Do individual investors have information processing skills?

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Combining a large archive of public corporate news events with retail trading records from NYSE, we examine the profitability of individual investors' trades around public news releases. We find that individual investors benefit significantly from the news releases when trading. The relation between net trading by individual investors and future returns is four times as large on positive news days as that on no news days. Moreover, the results are more pronounced for firms with higher information uncertainty and at times of high market uncertainty. Individual investors do not anticipate news and our results are not explained by liquidity provision, higher investor attention, or changes in liquidity around news days. Overall, the evidence suggests that an important channel through which individual traders predict future stock returns is their ability to successfully process the information revealed in the news events.

1. Introduction

Recent studies provide strong empirical evidence that individual investors' trades are informative about future prices (Kaniel, Saar, and Titman, 2008; Kaniel, Lie, Saar, and Titman, 2012; Kelley and Tetlock, 2013; Barrot, Kaniel, Sraer, 2016; and Boehmer, Jones, and Zhang, 2016). This evidence casts doubt on the traditional view that individual investors are uninformed agents who distort market efficiency by pushing prices away from fundamentals and create risk for arbitrageurs.[1] Although the strong surprising evidence in these recent studies suggests that the group of retail investors they examine are informed, it does not hint us on the sources of these informed individual traders' informational advantage.[2]

In this paper, we combine a large archive of corporate news events with a unique data set of NYSE retail trading records and examine whether public news events create opportunities for individual investors to execute profitable trades. Confirming the findings in the prior literature, we find a strong positive relation between net trading by individual investors on a given day and subsequent monthly stock returns. More importantly, we find that the predictive power of individual investors' trades increases significantly on days with a public news release. In particular, the association between net trading by individual investors and future returns is four times larger when they trade on days with a positive public news event about a firm than when there is no news event. We find little or no evidence of an increase in return predictability of trades by individual investors following neutral or negative news events. In addition, individual

[1] For example, Kyle (1985) or Black (1986) describe these traders as uninformed-noise traders. Also see Shleifer and Summers (1990), DeLong, Shleifer, Summers, and Waldman (1990a), DeLong, Shleifer, Summers, and Waldman (1991), and Shleifer and Vishny (1997) for more details on how individual traders create noise and become risky for rational arbitrageurs. Moreover, the early evidence indicates that individual traders exhibit behavioral biases that decreases their performance (Odean (1998), Barber and Odean (2000), and Benartzi and Thaler (2001)).
[2] Kelley and Tetlock (2012) suggest that one source of individual agents' information advantage is their ability to correctly predict news about firm cash flows using market orders. Barrot, Kaniel, and Sraer (2016) show that individual investors provide liquidity to the market but fail to reap the rewards.

investors do not seem to anticipate public news announcements. Finally, individual investors benefit significantly more from public news during times of elevated market uncertainty and when trading stocks of firms which have more information uncertainty. Overall, our findings suggest that public news releases significantly increase the predictive ability of individual investors' trades about future stock returns.

We believe that the best explanation for our findings is that the group of informed individual traders we study in this paper possess superior information processing skills and the news releases create trading opportunities for these investors. While public news releases is generally predicted to be reduce information asymmetry, according to Kandel and Pearson (1995), public news releases create trading opportunities for traders with superior information processing skills.[3] In particular, differences in investors' information-processing skills could result in more informed trading when less precise information is released (McNichols and Trueman, 1994). These skillful investors can carefully analyze otherwise hard to interpret value-relevant information and obtain informational advantage compared to other investors who do not have these skills. Individual traders, unlike institutional traders, cannot allocate vast amount of resources to periodically monitor and gather information about various firms in advance of the news events.[4] Moreover, the release of news would alleviate the search problem for potential buyers by increasing the visibility of a particular stock (Barber and Odean, 2008) and skillful individual investors can limit their focus on these attention grabbing stocks to process the released information. Therefore, public news can create a relatively easier-to-obtain and cheaper information advantage to individuals if they possess information processing skills. Accordingly,

[3] See Engelberg, Reed, and Ringgenberg (2012) and Hendershot, Livdan, and Shurhoff (2015).
[4] Hendershot, Livdan, and Shurhoff (2015) argue that institutional traders' strong connections with various market players including sell side analysts, firm managers, and brokerage firms and can allocate large amount of resources to interpret news.

the news interpretation channel provides a plausible explanation for how some group of individual investors become informed about future stock returns. To the best of our knowledge, our paper is the first study to provide evidence that information processing around public news is an important channel through which individual investors' trades predict future returns.

