association between net trading by individual investors and future stock returns. In other words, unlike short sellers who profit from both positive, neutral, and negative news events (Engelberg, Reed, Ringgenberg, 2012), individual investors seem to be benefiting from only good news when processing information.

Overall, the findings in Table 5 suggest that individual investors' trades have a larger positive association with future returns when they buy stocks with positive public news. Hence,

[17] All continuous regressors are standardized to be mean zero and variance one. Therefore, on positive news days, the marginal effect of OIB on future returns is the sum of the coefficient on OIB and Positive News Event xOIB.

an important source of individual investors' informational advantage is their information processing skills, especially for news with a positive sentiment.

4. Exploring Alternative Explanations

Our findings thus far are consistent with the interpretation that individual investors in our sample possess news interpretation skills. In this section, we explore various plausible alternative interpretations of our findings.

4.1. Increase in firm visibility following news events

Barber and Odean (2008) show that individual investors are net buyers following attention-grabbing events such as public news. Under this explanation, public news increases the visibility of a stock. Since, investors have limited resources or cognitive skills that deter them from investigating all stocks, individual investors may buy attention-grabbing stocks without processing the content of the news event. The increase in firm visibility may lead to a demand shock and create a positive price pressure. Therefore, the visibility argument predicts that the predictive power of net trading by individual investors with respect to future returns should be higher following attention-grabbing events.

Inconsistent with the visibility argument, in column (1) in Panels A and B of Table 5, we find that the mere existence of public news does not result in a larger positive relationship between *OIB* and future returns. However, it could still be argued that it is the positive news events that would mainly catch individual investors' attention and the price pressure would occur only following good news events. Since individual investors are documented to refrain from short selling (Boehmer, Jones, Xhang, 2008) and are more inclined to buy stocks, it is possible that positive news events would catch their attention more than negative and neutral news events. Accordingly, our findings in column (4) in Panels A and B of Table 5 that the positive relation between OIB and future returns is more pronounced among positive news stocks would also be consistent with the visibility argument. We conduct two tests to address this alternative explanation. First, we examine whether the predictive ability of individual *OIB* is a short-lived phenomenon that reverses in longer horizons. Second, we explore the effect of short-sale restrictions on the relationship between OIB and future returns.

4.1.1. Return reversals

One important testable implication of the visibility argument is that since the positive price change is due to the excessive demand pressure and cannot be justified by changes in firm fundamentals, it should be temporary. Therefore, if our results are simply driven by elevated investor attention following positive news events, then the return predictability should reverse over longer holding horizons.

We formally test this argument by extending our return measurement window from 20 to 60-day holding horizon. Specifically, we use buy and hold returns over the [21,60] window as our dependent variable. If the visibility argument explains our results, we should find a negative relationship between *OIB* and returns over the [21,60] window returns for positive news events. Therefore, the coefficient on the interaction between positive news and *OIB* should be negative.

Table 6 presents the results. In all specifications, the dependent variables are either raw returns (columns (1) and (2)) or abnormal returns (columns (3) and (4)) measured over the [21,60] trading day window. According to the results, before including news sentiment indicators to the analysis (columns (1) and (3)), we do not find any significant relation between *OIB* and future returns. This suggests that, unconditionally, *OIB* does not contain information about future returns beyond the first month (i.e., the [1,20] window). In columns (2) and (4), we include the three news sentiment indicators and their interactions with *OIB* to test the reversal argument following positive sentiment news. The coefficient on the interaction between positive news event and future returns is positive but insignificant. We find similar results for both the neutral and negative news sentiment interactions with *OIB*. Therefore, the results in Table 6 show that the return predictability in retail order imbalance following positive news does not reverse over longer holding periods.

4.1.2. The role of short selling constraints

According to the visibility argument, following public news, excess demand from individual investors could cause a positive price pressure which pushes stock prices away from fundamentals. Thus, the positive relationship between daily OIB and future stock returns could be due to the visibility-driven individual investor demand rather than these investors' news processing capabilities. However, the visibility argument also implies that the ease with which sophisticated investors such as short-sellers can arbitrage away pricing inefficiencies should diminish the relationship between *OIB* and future returns following positive news events. Accordingly, if our results are explained by the visibility argument, then we should find a less positive relationship between *OIB* and future returns in stocks with less binding short-sale restrictions. Note, however, that particularly for positive news for which our results are more pronounced, the information processing argument predicts no relation between short-sale constraints and the predictive ability of net retail trading volume.

Following Akbas (2016), we use the exchange traded put option volume, *PV*, as our measure of short selling restrictions. Specifically, we calculate *PV* as the decile ranked total put option volume over the one-month period ending three weeks before a given day. [18] Larger values of PV indicate less binding short-sale constraints. Put options give investors the ability to

[18] We subsequently standardize PV to have a mean of zero and variance of one to ease the interpretation of interacted variables.

short stocks when they are restricted from regular short selling in the stock market. Our measure ensures that the stock has enough liquidity in its put option to make it easy for traders to act on their negative information in the options market.[19]

We modify model (4) of Table 5 to include our proxy for short selling restrictions, *PV*, and its interactions with individual order imbalance and news sentiment indicators. The results are presented in Table 7. In column (1), the dependent variable is buy-and-hold raw returns and in column (2), the dependent variable is cumulative abnormal returns over the [t+1,t+21] window. The coefficient on *OIB x Positive News Event*$_t$, which captures the relationship between *OIB* and future returns around positive news events when *PV* is at its mean value, is significantly positive (0.097, t-stat=2.64). However, the coefficient on the three-way interaction term, *OIB x Positive News Event*$_t$ *x PV*, is insignificant. The results suggest that the predictive ability of net retail volume following positive news events does not depend on short-sale constraints consistent with the interpretation that individual investors possess news processing capabilities but inconsistent with the visibility argument.

4.2. Persistence in retail order imbalance

Certain stocks might be more prone to persistent buying or selling pressure from individual traders which might lead to a positive association between retail volume and future stock returns. Indeed, Kelley and Tetlock (2013) find that part of the return predictability based on individual trading can be explained by the persistence in retail order flows. Moreover, the arrival of news might amplify the existing buying or selling pressure, resulting in a more pronounced relationship between retail volume on news days and future stock returns. Hence,

[19] In the literature, the level of shares held by institutions is also used as a measure of short selling constraints. However, since institutional ownership is inversely related to the level of individual holdings, using option volume as a measure of short selling constraints alleviates any concern that our results might be driven by this negative relation.

our results might be driven by persistent individual investor order flow rather than news interpretation skills. Accordingly, a testable implication of this argument is that our results should be more pronounced among stocks with more persistent retail order flows.

To test this argument, we follow Kelley and Tetlock (2013) and calculate the persistence in order flow, *OP*, as the decile ranked autocorrelation coefficient from regressing daily *OIB* on one-day lagged *OIB* for each firm-quarter. [20] We then modify model (4) in Panel A of Table 5 by including the interaction of firm-level persistence in net retail trading volume with daily order imbalance, *OIB,* and news sentiment indicators. If the increase in the predictive ability of retail volume following public news is driven by the persistence in order flows, then we expect to find the interaction between the news sentiment and order imbalance to be higher among stocks with more persistent order flows. Table 8 reports the results. The coefficient on the three-way interaction term *OIB x Positive News Event*$_t$ *x OP* is insignificant, while the coefficient on the two-way interaction coefficient, *OIB x Positive News Event*$_t$, is positive and significant at the 1% level. In other words, the predictive ability of retail volume on positive news event days is not driven by the persistence in order flow.

4.3. Persistence in news sentiment

Another important factor that might affect the price pressure of retail investors is the persistence in the news sentiment. If news days cluster together and good (bad) news today are followed by good (bad) news in the following days, then individual investors might simply take advantage of the persistence in the news sentiment by simply identifying stocks with more persistent news sentiment. Note that, in this scenario, rather than analyzing the content of the current news, retail traders simply focus on the persistence in news sentiment and they only trade

[20] We standardize the order flow persistence measure to have a mean zero and variance of one in order to ease the interpretation of the interacted variables.

in stocks which are more likely to continue to deliver positive news. Obviously, while identifying such stocks also requires some skills, this skill is different than the news processing skills which we propose as an explanation for our findings.

We examine this issue by employing a similar analysis to that in section 4.2. Specifically, we calculate the news sentiment persistence, *NSP*, as the decile ranked autocorrelation coefficient from regressing the daily sentiment score on the one-day lagged sentiment score for each firm-quarter.[21] We then modify model (4) in Panel A of Table 5 by including the interaction of *NSP* with daily order imbalance, *OIB*, and news sentiment indicators. If the increase in the predictive ability of retail volume following public news is driven by the persistence in news sentiment, then we expect to find the interaction between the news sentiment and order imbalance to be higher among stocks with more persistent news sentiment. Table 9 reports the results. The coefficient on the three-way interaction term *OIB x Positive News Event*$_t$ *x NSP* is insignificant, while the coefficient on the two-way interaction coefficient, *OIB x Positive News Event*$_t$, is positive and significant at the 1% level. Thus, the predictive ability of retail volume on positive news event days is not driven by the persistence in news sentiment.