Our sample is based on retail trades executed on the New York Stock Exchange (NYSE), which is similar to the sample used in Kaniel, Saar, and Titman (2008) and Kaniel et al. (2012) but covers a longer sample period. According to Battalio and Loughran (2008), retail brokers have incentives to route naive orders away from NYSE which may bias our sample towards retaining mainly informed individual traders in our sample. However, this bias is indeed helpful for this study, since, our goal is to examine the sources of return predictability among "informed" individuals. In other words, we examine whether informed individual agents have information processing abilities and, therefore, examining a sample of informed individual investors is vital for our paper. However, due to this bias towards more informed retail trading, inferences should be drawn carefully from our paper. In other words, while our results suggest that an average "informed" individual trader in our sample has information processing skills and these skills account for a significant portion of his/her trades' predictive ability about future returns, our results cannot be generalized to the entire population of individual investors.

We consider several alternative explanations for our findings. First, our findings might be driven by individual investors' tendency to buy attention grabbing stocks (Barber and Odean, 2008). In this view, the public news increases 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 causes the positive relation between net order imbalance and future returns rather than the information processing argument we propose.

An important implication of the investor attention argument is that, since the price pressure due to investor attention cannot be justified by changes in firm fundamentals, over longer holding horizons, the price should revert back to the fundamentals and the return predictability should reverse. We test this argument by examining whether the relation between individual trading and future returns reverses over longer holding horizons. We find no evidence of a price reversal up to 60 day holding periods following news events. [5]

Another implication of the investor attention argument is that all types of news events (i.e. positive, negative, and neutral) should cause an increase in the visibility of a stock and generate a similar relation between individual investor trading and future returns. However, we do not find any improvement in return predictability for individual trades following neutral or negative news. Overall, we believe our results are inconsistent with individual investors' tendency to buy attention grabbing stocks.

Next, we examine whether our results are driven by increased 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

[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 (2016) document that following unusual firm-level news flows, firm experience price reversal over the following six months.

of improvement in market liquidity on news days. This result negates the view that our results can be explained by liquidity improvement around event dates.

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 (Hendershot et. al 2014). 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 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

[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 (2014) present empirical evidence on such behavior.

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, Saar, and Titman (2008), Kaniel et al. (2012), and Kelley and Tetlock (2013) show that individual investors' trades are informative about future stock returns. Our paper contributes to this literature by documenting that, similar to well established informed traders such as short sellers, individual investors also have news processing skills. More importantly, this skill plays an important role in individual investors' ability to predict future returns.

The rest of the paper is organized as follows: Section 2 describes the sample. Section 3 explores the effect of news events on the predictive ability of individual investors' trades for future returns. Section 4 examines the plausibility of alternative explanations. Section 5 explores the effect of market- and firm-level uncertainty on individual investors' news interpretation

[7] In alternative argument, if some buyers make systematic mistakes when trading before the news events, then they need immediacy to cover their wrong positions after the news is revealed to the market. Hence individual investors will take the opposite side of the trade and their trade will reflect the institutions systematic mistakes rather than their 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 can 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 push 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. Our findings suggest that individuals profit more when they purchase following positive news suggesting that this view cannot explain our findings.

abilities. Section 6 examines the robustness of our main findings to the exclusion of earnings announcement events or the inclusion of additional control variables. Section 7 concludes.

2. Sample and Descriptive Statistics

Trading records of individual investors come from NYSE's historical end of day Retail Execution Reports (ReTrac) for the period April 1, 2004 to December 31, 2011. 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 retail buy and sell shares executed in separate quantities. Since classification of daily aggregate retail volume into buy and sell volumes is exact (Kaniel et al., 2012), we do not have to use Lee and Ready's (1991) volume classification algorithm.

We obtain the news data from the 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 (2012), Infoic (2008), and Hendershott et al. 2012 for further details on TRNA's text processing). [8]

Following Hendershot et al. 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

[8] In order to examine whether the sentiment score generated via a neural-network captures the news content it supposed to measure, we examine the average daily returns by positive, negative, and neutral sentiment groups. We find that the average daily returns are 0.27%(t-value= 7.02), 0-0.31%(t-value= -7.05), and 0.07% (t-value= 1.84) for positive, negative, and neutral news, respectively. This results suggest that market reaction and the sentiment are aligned.

trading date as the story date in order to align the story date with price and individual trading (Hendershott et al.).

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 2,648,507 firm-day observations for 1,697 unique NYSE-listed firms over the period April 1, 2004-December 31, 2011 (1,953 trading days).

Table 1 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 the 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 1.33 and the mean sentiment score for news is 0.05. The mean (median) firm size is $7.858 (1.906) Billion and suggests that our sample contains relatively bigger firms.

In Panel B of Table 1, we present the firm level news statistics. The sample includes 1,697 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 1, we present summary statistics on the number of firms, news events, and firms with various types of news events. On average there are 1356 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 in our sample should predict future returns.

To shed light on the predictive power of individual investors' trades, for every day *t* we sort stocks into terciles based on the daily net individual order imbalance, OIB_{it}, defined 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. 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 2, we present the time series averages of these daily portfolio returns. In Column 1, we present the average net individual order imbalance for each OIB tercile. We find that the average OIB is -0.016 in the lowest tercile and 0.007 in the highest tercile. The negative (positive) order imbalance in the lowest (highest) tercile suggests that the individual investors are net sellers in group T1 and net buyers in group T3.

Next, we examine future buy and hold raw and abnormal returns over the [1,20] window in Columns 2 and 3.[9] The average monthly raw return is 66 basis points for the lowest OIB tercile (T1) and increases to 99 basis points for the highest OIB tercile (T3). 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 6.58. The t statistics are based on Newey-West (1987) standard errors corrected for serial correlation up to 20 lags. 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 14 basis points for the lowest OIB tercile (T1) and increases to 47 basis points for the highest OIB tercile (T3). The difference between the highest and lowest OIB terciles (T3-T1) is 33 basis points and is significant with a Newey-West t-statistic of 6.57. 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 abnormal return in tercile T1 is not significant at conventional statistical levels (t-statistic= 0.94) while the abnormal return in tercile T3 is significant with a Newey-West t statistic of 2.79. This finding confirms the results documented in the literature that individual investors are mainly informed when they are net buyers.

Overall, the findings in Table 2 suggest that individual investors in our sample are informed about future returns up to 20 days following portfolio formation.

[9] In order 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.

3.2. Individual Investor Trading Around Public News

In this section, we examine individual investor trading activity around public news events. One potential channel through which individual investors can obtain trading advantage is through successful timing of the news events. Put differently, if individual investors are able to anticipate the content of the news, then they should trade accordingly over the window preceding news events.

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. The 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 the positive (negative) news. Rather, individual investors seem to trade based on the news content mainly on the news day and increase (decrease) their positions on the positive (negative) news days. This finding is in line with the idea that, on average, individual traders are not informed about the news before they become public and only trade on the news after they become public.

Next, we turn to our more 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:

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

where $OIB_{i\tau}$is individual order imbalance in stock *i* on day τ. *News Event*$_{it}$, is a dummy variable that equals one if firm *i* is covered in a news story on day *t* and zero otherwise. The timing of the dependent variable, τ, varies between t-2 and t+2. *Return*$_{it-1}$ and *Return*$_{it-2}$ are daily raw stock returns one and two days before the day of the dependent variable, respectively. We present the results in Panels A to C of Table 3 for positive, negative, and neutral news, respectively.

According to the results in Panels A and B of Table 3, the coefficient on the news event dummy, *News Event*$_{it}$, is insignificant prior to the news for both negative and positive news events. In other words, confirming our findings in figure 1, individual investors do not seem to anticipate the positive or negative news events; rather, individual investors trade on the day the news becomes public. On the other hand, an interesting pattern of individual order imbalance emerges prior to the neutral news. According to the results in Panel C of Table 3, individual investors seem to buy excessively prior to the neutral news and sell following the news. Obviously, given that the news are neutral, the motives of other investors trading on the stock remains puzzling. Nonetheless, the results in neither panel of Table 3 provide any evidence in support of the idea that individual investors are informed about the upcoming news. Rather, we have clear evidence suggesting that individual investors trade mainly on the day the news becomes public.

3.3. Individual Investors and Information Processing

So far our analysis suggests that individual investors are informed traders but their ability to predict future returns does not stem from anticipating the news before they become public. In this section, we examine whether individual investors' ability to predict future returns stems from their ability to better process public information. If individual investors have information processing skills, then we expect their trades to have a stronger association with future returns when they trade on news days.

To answer this question, similar to Engelberg et al. (2012) 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 $Ln(MV)_{t-1}$ (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 stock returns on days t, t-1, and t-2, respectively). 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 4. In Columns I, II, and III the dependent variable is raw returns and in columns IV, V, and VI the dependent variable is abnormal returns. Columns I and IV provide regression evidence in support of our earlier portfolio results reported in Table 3. Specifically, we continue to find a statistically significant positive relation between future stock returns and net order imbalance on a given day even after controlling for past returns and firm size. We also interact the News Event dummy with OIB to examine whether individual investors better predict future returns on news days regardless of the sentiment of the news. The coefficient on the interaction term is not significant in any of the specifications suggesting that the mere presence of public news does not increase the informativeness of individual investors' trades about future returns.