4.4. The role of high-volume return premium

Gervais et al. (2001) document that stocks experiencing abnormally high trading volume over a day or a week tend to appreciate over the course of the following month. Also, it is well documented in the literature that when public news is released, absolute price changes are accompanied by increases in trading volume (Harris and Raviv, 1993). Hence, one might argue that when positive news arrives and trading volume spikes, individual investors might observe the abnormal volume and take position to take the advantage of the high-volume premium

[21] We standardize the news sentiment persistence measure to have a mean zero and variance of one in order to ease the interpretation of the interacted variables.

without processing the information content of the news. To ensure that our results are not driven by the return premium stemming from trading volume spikes around news events, we repeat our analysis in Table 5 by controlling for abnormal trading volume on news days. In particular, we include the abnormal CRSP trading volume on the news day and its interactions with the three news sentiment indicators. Results (untabulated for brevity) suggest that controlling for the abnormal trading volume around the news days does not alter any of our inferences.

4.5. Liquidity changes around public news event

Another potential explanation for our findings is that stock liquidity might be higher on news days, particularly those with a positive news sentiment. Thus, due to the lower cost of trading on these days, individual investors might find it more profitable to trade on their information (obtained from other sources) on positive news days. In this case, the net retail trading volume would have a more positive association with future returns on positive news days due to individual investors' incentives to time the lower transaction cost days rather than their superior news interpretation skills.

Following Engelberg, Reed, and Riggenberg (2008), we examine this issue by analyzing the transaction costs around positive news events. We use the bid-ask spread as our measure of liquidity. Bid-ask spread (in percent) is defined as the spread between bid and ask price quoted at the end of the trading day, divided by the mid-point of the spread. The transaction cost argument implies that the cost of trading should be lower on days with positive news. Table 10, Panel A reports the time-series averages of daily cross-sectional summary statistics on bid-ask spreads over the [-15, +15] trading day interval around positive news event days and Panel B reports tests of differences in mean bid-ask spreads between day t=0 and various days before and after the news event day. We find that the mean bid ask spread on day 0 is not significantly different from the average spreads on days -15, -10, -5, +10 and +15. We find, however, that the day 0 spread is marginally significantly higher than the day +5 spread (t-stat=1.67).

Figure 2 provides a graphical representation of the daily cross-sectional average bid-ask spreads over the [-15, 15] window around positive news event days. The bid ask spread is almost flat over the [-15,-2] interval and increases slightly one day before and on the news day. The bid-ask spread reverts to the pre-event levels after the event.

Overall, the bid ask spread pattern suggests that liquidity decreases slightly around positive news events and it is costlier for investors to trade on their information on these days.[22] This finding is inconsistent with the idea that the significant relation between *OIB* and future returns on positive news days can be explained by individual investors' tendency to benefit from a decrease in transaction costs on positive news days. Hence, changes in liquidity around news events cannot explain our findings.[23]

4.6. Liquidity provision to other market participants

Individual investors might be providing liquidity to meet the demand for immediacy from other informed market participants who trade before news events. Hendershott et al. (2015) show that institutional investors are such a group of informed traders and they skillfully predict the outcome of public news. For example, in expectation of positive news, institutional traders would buy the stock before the news and immediately cover their positions after the news realize their profits., Accordingly, selling pressure by institutional investors after positive news events could lead to an incomplete price adjustment on these days. If individual investors take the

[22] The increase in illiquidity on the news days is also consistent with the theoretical arguments of Glosten and Milgrom (1985) and Kyle (1985) that presence of informed agents and elevated information asymmetry between the informed agents and market makers increases the spread.

[23] The pattern in Figure 2 and inferences from Table 6 are similar when we conduct the bid-ask spread analysis around all news events instead of only positive news events.

counter part of the trade (i.e., buy following positive news) to provide liquidity to institutional investors, then the net retail order imbalance will have a more positive association with future returns on positive news days. Hence, in this view, it is the liquidity provision tendency of individual investors rather than their superior information processing skills that causes their trades to be more predictive of future returns on positive news days.

The liquidity provision story we outlined above requires institutional investors to reverse their positions following positive price increases. In other words, the positive news should be accompanied by positive abnormal returns for institutional traders to reverse their orders. Otherwise, even if the news sentiment is positive, institutions would not sell their shares unless they observe a positive return and profit from their trades.

In order to examine whether our findings can be explained by this story, we estimate model (4) of Table 5 by limiting our sample to news events that are not accompanied by significant stock returns on news days. To retain no return days, we group stocks into five groups based on the absolute value of the daily return on news days and keep the stocks at the bottom two quintiles, which are firm-days where the firm is covered in a news story but no significant change in stock returns. The liquidity provision argument implies that there should be no improvement in the predictive ability of net retail volume on days with positive news but no change in stock prices. The results are presented in Table 11. Inconsistent with the liquidity provision story, the coefficient on the interaction between OIB and positive news event indicator is positive and significant in both columns (1) and (2).

5. Information Uncertainty and Individual Investors' News Interpretation Ability

5.1. Market level uncertainty

Barrot, Kaniel and Sraer (2016) document that the ability of aggregate net trading by individual investors to predict short term future returns is significantly higher during periods of elevated market uncertainty. During times of higher market uncertainty, it might be harder for the general market participants to correctly interpret the news and value stocks. Hence, market uncertainty might provide more profitable trading opportunities to investors who are skillful in interpreting public news. Therefore, the higher return predictive ability of individual investors' trades on news days might be stronger when the uncertainty in the market is higher.

To test this idea, we follow Barrot, Kaniel and Sraer (2016) and Boehmer, Jones, and Zhang (2016) and use the Chicago Board Options Exchange (CBOE) volatility index, *VIX*, as our measure of market uncertainty. We then examine whether the predictive ability of net retail order imbalance about future returns differs when *VIX* is higher than the median from when *VIX* is lower than the median over the sample period.[24] In particular, we repeat our analysis in column (4) of Table 5 and keep the daily time series of coefficient estimates on individual order imbalance, *OIB*, and its interactions with the news type indicators obtained from daily cross sectional regressions where the dependent variable is abnormal future returns.[25] Then, we regress each of these coefficients on a constant and *High VIX*, which is an indicator that equals one if *VIX* is higher than the median value over the sample period and zero otherwise. For each coefficient estimate from column (4) of Table 5, the coefficient on *High VIX* represents the

[24] We also use the historical median (18%) of VIX following Boehmer, Jones, and Zhang (2016) and obtain similar results.

[25] We obtain similar results when we use the model in column III of Table 4 where the dependent variable is future raw returns.

change in the predictive ability of net retail trading volume on news days when *VIX* is high (equals one) and the constant represents the average coefficient when *VIX* is low.

The results are presented in Table 12. The coefficient on *OIB* is positive and significant during periods of low uncertainty and is significantly larger during periods of high market uncertainty. Thus, the predictive ability of net retail volume for future returns is more pronounced in high market uncertainty periods. More importantly, we find that positive news disseminated during periods of low market uncertainty does not provide an incremental benefit to individual investors while positive news disseminated during periods of high market uncertainty does. This suggests that individual traders' success in interpreting positive news is time varying and they are successful in analyzing positive news events only during times of elevated market uncertainty.[26] Another interesting finding in Table 12 is that, unlike unconditional results in Table 5, individual investors also successfully trade on neutral news days when market uncertainty is high and are slightly worse off from trading on neutral news days when market uncertainty is low.

Overall, the results in Table 12 imply that individual investors are more successful in interpreting news when the market uncertainty is high. Hence, the previously documented time varying nature of the predictive ability of individual investors' net trading can, at least partially, be attributed to their ability to better interpret positive news during high uncertainty periods.

[26] Alternatively, one might argue that the information content of positive news on high uncertainty times might be more informative about future returns and individual investors profit more due to the different nature of positive news in high vs. low uncertainty times. In this case, we would expect a significantly positive coefficient on VIX dummy when we repeat the analysis on positive news coefficient. The results, untabulated, show that this is not the case. The coefficient on the VIX dummy is not significant when we regress positive, neutral or, negative news coefficients on a constant and the VIX dummy.

5.2. Firm level uncertainty

In this section, we examine whether firm level information uncertainty affects individual investors' information processing skills on news days. When there is more firm specific information uncertainty, interpreting public news might be more difficult and these news events might provide more information advantage to investors who can skillfully analyze the news.

Following Hong, Lim and Stein (2000), we use analyst following to capture firm level information uncertainty.[27] Specifically, for each firm *i* and day *t* we determine the number of analysts who issue a one-year ahead EPS forecast on the firm over the one year ending on day t-1 and calculate *AF* as the yearly decile ranked analyst following. [28]

We then estimate model (4) of Table 5 by including *AF* and its interactions with OIB and news event sentiment indicators. If individual investors have a better interpretation advantage when firm specific information uncertainty is high, then we expect a positive coefficient on the three-way interaction between *AF*, *OIB*, and the news event sentiment indicators.

The results are presented in Table 13. The coefficient on the interaction between *AF*, *Positive News Event*, and *OIB* is negative and is significant at the 1% level, suggesting that the predictive ability of retail volume on positive news days is decreasing in analyst following. Put differently, the predictive ability of retail order imbalance on positive news days is more pronounced for firms with higher uncertainty as measured by lower analyst following. Overall, these results are consistent with the view that, besides high market level uncertainty, individual investors benefit more from public news when firm specific uncertainty is higher.

[27] Zhang (2006) uses analyst coverage and analyst forecast dispersion as proxies for firm specific information uncertainty. We repeat our analysis using the dispersion in analyst earnings forecasts, idiosyncratic volatility of stock returns, and cash flow volatility and obtain similar results, which are untabulated for brevity but available upon request.

[28] We standardize the decile ranked analyst following to have mean zero and variance one to ease the interpretation of the interacted variables.

6. Individual Investor Trading and Future Returns by News Category

In this section, we explore the relation between daily individual trading order imbalance and future returns across different news categories. Besides the sentiment and relevance of the news items to the underlying security, Thomson Reuters (TR) provides a news category for each story item. If more than one news category code is provided for the same news item, then we populate the firm-day observations as many times as the number of news categories on a firm-day. Since in our main tests we find that individual investors' news processing ability is limited to positive news event days, we retain only positive news items in this section and identify in which news categories the information is best processed by individual investors when the sentiment of the news is positive. In our final data set, we have 59 news categories with enough number of observations left to perform our analysis.

To examine whether individual investors' information processing ability differs across news categories, following Engelberg et al. (2012), we run panel regressions for each of the 59 news categories where the dependent variable is abnormal returns over the [1,21] window following the news day. We control for the same variables as those in Table 5 but suppress them for brevity. We also include firm fixed effects to account for potential cross-firm heterogeneity in the panel and cluster standard errors by date. The variable of interest is *OIB* and the differences in the coefficient on this variable show us how individual investors' news processing ability varies across different news categories.

The results are presented in Table 14. The table suggests that individual investors seem to successfully process information in 10 of the 59 news categories as is revealed by the statistically significant positive coefficient on *OIB*. These ten categories represent roughly 44% of total news by frequency count and include the following categories: Business Activities, Corporate

Financial Results (e.g., annual reports, tabular and textual reports, dividends, etc.), Dividends, Internet/World Wide Web, Domestic Policies, New Issues, Mortgage Backed Debt, Corporate Analysis, International Trade, and Short Term Interest Rates (p-value>0.10 or better).[29]

In order to assess whether the distribution of the p-values for the coefficients on OIB across news categories differs from a uniform distribution on the [0, 1] interval, we conduct a *Fisher* test of combined probability. The Fisher statistic, which has a Chi-squared distribution with 2k degrees of freedom where k is the number of categories, is equal to 156 and has a p-value less than 0.01.[30] For the remaining news categories, the coefficient on *OIB* is positive but statistically insignificant. Arguably, the lack of significance for the remaining news types might be due to a lack of power in these tests since these news types are fewer in our sample.

Our finding that individual investor trading around news stories about corporate financial results predicts future returns is consistent with Kaniel et al. (2012), who find that intense aggregate individual investor trading around earnings announcements predicts future returns. We extend Kaniel et al. (2012) by showing that the predictive ability of trading by individual investors is not limited to news stories about earnings announcements; individual investors seem to have information processing skills across a broader spectrum of news categories.

7. A Discussion on Information Processing around Negative News Events

It is important to note that, according to our findings, while individual investors benefit significantly from positive and neutral news, they do not benefit from negative news. However, if individual investors possess news processing skills, then one would expect them to also benefit

[29] Thomson Reuters news codes can be accessed at:
https://customers.reuters.com/training/trainingCRMdata/promo_content/ReutersCodes.pdf

[30] The Fisher test statistic ignores the number of observations in each news category. Therefore, we also calculate a Stouffer Z-statistic weighted by the number of observations in each category. The resulting Stouffer's Z is equal to 6.15 (p-value<0.01).

from negative news events. We believe that there are three important reasons that could drive the asymmetry in individual investors' news processing ability following positive vis-à-vis negative news and the lack of an association between individual order imbalance on negative news events and future returns.

First, if individual investors believe that the market underreacted to the negative news and prices indeed remain overvalued by not fully incorporating the information content of the negative news, then a plausible strategy for individual investors is to short the stock. However, according to Boehmer, Jones, and Zhang (2008) individual investors generally avoid shorting stocks[31] and therefore, it is unlikely that individual investors will spend the time and effort to detect negative news events to which the market underreacted. Of course, individual investors can also benefit from negative news by selling the shares they own to reduce their losses. However, compared to the number of potential buyers who do not own the stock, the number of individual investors who own the stock and react on negative news is limited. Hence, even if some individual investors can correctly interpret the news and sell their shares their effect would be limited in our sample since they are outnumbered by other individual investors who might trade in mixed directions for various reasons.

Second, in case the market overreacts to negative news by pushing prices below the fair value, the stock price becomes undervalued and individual investors who can detect this undervaluation by processing the news would benefit from the news event by simply buying the stock. In Table 4, however, we find that, future stock returns (both raw and abnormal) are significantly negative on average following negative news events. Hence, on average, the market

[31] For example, in the study of the individual investors from a large discount brokerage firm, Barber and Odean (2006) document that only 0.29% of positions are short positions.

is underreacting to negative news as opposed to overreacting. While our sample includes observations where negative news is followed by positive stock returns over the next month, these observations constitute less than 1% of our sample, which makes it statistically difficult to detect an association between individual order imbalance and future returns after negative news events. Relatedly, negative news event days constitute only 1.8% of all our firm-day observations, which reduces the power of our test for this news category. Potential reasons for the lower number of firm-days with negative news sentiment could be managers' tendency to withhold bad news (Kothari, Shu, and Wysocki, 2009) or a positive slant induced by the firms' media advertising expenditures (Gurun and Butler, 2012). Hence, the limited number of observations in the negative news category might be one of the potential reasons that we do not find any significant result.

Finally, individual investors might also sell for liquidity and diversification reasons, which are not related to information. Indeed, supporting this conjecture, the results in Table 3 suggest that individual investors only profit from trading when they buy stocks and their trades do not predict any abnormal returns when they sell. Hence, individual investor trading following negative news is likely dominated by less informed trades, which makes it harder to find trades that are the result of information processing that requires a significant time and effort.

8. Conclusion

In this paper, we examine the profitability of individual investors' trades around firm specific public news events. We find that individual investors' trades are significantly more profitable on days with positive news. The association between retail order imbalances and future monthly returns increases roughly twofold on days when the firm is covered in a news event with a positive sentiment. However, we find little or no evidence of incremental ability for retail trades to predict future returns on negative news event days. Moreover, individual investors cannot predict the news content and they are more successful in interpreting news for firms with high information uncertainty and during times of elevated market uncertainty.

Our results are consistent with the idea that informed individual investors in our sample possess superior information processing skills and that news releases create trading opportunities for these investors. We explore a multitude of potential alternative explanations such as liquidity provision by retail traders to other investors, increase in firm visibility, persistence in news sentiment and retail order imbalance, and reduced transaction costs around news events. Our results cannot be explained by any of these alternative explanations.

Our paper contributes to the ongoing debate on whether and how individual investors are informed about future stock returns. Our evidence suggests that information processing around public news is an important channel through which individual investors obtain an informational advantage and execute profitable trades. However, our results and inferences are only limited to the retail orders executed on the New York Stock Exchange and may not be generalized to the entire individual investor universe. Hence, we do not argue that all individual investors can skillfully process news. Rather, the group of informed individual investors we examine in this study seems to exhibit this important skill. Whether net trading by individual investors has predictive ability for future returns in other markets or stock exchanges would be a potentially fruitful area of inquiry.

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Figures

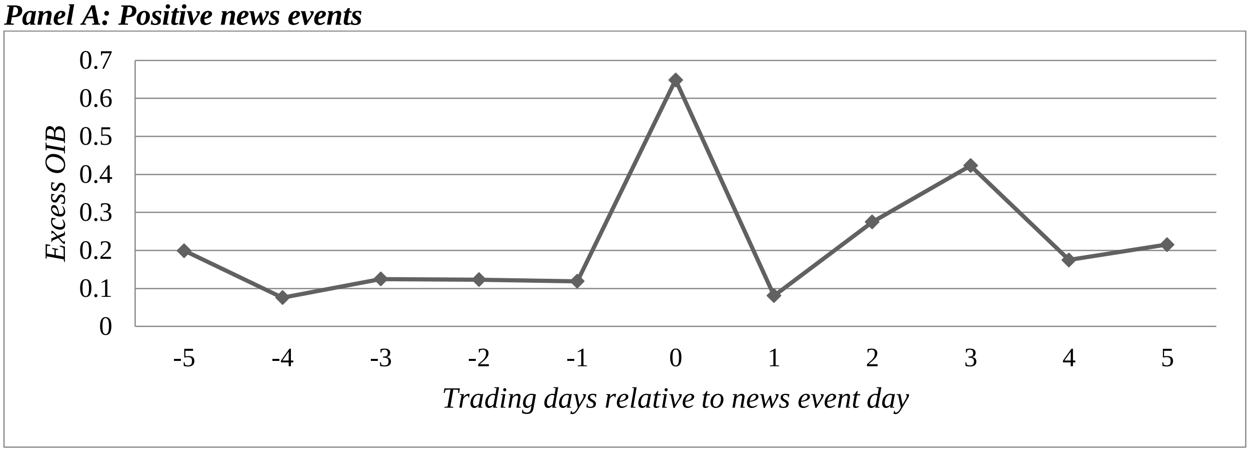
Figure 1: Excess order imbalance around news events

This figure plots excess individual order imbalance from trading day -5 to day +5 around positive (Panel A), neutral (Panel B), and negative (Panel C) news events. For a given stock *i*, excess order imbalance on day t (*Excess OIB*$_{it}$) is calculated as follows:

$$Excess\ OIB_{it} = \frac{Net\ Volume_{it} - (\sum_{\tau=-30}^{\tau=-11} Net\ Volume\ i\tau)/20}{|(\sum_{\tau=-30}^{\tau=-11} Net\ Volume\ i\tau)/20|}$$

where $Net\ Volume_{it} = \sum_{j=1}^{j=N} Buy\ Volume_{ijt} - \sum_{k=1}^{k=N} Sell\ Volume_{ikt}$ and N denotes the number of individual investors in the sample. *Buy Volume*$_{ijt}$ (*Sell Volume*$_{ijt}$) is the total number of shares of stock *i* bought (sold) by investor j on day t. The sample is restricted to firm-day observations where there is at least one news story covering the firm and includes 727,550 firm-day observations for 1,659 firms over the period April 1, 2004-December 31, 2011 (1,953 trading days). Firms with stock prices less than $2 on a given day or CRSP share codes other than 10 and 11 (ordinary common shares) are eliminated. News events are classified as positive (159,822 firm-day observations), negative (48,010 observations) or neutral (519,718 firm-day observations) if the relevance weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively.

Panel A: Positive news events



Panel B: Neutral news events

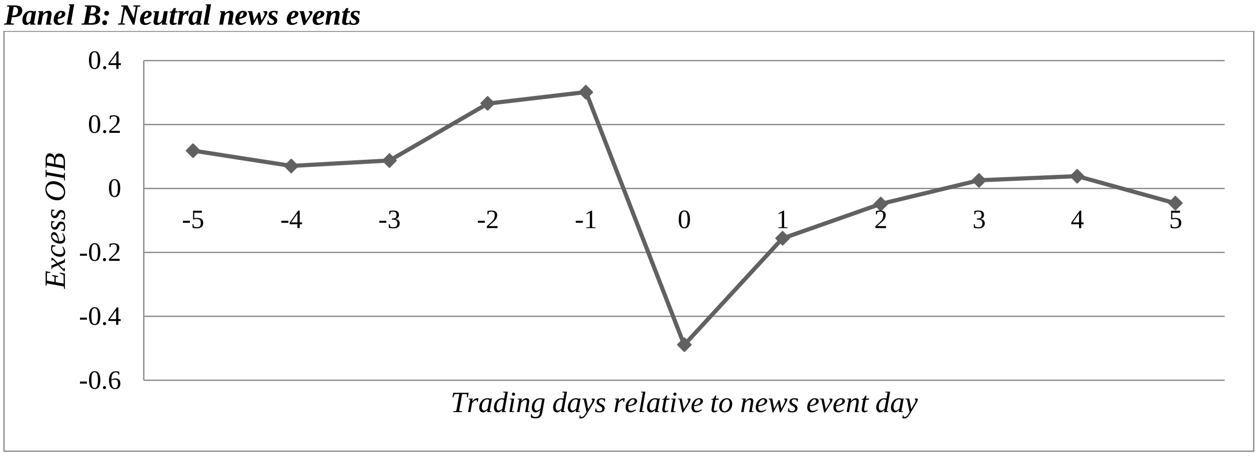


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Figure 1 Cont'd.
Panel C: Negative news events

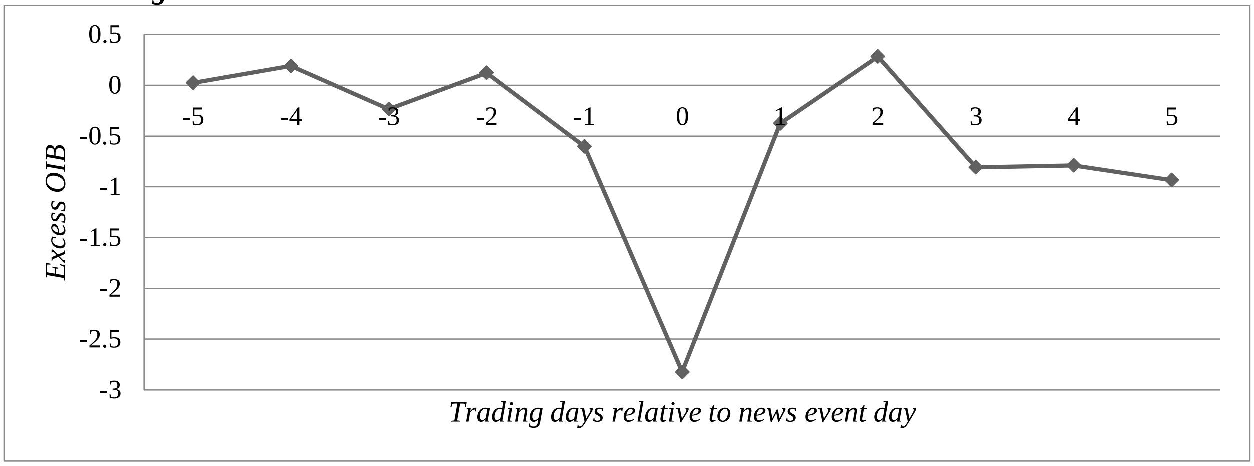

Figure 2: Stock liquidity around positive news event days

This figure plots the time series average of the cross-sectional mean bid-ask spread for the 30 trading-day window centered on positive news event days. Bid-ask spread (in percent) is defined as the spread between bid and ask price quoted at the end of the trading day, divided by the mid-point of the spread.

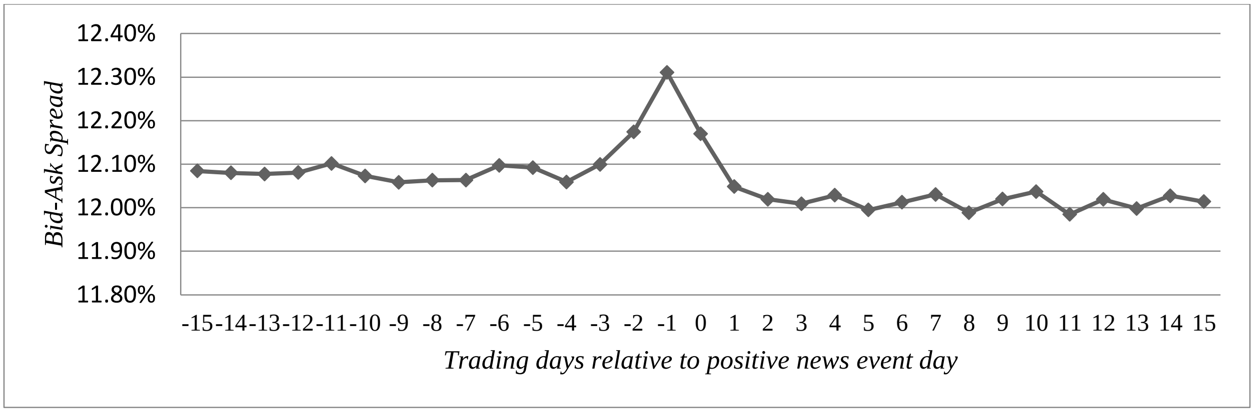

Table 1: Description of NYSE retail trading activity

This table presents summary information on the trading activity of retail traders in the NYSE RetRac data set between April 2004 and December 2011. The sample includes all days with retail trading activity (i.e., excluding firm-days with no retail trades) over the period April 1, 2004-December 31, 2011 for 1,656 unique NYSE listed stocks for which price data are available from Center for Research in Security Prices (CRSP) and news data from the Thomson Reuters News Analytics Database. Firms with stock prices less than $2 on a given day or CRSP share codes other than 10 and 11 (ordinary common shares) are eliminated.

Year	Firms	Firm-Days	Aggregate Dollar Volume ($Billion)	Aggregate Share Volume (Billion Shares)	Number of Orders	Average Order Size ($)	Average Order Size (Shares)
2004	1,287	231,256	196.46	6.45	15,593,913	12,598	413
2005	1,333	315,759	278.94	8.29	19,747,870	14,125	420
2006	1,368	319,367	274.82	7.65	19,334,186	14,214	395
2007	1,397	321,941	247.34	6.55	20,505,360	12,062	319
2008	1,402	294,787	130.29	4.10	13,859,506	9,401	296
2009	1,323	259,354	64.77	2.72	9,480,937	6,832	287
2010	1,342	253,835	56.13	1.97	6,912,683	8,120	285
2011	1,343	239,907	54.49	1.75	6,186,415	8,809	283
All Years	1,659	2,236,206	1,303.25	39.48	111,620,870	11,676	354

Table 2: Summary statistics

Panel A reports time series averages of daily cross-sectional summary statistics for variables used in subsequent analyses. Panel B reports firm-level summary statistics on proportion of days with various types of news events. Panel C reports day-level summary statistics on the number of firms and various types of news events on a given trading day. The sample includes 2,442,638 firm-day observations (including days with no retail trading activity) for 1,656 unique NYSE listed stocks from April 1, 2004 to December 31, 2011 (1,953 trading days) and is restricted to NYSE listed stocks for which price data are available from Center for Research in Security Prices (CRSP) and news data from the Thomson Reuters News Analytics Database. Firms with stock prices less than $2 on a given day or CRSP share codes other than 10 and 11 (ordinary common shares) are eliminated. *OIB* is individual investor order imbalance and defined as the total number of stock *i* shares bought minus sold on day t across all individual investors in the sample, divided by the total CRSP volume in stock *i* on day *t*. *Total Ind. Volume* is the total number of stock *i* shares bought plus shares sold on day t, divided by the total CRSP volume in stock *i* on day *t*. *Sentiment Score* is the relevance weighted sentiment score across all news stories published on firm *i* on day t and varies between -1 and 1. *MV is* the market value of equity on day t-1; *Momentum* is cumulative raw stock returns over trading days t-63 through t-3; $Return_t$, $Return_{t-1}$, and $Return_{t-2}$ are daily stock returns on days t, t-1, and t-2, respectively. *Raw Return [1,20]* is buy and hold (compound) raw stock returns over days t+1 through t+20. *Abnormal Return [1,20]* is buy and hold (compound) abnormal returns (raw return minus CRSP value weighted index return) over trading days t+1 through t+20. News events are classified as positive (152,764 firm-day observations), negative (46,055 observations) or neutral (506,461 firm-day observations) if the relevance weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively.

Panel A: Firm-Day level statistics

	Mean	Std Dev	5^{th} Pctl	25^{th} Pctl	Median	75^{th} Pctl	95^{th} Pctl
OIB_t	-0.29%	1.72%	-2.97%	-0.44%	-0.07%	0.09%	1.57%
Total Ind.Volume$_t$	1.77%	4.24%	0.00%	0.26%	0.70%	1.66%	6.76%
Sentiment Score$_t$	0.05	0.27	-0.15	0.00	0.00	0.00	0.73
News stories per firm-day	1.44	4.71	0.00	0.00	0.01	0.90	7.84
MV[$Mil]	7,858	23,032	156	676	1,906	5,501	33,792
Momentum	3.07%	18.93%	-22.94%	-7.49%	1.62%	11.43%	33.51%
$Return_t$	0.06%	2.36%	-3.20%	-1.05%	-0.01%	1.08%	3.50%
$Return_{t-1}$	0.06%	2.36%	-3.21%	-1.05%	0.00%	1.08%	3.50%
$Return_{t-2}$	0.06%	2.36%	-3.21%	-1.05%	-0.01%	1.08%	3.50%
Raw Return[1,20]	0.80%	9.31%	-13.90%	-4.58%	0.51%	5.86%	16.54%
Abnormal Return [1,20]	0.29%	9.31%	-14.42%	-5.10%	-0.01%	5.34%	16.03%

Continued on the next page.

Table 2 Cont'd.
Panel B: Firm level statistics (1,659 Unique Firms)

% of Days with a	Mean	Std Dev	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
News event	26.75%	22.27%	4.98%	11.07%	18.49%	35.84%	76.93%
Positive news event	5.93%	4.99%	0.62%	2.53%	4.56%	7.83%	16.23%
Negative news event	1.81%	1.66%	0.18%	0.75%	1.33%	2.41%	5.07%
Neutral news event	19.01%	19.65%	2.90%	6.40%	11.15%	24.78%	65.23%

Panel C: Day level statistics (1,953 Days)

	Mean	*Std Dev*	*5th Pctl*	*25th Pctl*	*Median*	*75th Pctl*	*95th Pctl*
Firms	1,356	45	1,286	1,326	1,346	1,399	1,420
News Events	1,953	798	822	1,419	1,832	2,399	3,475
Firms with a News Event	373	87	226	326	370	420	509
Firms with a Positive News Event	82	22	40	69	84	97	112
Firms with a Negative News Event	25	8	13	19	24	29	38
Firms with a Neutral News Event	266	84	147	214	259	307	410

Table 3: Daily net retail order imbalance and future stock returns

This table reports time series averages of daily mean order imbalance (OIB), stock returns, and firm size for each daily OIB tercile. The sample includes 2,442,638 firm-day observations (including days with no retail trading activity) for 1,656 unique NYSE-listed stocks from April 1, 2004 to December 31, 2011. Newey-West (1987) t-statistics are reported next to average future returns calculated using standard errors corrected for serial correlation with 20 lags.

	OIB		*Raw Returns [1,20] in percent*		*Abnormal Returns [1,20] in percent*		*Firm Size ($Mil)*	*Return$_t$*	*Return$_{t-1}$*	*Return$_{t-2}$*
	(1)		(2)		(3)		(4)	(5)	(6)	(7)
OIB Tercile	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	Mean	Mean	Mean
T1	-0.016	(-12.02)	0.65%	(1.21)	0.13%	(0.86)	9,178	0.28%	0.16%	0.13%
T2	-0.001	(-8.44)	0.72%	(1.36)	0.22%	(1.54)	8,723	0.05%	0.04%	0.05%
T3	0.007	(14.33)	0.97%	(1.76)	0.46%	(2.68)	6,851	-0.14%	-0.01%	0.01%
Test of difference: T3-T1	0.0026	(12.75)	0.33%	(6.63)	0.33%	(6.51				

Table 4: Regression analysis of individual investor trading before and after news events

This table reports coefficient estimates from the following panel regression estimated separately for positive, neutral, and negative news events:

$$OIB_{i\tau} = \beta x News\ Event_{it} + a_1 Return_{i\tau-1} + a_2 Return_{i\tau-2} + Firm\ FE + Year\_Month\ FE + \varepsilon_{i\tau}$$

where $OIB_{i\tau}$ is the ratio of net retail volume divided by CRSP total volume in stock *i* on day τ. τ varies between *t*-2 and *t*+2 where *t* is the day of the news event. Panel A, B, and C report coefficient estimates for positive, negative, and neutral news events, respectively. A news event is classified as positive, negative, or neutral if the TRNA relevance-weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively. $Return_{i\tau-1}$ and $Return_{i\tau-2}$ are daily raw stock returns one and two days before the day the dependent variable is measured, respectively. *After minus before* is equal to the cumulative order imbalance on days *t*+1 and *t*+2 minus the cumulative order imbalance on days *t*-1 and *t*-2. All regressions include firm and calendar month fixed effects. We require the firm to have no news event days on days t-1 and t-2. The sample used in this analysis includes 1,578,570 firm-day observations on 1,659 NYSE-listed stocks over the period April 1, 2004-December 31, 2011. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Positive News

	Dependent Variable: $OIB_{i\tau}$					
	τ=t-2	τ=t-1	τ=t	τ=t+1	τ=t+2	After minus before
News Event$_{it}$	-0.005	0.005	0.012***	0.001	0.001	0.002
	(-1.36)	(1.41)	(3.20)	(0.18)	(0.16)	(0.40)
Return$_{\tau-1}$	-0.012***	-0.011***	-0.011***	-0.010***	-0.012***	-0.021***
	(-15.78)	(-14.21)	(-14.40)	(-13.00)	(-14.99)	(-25.91)
Return$_{\tau-2}$	-0.012***	-0.011***	-0.011***	-0.013***	-0.014***	-0.029***
	(-15.28)	(-14.72)	(-14.22)	(-17.22)	(-17.62)	(-36.01)
Adjusted R^2(%)	5.26	5.21	5.17	5.18	5.16	0.06

Panel B: Negative News

News Event	0.007	0.002	-0.017**	-0.005	-0.007	-0.013*
	(0.92)	(0.34)	(-2.30)	(-0.70)	(-0.92)	(-1.78)
Return$_{\tau-1}$	-0.012***	-0.011***	-0.011***	-0.010***	-0.012***	-0.021***
	(-15.78)	(-14.21)	(-14.40)	(-13.00)	(-15.00)	(-25.94)
Return$_{\tau-2}$	-0.012***	-0.011***	-0.011***	-0.013***	-0.014***	-0.029***
	(-15.28)	(-14.72)	(-14.22)	(-17.23)	(-17.62)	(-36.02)
Adjusted R^2(%)	5.26	5.21	5.17	5.18	5.16	0.06

Panel C: Neutral News

News Event	0.003	0.011***	-0.004	-0.006**	-0.010***	-0.016***
	(1.11)	(3.86)	(-1.38)	(-2.09)	(-3.47)	(-5.62)
Return$_{\tau-1}$	-0.012***	-0.011***	-0.011***	-0.010***	-0.012***	-0.021***
	(-15.78)	(-14.21)	(-14.40)	(-12.98)	(-14.96)	(-25.86)
Return$_{\tau-2}$	-0.012***	-0.011***	-0.011***	-0.013***	-0.014***	-0.029***
	(-15.28)	(-14.71)	(-14.20)	(-17.20)	(-17.63)	(-36.03)
Adjusted R^2(%)	5.26	5.21	5.17	5.18	5.16	0.06

Table 5: News events and predictive ability of daily retail trading order imbalance for future stock returns

This table reports coefficient estimates from Fama-MacBeth (1973) regressions of the following form:

$$Return_{i;t+1,t+20} = \beta_0 + \beta_1 OIB_{i,t} + \beta_2 News\ Event_{it} + \beta_3 OIB_{it} x News\ Event_{it} + \gamma Controls + \varepsilon_{it}$$

$Return_{i;t+1,t+20}$, is compounded returns over trading days t+1 through t+20. *In Panel A* the dependent variable is compounded raw return (in percent) while in Panel B the dependent variable is buy and hold abnormal return (raw return minus CRSP value-weighted index return). The sample includes 2,442,638 firm-day observations (including days with zero total retail trading volume) for 1,656 unique NYSE-listed stocks from April 1, 2004 to December 31, 2011. We run 1,953 separate daily cross-sectional regressions and report time series means for each coefficient. T-statistics use standard errors corrected for serial correlation via the Newey-West (1987) procedure with 20 lags. *OIB* is individual investor order imbalance and defined as the total number of stock *i* shares bought minus sold on day t, divided by the total CRSP volume in stock i on day t. $News\ Event_{it}$ is a dummy variable that equals one if there is a news story covering stock i on day t and zero otherwise. News events are classified as positive, negative, or neutral if the TRNA relevance-weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively. All continuous variables are standardized to have mean zero and variance one. Definitions for control variables are provided in Table 1. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Dependent Variable: Raw return [1,20]

	(1)		(2)		(3)		(4)	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Intercept	0.658	(1.49)	0.660	(1.49)	0.639	(1.42)	0.636	(1.41)
OIB_t	0.079***	(4.79)	0.061***	(3.28)	0.078***	(4.77)	0.095***	(4.08)
$NewsEvent_t$	-0.065	(-0.94)	-0.072	(-1.06)				
OIBt x $News\ Event_t$			0.068	(1.40)				
Negative $News\ Event_t$					-0.025**	(-2.31)	-0.020	(-1.45)
Neutral $News\ Event_t$					-0.033	(-1.04)	-0.037	(-1.18)
Positive $News\ Event_t$					0.005	(0.48)	-0.012	(-1.16)
OIB x Negative $News\ Event_t$							-0.046	(-0.80)
OIB x Neutral $News\ Event_t$							0.025	(1.11)
OIB x Positive $News\ Event_t$							0.111***	(3.71)
$OIB_{t-20,-t-1}$	-0.005	(-0.06)	-0.002	(-0.03)	-0.006	(-0.07)	-0.001	(-0.02)
$Sentiment_{t-20,t-1}$	0.027	(0.76)	0.027	(0.76)	0.023	(0.68)	0.024	(-0.70)
$Ln(MV)_{t-1}$	-0.102	(-1.02)	-0.102	(-1.01)	-0.099	(-0.96)	-0.099	(-0.96)
$Return_t$	-0.058*	(-1.90)	-0.058*	(-1.89)	-0.060**	(-1.96)	-0.061**	(-1.99)
$Return_{t-1}$	-0.017	(-0.57)	-0.017	(-0.55)	-0.018	(-0.60)	-0.019	(-0.61)
$Return_{t-2}$	-0.002	(-0.06)	-0.002	(-0.07)	-0.002	(-0.06)	-0.003	(-0.11)
Momentum	0.208	(1.57)	0.208	(1.58)	0.207	(1.57)	0.206	(1.56)
Adjusted R^2	5.05%		5.08%		5.08%		5.16%	

Continued on the next page.

Table 5 Cont'd.
Panel B: Dependent Variable: Abnormal return [1,20]

	(1)		(2)		(3)		(4)	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Intercept	0.138	(1.21)	0.140	(1.22)	0.119	(1.03)	0.116	(1.00)
OIB_t	0.079***	(4.88)	0.062***	(3.33)	0.079***	(4.85)	0.095***	(4.12)
$NewsEvent_t$	-0.066	(-0.96)	-0.074	(-1.07)				
$OIBtxNews\ Event_t$			0.066	(1.35)				
$Negative\ News\ Event_t$					-0.026***	(-2.34)	-0.020	(-1.48)
$Neutral\ News\ Event_t$					-0.034	(-1.05)	-0.038	(-1.20)
$Positive\ News\ Event_t$					0.004	(0.45)	-0.012	(-1.15)
$OIBxNegative\ News\ Event_t$							-0.046	(-0.79)
$OIBxNeutral\ News\ Event_t$							0.025	(1.11)
$OIBxPositive\ News\ Event_t$							0.108***	(3.63)
$OIB_{t-20,-t-1}$	0.001	(0.02)	0.004	(0.05)	0.000	(0.01)	0.005	(0.06)
$Sentiment_{t-20,t-1}$	0.026	(0.75)	0.026	(0.75)	0.023	(0.67)	0.024	(0.69)
$Ln(MV)_{t-1}$	-0.100	(-0.99)	-0.100	(-0.99)	-0.096	(-0.94)	-0.096	(-0.94)
$Return_t$	-0.057*	(-1.89)	-0.057*	(-1.88)	-0.059	(-1.95)	-0.060**	(-1.97)
$Return_{t-1}$	-0.017	(-0.56)	-0.016	(-0.54)	-0.018	(-0.59)	-0.018	(-0.60)
$Return_{t-2}$	-0.001	(-0.04)	-0.001	(-0.05)	-0.001	(-0.04)	-0.003	(-0.09)
Momentum	0.208	(1.57)	0.208	(1.57)	0.206	(1.56)	0.206	(1.56)
Adjusted R^2	5.06%		5.08%		5.09%		5.17%	

Table 6: The predictive ability of retail trading order imbalance: Longer period returns

This table reports coefficient estimates from Fama-MacBeth (1973) regressions of the following form:

$$Return_{i;t+21,t+40} = \beta_0 + \beta_1 OIB_{i,t} + \beta_2 News\ Event_{it} + \beta_3 OIB_{it} x News\ Event_{it} + \gamma Controls + \varepsilon_{it}$$

$Return_{i;t+21,t+40}$, is compounded returns over trading days t+21 through t+60. The sample includes 2,442,638 firm-day observations (including days with zero total retail trading volume) for 1,656 unique NYSE-listed stocks from April 1, 2004 to December 31, 2011. We run 1,953 separate daily cross-sectional regressions and report time series means for each coefficient. T-statistics use standard errors corrected for serial correlation via the Newey-West (1987) procedure with 20 lags. *OIB* is individual investor order imbalance and defined as the total number of stock *i* shares bought minus sold on day t, divided by the total CRSP volume in stock *i* on day t. News events are classified as positive, negative, or neutral if the TRNA relevance-weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively. All continuous variables are standardized to have mean zero and variance one. Definitions for control variables are provided in Table 1. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: Raw return [+21, +60]				*Dependent variable: Abnormal return [+21, +60]*			
	(1)		(2)		(3)		(4)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Intercept	2.032**	(2.15)	1.364*	(1.77)	0.822**	(2.53)	0.164	(0.81)
OIB_t	0.064	(1.37)	0.007	(0.20)	0.066	(1.39)	0.009	(0.25)
Negative News $Event_t$			-0.016	(-0.54)			-0.017	(-0.58)
Neutral News $Event_t$			0.002	(0.03)			-0.002	(-0.03)
Positive News $Event_t$			0.015	(0.59)			0.014	(0.54)
OIBxNegative News $Event_t$			0.118	(1.12)			0.111	(1.06)
OIBxNeutral News $Event_t$			-0.004	(-0.13)			-0.004	(-0.11)
OIBxPositive News $Event_t$			0.017	(0.31)			0.016	(0.30)
OIB[-20,-1]			0.242	(1.47)			0.244	(1.51)
Sentiment[-20,-1]			-0.092	(-1.33)			-0.090	(-1.31)
$Ln(MV)_{t-1}$			-0.466**	(-2.13)			-0.457**	(-2.07)
$Return_t$			-0.025	(-0.47)			-0.025	(-0.47)
$Return_{t-1}$			-0.017	(-0.29)			-0.017	(-0.30)
$Return_{t-2}$			-0.004	(-0.07)			-0.004	(-0.08)
Momentum			0.226	(0.92)			0.231	(0.94)
Adjusted R^2	0.05%		4.78%		0.05%		4.81%	

Table 7: Short selling constraints and the predictive ability of retail trading order imbalance

This table reports results from estimating model (4) of Table 4 modified to include our proxy for short selling restrictions, put volume (*PV*), and its interactions with individual order imbalance and news sentiment indicators. *PV* is the decile ranked total put option volume over the one-month period ending three weeks before a given day. The sample includes 2,442,638 firm-day observations (including days with zero total retail trading volume) for 1,656 unique NYSE-listed stocks from April 1, 2004 to December 31, 2011.We run 1,953 separate daily cross-sectional regressions and report time series means for each coefficient. T-statistics use standard errors corrected for serial correlation via the Newey-West (1987) procedure with 20 lags. *OIB* is individual investor order imbalance and defined as the total number of stock *i* shares bought minus sold on day t, divided by the total CRSP volume in stock i on day t. News events are classified as positive, negative or neutral if the relevance weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively. All continuous variables (including decile ranked variables) are standardized to have mean zero and variance one. The set of controls includes the same variables as those in table 5. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: Raw return [1,21]		*Dependent variable: Abnormal return [1,21]*	
	(1)		(2)	
	Coeff.	t-stat	Coeff.	t-stat
Intercept	0.592	(1.27)	0.072	(0.60)
OIB_t	0.145***	(2.86)	0.144***	(2.86)
PV	-0.066	(-0.69)	-0.066	(-0.69)
OIB x PV	-0.026	(-0.72)	-0.026	(-0.74)
Negative News $Event_t$	-0.043	(-1.00)	-0.043	(-1.00)
Neutral News $Event_t$	-0.031	(-1.17)	-0.031	(-1.19)
Positive News $Event_t$	-0.003	(-0.32)	-0.003	(-0.31)
Negative News $Event_t$ x PV	0.022	(0.65)	0.022	(0.66)
Neutral News $Event_t$ x PV	0.005	(0.21)	0.004	(0.21)
Positive News $Event_t$ x PV	-0.006	(-0.49)	-0.007	(-0.52)
OIB x Negative News $Event_t$	0.126	(0.45)	0.126	(0.45)
OIB x Negative News $Event_t$ x PV	-0.139	(-0.63)	-0.138	(-0.63)
OIB x Neutral News $Event_t$	0.026	(0.91)	0.026	(0.92)
OIB x Neutral News $Event_t$ x PV	-0.039*	(-1.65)	-0.038	(-1.62)
OIB x Positive News $Event_t$	0.097***	(2.64)	0.094***	(2.60)
OIB x Positive News $Event_t$ x PV	-0.066	(-1.42)	-0.064	(-1.38)
Controls	Included		Included	
Adjusted R^2	5.88%		5.89%	

Table 8: Persistence in order imbalance and the predictive ability of retail trading order imbalance around news events

This table reports results from estimating model (4) in Panel A of Table 4 modified to include the interaction of firm-level persistence of net retail trading volume with daily order imbalance, *OIB*, and news sentiment indicators. The persistence in order imbalance, *OP*, is the autocorrelation coefficient from regressing daily *OIB* on one-day lagged *OIB* for each firm-quarter. The sample includes 2,442,638 firm-day observations (including days with zero total retail trading volume) for 1,656 unique NYSE-listed stocks from April 1, 2004 to December 31, 2011. We run 1,953 separate daily cross-sectional regressions and report time series means for each coefficient. T-statistics use standard errors corrected for serial correlation via the Newey-West (1987) procedure with 20 lags. OIB is individual investor order imbalance and defined as the total number of stock i shares bought minus sold on day t, divided by the total CRSP volume in stock i on day t. News events are classified as positive, negative or neutral if the relevance weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively. All continuous variables (including decile ranked variables) are standardized to have mean zero and variance one. The set of controls includes the same variables as those in table 5. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: Raw return [1,21]		*Dependent variable: Abnormal return [1,21]*	
	Coeff.	t-stat	Coeff.	t-stat
Intercept	0.638	(1.42)	0.118	(1.01)
OIB_t	0.092***	(3.58)	0.091***	(3.56)
OP	0.035	(1.39)	0.035	(1.41)
OIB_t x OP	0.026	(0.91)	0.027	(0.96)
Negative News $Event_t$	-0.001	(-0.06)	-0.001	(0.09)
Neutral News $Event_t$	-0.042	(-1.32)	-0.042	(-1.34)
Positive News $Event_t$	-0.018	(-1.61)	-0.018	(-1.61)
Negative News $Event_t$ x OP	0.009	(0.45)	0.009	(0.45)
Neutral News $Event_t$ x OP	0.004	(0.39)	0.004	(0.37)
Positive News $Event_t$ x OP	-0.005	(-0.54)	-0.005	(-0.55)
OIB x Negative News $Event_t$	-0.163*	(-1.85)	-0.162*	(-1.84)
OIB x Negative News $Event_t$ x OP	-0.021	(-0.19)	-0.021	(-0.18)
OIB x Neutral News $Event_t$	0.064**	(2.35)	0.065**	(2.36)
OIB x Neutral News $Event_t$ x OP	-0.063***	(-2.89)	-0.064***	(-2.92)
OIB x Positive News $Event_t$	0.144***	(3.57)	0.142***	(3.53)
OIB x Positive News $Event_t$ x OP	0.058	(1.38)	0.058	(1.39)
Controls	Included		Included	
Adjusted R^2	5.26%		5.27%	

Table 9: Persistence in news sentiment and the predictive ability of retail trading order imbalance around news events

This table reports results from estimating model VI in Panel A of Table 4 modified to include the interaction of firm-level persistence of news sentiment with daily order imbalance (OIB) and news sentiment indicators. News sentiment persistence, *NSP*, is the decile ranked autocorrelation coefficient from regressing the daily news sentiment score on the one-day lagged sentiment score for each firm-quarter. The sample includes 2,442,638 firm-day observations (including days with zero total retail trading volume) for 1,656 unique NYSE-listed stocks from April 1, 2004 to December 31, 2011. We run 1,953 separate daily cross-sectional regressions and report time series means for each coefficient. T-statistics use standard errors corrected for serial correlation via the Newey-West (1987) procedure with 20 lags. OIB is individual investor order imbalance and defined as the total number of stock i shares bought minus sold on day t, divided by the total CRSP volume in stock i on day t. News events are classified as positive, negative or neutral if the relevance weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively. All continuous variables (including decile ranked variables) are standardized to have mean zero and variance one. The set of controls includes the same variables as those in table 5. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: Raw return [1,21]		*Dependent variable: Abnormal return [1,21]*	
	Coeff.	t-stat	Coeff.	t-stat
Intercept	0.634	(1.41)	0.114	(0.98)
OIB_t	0.073	(1.28)	0.073	(1.29)
NSP	-0.072***	(-2.81)	-0.072***	(-2.82)
OIB_t x NSP	-0.076*	(-1.77)	-0.074	(-1.74)
Negative News $Event_t$	0.019	(0.34)	0.019	(0.33)
Neutral News $Event_t$	-0.035	(-1.12)	-0.036	(-1.14)
Positive News $Event_t$	-0.011	(-1.01)	-0.011	(-1.00)
Negative News $Event_t$ x NSP	0.067	(1.49)	0.067	(1.49)
Neutral News $Event_t$ x NSP	-0.015	(-1.20)	-0.014	(-1.16)
Positive News $Event_t$ x NSP	0.012	(1.18)	0.012	(1.17)
OIB x Negative News $Event_t$	-0.293	(-0.79)	-0.293	(-0.79)
OIB x Negative News $Event_t$ x NSP	-0.447	(-1.53)	-0.447	(-1.53)
OIB x Neutral News $Event_t$	0.042	(1.52)	0.042	(1.51)
OIB x Neutral News $Event_t$ x NSP	-0.029	(-1.27)	-0.029	(-1.27)
OIB x Positive News $Event_t$	0.108***	(3.05)	0.106***	(3.00)
OIB x Positive News $Event_t$ x NSP	-0.051	(-1.31)	-0.051	(1.30)
Controls	Included		Included	
Adjusted R^2	5.26%		5.27%	

Table 10: Bid-Ask spreads around positive news events

This table reports time-series averages of daily cross-sectional summary statistics on bid-ask spreads around positive news event days. The sample includes 2,442,638 firm-day observations (including days with zero total retail trading volume) for 1,656 unique NYSE-listed stocks from April 1, 2004 to December 31, 2011. t=0 represents the day of the news event. Panel A reports the summary statistics and Panel B reports tests of differences in mean bid-ask spreads between day t=0 and various days before and after the news event day. Bid-ask spread is measured as a percentage of the closing mid-price on each day. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Average Bid-Ask Spread

	Mean	*Std Dev*	*5th Pctl*	*25th Pctl*	*Median*	*75th Pctl*	*95th Pctl*
t-15	0.1339	0.1959	0.0175	0.0405	0.0749	0.1453	0.4495
t-10	0.1340	0.1957	0.0175	0.0400	0.0747	0.1457	0.4546
t-5	0.1337	0.1960	0.0175	0.0400	0.0744	0.1454	0.4482
t=0	0.1335	0.1949	0.0176	0.0401	0.0746	0.1455	0.4472
t+5	0.1318	0.1895	0.0175	0.0396	0.0744	0.1449	0.4427
t+10	0.1326	0.1938	0.0174	0.0398	0.0741	0.1443	0.4504
t+15	0.1324	0.1920	0.0176	0.0399	0.0739	0.1444	0.4478

Panel B: Tests of differences in mean

	Mean Difference	t-stat
t=0 vs t-15	-0.0005	-0.42
t=0 vs t-10	-0.0005	-0.45
t=0 vs t-5	-0.0002	-0.22
t=0 vs t+5	0.0017*	1.67
t=0 vs t+10	0.0009	0.79
t=0 vs t+15	0.0011	0.92

Table 11: Liquidity provision by retail investors and the predictive ability of retail trading order imbalance

This table reports results from estimating models III and VI in Panel A of Table 4 using only observations where the absolute value of stock return on any given day is in the bottom two quintiles of the cross-sectional distribution of absolute stock returns on that day. The sample includes 976,142 firm-day observations for 1,656 unique NYSE listed stocks from April 1, 2004 to December 31, 2011. We run 1,953 separate daily cross-sectional regressions and report time series means for each coefficient. T-statistics use standard errors corrected for serial correlation via the Newey-West (1987) procedure with 20 lags. *OIB* is individual investor order imbalance and defined as the total number of stock *i* shares bought minus sold on day t, divided by the total CRSP volume in stock i on day t. News events are classified as positive, negative or neutral if the relevance weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively. All continuous variables (including decile ranked variables) are standardized to have mean zero and variance one. Definitions for control variables are provided in Table 1. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variable: Raw return [1,20]		*Dependent Variable: Abnormal return [1,20]*	
	I		II	
	Coeff.	t-stat	Coeff.	t-stat
Intercept	0.837*	(1.75)	0.315	(1.32)
OIB_t	-1.330	(-0.97)	-1.325	(-0.96)
Negative News Event$_t$	1.623	(1.07)	1.618	(1.07)
Neutral News Event$_t$	-0.012	(-0.40)	-0.013	(-0.42)
Positive News Event$_t$	-0.030*	(-1.86)	-0.030*	(-1.87)
OIB x Negative News Event$_t$	-10.475	(-1.03)	-10.449	(-1.03)
OIB x Neutral News Event$_t$	0.004	(0.10)	0.004	(0.11)
OIB x Positive News Event$_t$	0.215***	(2.60)	0.214***	(2.58)
$OIB_{t-20,t-1}$	0.013	(0.17)	0.021	(0.27)
$Sentiment_{t-20,t-1}$	0.026	(0.92)	0.026	(0.93)
$Ln(MV)_{t-1}$	-0.095	(-0.95)	-0.093	(-0.93)
$Return_t$	-0.005	(-0.07)	-0.005	(-0.06)
$Return_{t-1}$	-0.012	(-0.31)	-0.012	(-0.32)
$Return_{t-2}$	-0.026	(-0.73)	-0.025	(-0.71)
Momentum	0.164	(1.24)	0.164	(1.25)
Adjusted R^2	5.17%		5.17%	

Table 12: Market level uncertainty and the predictive ability of retail trading order imbalance

This table presents result from a time series regression of coefficient estimates on a constant and a *VIX* dummy. *High VIX* equals one if the *VIX* is higher than the median value over the sample period and zero otherwise. The coefficient estimates are obtained from daily cross-sectional regressions in Model VI of Table 4 where the dependent variable is abnormal future returns**.** Newey-West t-statistics with 20 lags are reported below the coefficient estimates. ***, **, and * denote statistical significance level at the 1%, 5%, and 10% levels, respectively.

	OIB	*OIB* x *Negative News Event*	*OIB* x *Neutral News Event*	*OIB* x *Positive News Event*
Constant	0.051***	-0.079	-0.035*	0.025
	(2.94)	(-0.173)	(-1.91)	(1.48)
High VIX	0.092**	0.069	0.124***	0.173***
	(1.99)	(0.57)	(2.71)	(2.84)

Table 13: Firm level uncertainty and the predictive ability of retail trading order imbalance

This table reports results from estimating model (4) of Table 4 modified to include our proxy for firm level information uncertainty captured with the decile ranked number of analysts covering the firm over the one year before a given day, *AF*, and its interaction with individual order imbalance and news sentiment indicators. The sample includes 2,442,638 firm-day observations (including days with zero total retail trading volume) for 1,656 unique NYSE-listed stocks from April 1, 2004 to December 31, 2011. We run 1,953 separate daily cross-sectional regressions and report time series means for each coefficient. T-statistics use standard errors corrected for serial correlation via the Newey-West (1987) procedure with 20 lags. *OIB* is individual investor order imbalance and defined as the total number of stock *i* shares bought minus sold on day t, divided by the total CRSP volume in stock i on day t. News events are classified as positive, negative or neutral if the relevance weighted sentiment score on a given day is larger than 0.5, smaller than -0.5, or between -0.5 and 0.5, respectively. All continuous variables (including decile ranked variables) are standardized to have mean zero and variance one. The set of controls includes the same variables as those in table 5. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: Raw returns [1,21]		*Dependent variable: Abnormal returns [1,21]*	
	(1)		(2)	
	Coeff	t-stat	Coeff	t-stat
Intercept	0.648	(1.45)	0.129	(1.08)
OIB_t	0.224***	(4.07)	0.224***	(4.06)
AF	0.147*	(1.67)	0.146	(1.67)
OIB_t x AF	-0.102	(-1.36)	-0.102	(-1.36)
Negative News $Event_t$	-0.117**	(-2.25)	-0.117**	(-2.26)
Neutral News	-0.037	(-1.29)	-0.037	(-1.30)
Positive News $Event_t$	-0.018	(-1.31)	-0.018	(-1.31)
Negative News $Event_t$ x AF	0.091	(1.12)	0.091	(1.13)
Neutral News $Event_t$ x AF	-0.017	(-0.91)	-0.017	(-0.93)
Positive News $Event_t$ x AF	0.015	(1.04)	0.015	(1.04)
OIB x Negative News $Event_t$	0.544	(1.55)	0.545	(1.55)
OIB x Negative News $Event_t$ x AF	-0.620	(-1.18)	-0.620	(-1.18)
OIB x Neutral News $Event_t$	0.028	(0.84)	0.030	(0.87)
OIB xNeutral News Event x AF	-0.029	(-0.83)	-0.028	(-0.83)
OIB x Positive News $Event_t$	0.117**	(2.12)	0.116**	(2.11)
OIB x Positive News Event x AF	-0.170***	(-3.00)	-0.170***	(-2.98)
Controls	Included		Included	
Adjusted R^2	6.18%		6.18%	

Table 14: Individual investor trading and future returns across news categories

This table reports coefficient estimates from panel regressions of the following form run separately for each news category:

$$Return_{i;t+1,t+20} = \beta_0 + \beta_1 OIB_{i,t} \ + \gamma \text{Controls} + FEi + \varepsilon_{it}$$

where $Return_{i;t+1,t+20}$, is compounded abnormal return over trading days $t+1$ through $t+20$. *OIB* is individual investor order imbalance and defined as the total number of stock *i* shares bought minus sold on day t, divided by the total CRSP volume in stock i on day t. The sample includes only news events classified as positive. Controls include $OIB_{t-20,t-1}$, $Sentiment_{t-20,t-1}$, $Ln(MV)_{t-1}$, *Momentum*, $Return_t$, $Return_{t-1}$, $Return_{t-2}$, and firm fixed effects. Coefficients on controls are not reported for brevity. Standard errors are clustered by firm in order to adjust for firm level serial correlation. All continuous variables are standardized to have mean zero and variance one. Definitions for control variables are provided in Table 1. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

News Category	β_1	t-stat	N	Freq.	Adj. R^2
Business Activities	0.202***	(4.03)	79,809	22.19%	4.30%
Corporate Financial Results	0.259***	(3.22)	31,263	8.69%	3.46%
Mergers and Acquisitions	0.031	(0.42)	21,962	6.11%	6.43%
All Corporate Crisis	0.096	(0.95)	19,247	5.35%	5.20%
Broker Research and Recom.	0.124	(1.13)	17,820	4.95%	6.06%
Dividends	0.150*	(1.91)	16,625	4.62%	2.92%
Debt Markets News	0.138	(1.40)	15,108	4.20%	6.51%
Internet/World Wide Web	0.296***	(2.82)	14,595	4.06%	5.00%
US Corporate Bonds	0.139	(1.31)	12,610	3.51%	7.21%
Management Issues/Policy	0.041	(0.33)	12,551	3.49%	6.99%
Corporate Results Forecasts	0.054	(0.47)	10,282	2.86%	7.42%
Ratings	0.005	(0.05)	9,264	2.58%	6.35%
Labor; (Un)employment	0.112	(0.56)	6,872	1.91%	3.87%
Lifestyle	-0.216	(-1.07)	6,818	1.90%	7.53%
Legislation	-0.006	(-0.06)	6,491	1.80%	9.73%
Stock Markets News	0.146	(0.78)	6,328	1.76%	7.23%
Hot Stocks	0.168	(0.73)	6,254	1.74%	5.95%
Domestic Politics	0.370**	(2.57)	6,137	1.71%	13.16%
Fund Industry News	0.072	(0.46)	5,909	1.64%	9.41%
Multi-Industry	0.164	(0.53)	5,043	1.40%	8.27%
Major Breaking News	-0.172	(-1.10)	4,858	1.35%	8.86%
New Issues	0.281*	(1.67)	4,244	1.18%	12.48%
Macro News	0.196	(0.72)	4,219	1.17%	12.40%
Wholesale	0.142	(0.48)	4,103	1.14%	4.58%
Regulatory Issues	0.078	(0.23)	3,925	1.09%	10.57%
Washington/US Govt. News	0.644	(1.61)	2,773	0.77%	14.55%
Initial Public Offerings	-0.037	(-0.17)	2,675	0.74%	20.60%
Loans	0.319	(1.06)	2,642	0.73%	10.46%
High-Yield Debt	0.39	(0.71)	2,076	0.58%	7.70%
Investment Grade Debt	-0.055	(-0.20)	1,937	0.54%	5.37%
Mortgage Backed Debt	0.485*	(1.81)	1,794	0.50%	7.66%
Macro-Economics	-0.315	(-0.66)	1,567	0.44%	10.49%

Continued on the next page.

Table 14 Cont'd.

News Category	β_1	t-stat	N	Freq.	Adj. R2
(Inter)national Security	-0.019	(-0.02)	1,107	0.31%	15.85%
Asset-Backed Debt	0.101	(0.41)	1,131	0.31%	4.77%
Diplomacy, Int. Relations	0.188	(1.05)	1,002	0.28%	23.51%
Terms of Bond Issues	0.458	(1.10)	852	0.24%	21.14%
Economic Indicators	-0.055	(-0.10)	839	0.23%	7.08%
Corporate Analysis	1.847*	(1.71)	695	0.19%	5.41%
Reuters Exclusive News	-0.318	(-0.83)	633	0.18%	29.26%
Exchange Activities	0.855	(1.29)	642	0.18%	3.32%
Credit Default Swaps	0.327	(0.40)	609	0.17%	20.61%
Government/Sovereign Debt	0.734	(0.95)	515	0.14%	14.37%
Forex Markets	-0.655	(-0.73)	439	0.12%	8.92%
Judicial Processes/Court Ca	-3.618	(-0.85)	407	0.11%	6.59%
Eurobonds	0.168	(0.38)	383	0.11%	24.71%
International Trade	1.406**	(2.31)	394	0.11%	18.48%
Reuters Summits	0.169	(0.18)	367	0.10%	28.46%
Interest Rates	-0.257	(-0.51)	313	0.09%	1.43%
Crime, Law Enforcement	1.705	(0.53)	238	0.07%	35.69%
Bankruptcies	1.089	(0.54)	218	0.06%	11.90%
Weather	-0.106	(-0.12)	190	0.05%	41.11%
Equity-Linked Bonds	1.311	(0.74)	192	0.05%	12.29%
Money Markets	0.338	(0.16)	132	0.04%	18.79%
Federal Reserve Board	-0.259	(-0.10)	135	0.04%	17.28%
Press Digests	-0.213	(-0.26)	122	0.03%	9.12%
Disasters and Accidents	0.626	(0.64)	125	0.03%	39.44%
US Agencies	0.339	(0.36)	88	0.02%	28.47%
Civil Unrest	-0.465	(-0.16)	56	0.02%	79.86%
Short-Term Interest Rates	4.006***	(3.07)	53	0.01%	73.02%
Fisher statistic	156				
p-value	<0.001				