In Columns II and V, 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 on analyzing such news. In other words, the sentiment of a news event might affect individual investors' ability and efforts 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 Columns III and VI, 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 these three news types and OIB. The benchmark group in these regressions is firm-day observations without any news event.

In both specifications, the interaction between P*ositive 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, the coefficient on the interaction of *OIB* with *Positive_News_Event* in Columns III and VI are 22.323 and 22.028 with t-statistics of 3.35 and 3.30, respectively. These coefficients represent a fourfold increase in the association between OIB and monthly returns and suggest that a one standard deviation increase in OIB during positive news events is associated with roughly 38 basis points increase in monthly stock returns.[10] 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, we do not find any significant effect of negative news or neutral news 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.

[10] In order to calculate the baseline association between individual order imbalance, OIB, and future monthly returns, in untabulated results we estimate specifications I and IV of Table 4 without including the News Event dummy and its interaction with OIB. The coefficient on OIB is 5.31 (Newey-West t-stat=4.62) when the dependent variable is raw returns and 5.33 (4.64) when the dependent variable is abnormal returns.

Overall, the findings in Table 4 suggest that individual investors' trades have a larger positive association with for future returns when they buy stocks with positive public news. Hence, an important source of individual investors' informational advantage in our sample is their information processing skills, especially when the news is containing positive sentiment.

4. Exploring alternative explanations

In this section we explore plausible alternative explanations for our evidence that the profitability of individual investors' trades is significantly higher when they trade on firm-days with positive sentiment news stories covering the stock.

4.1. Increase in Visibility

Barber and Odean (2008) show that individual investors are net buyers following attention grabbing events such as public news. Under this explanation, the public news increases a stock's visibility. Since, investors have limited resources or cognitive skills to investigate all stocks, individual investors may buy these attention-grabbing stocks without processing the content of the news event. Due to the increase in visibility, these demand shocks will create a positive price pressure. Therefore, the visibility argument predicts that the predictive power of net trading by individual investors for future returns should be higher following attention grabbing events such as public news.

Inconsistent with the visibility argument, in Columns 2 and 4 of Table 4, 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 conceivable to argue that positive news events would catch their attention more than negative and neutral news events. Accordingly, our findings in Columns 3 and 6 of Table 4 that the positive relation between OIB and future returns is more pronounced among positive news stocks would also be consistent with the visibility argument.

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 5 presents the results. In all specifications, the dependent variables are either raw returns (columns I and II) or abnormal returns (columns III and IV) measured over the [21,60] trading day window. According to the results, before including news sentiment indicators to the analysis (Columns I and III), 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 II and IV, 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.

On the other hand, 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 high volume premium Gervais et. al documented without processing information about the news. To ensure that our results are not driven by the return premium due to spike in trading volume around the news events, we repeat our analysis in Table 4 by controlling for abnormal trading volume on the news days. In particular, we include the abnormal trading volume on the news day and its interactions with the three news dummies. Our results suggest that controlling for the abnormal trading volume around the news days does not alter any of our results.

Overall, the findings in Table 5 suggest that there is no price reversal beyond the 20-day holding period and the information content of OIB about future returns following positive sentiment news points to a permanent change in stocks prices. Thus, the argument of increased visibility following positive news events cannot explain our findings.

4.2. Liquidity Changes Around Public News Event

The second potential explanation for our findings is that due to elevated market attention, particularly on positive news days, the trading volume and the liquidity in a stock might increase on the positive news days. Thus, due to the lower cost of trading, individual investors might find it more profitable to trade on their information on positive news days when compared to before or after the news events. In this case, net individual investor trading would be more informative about future returns on positive news days due to their incentives to time the lower transaction costs rather than superior information processing ability.

Following Engelberg, Reed, and Riggernberg (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. In Figure 2, we plot the times series averages of daily cross sectional mean bid-ask spreads over days -15 through +15 around positive news events. The transaction cost argument implies that the cost of trading should be lower on positive news days.

Figure 2 suggests that the transaction costs are not lower and even slightly higher on positive news days. The bid ask spread is almost flat over the 15 trading days prior to positive news events and slightly increases one day before and on the news day. The bid-ask spread reverts back to the pre-event levels after the event. We also formally test this idea in Table 6 by examining the significance of the difference in mean bid ask spreads around positive news events. 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).

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 the news days.[11] This finding refutes the idea that the significant relation between OIB, positive news

[11] 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.

events, and future returns can be explained by individual investors' tendency to benefit from a decrease in transaction cost on positive news days. Hence, changes in liquidity around news events cannot explain our findings. [12]

4.3. Providing Liquidity to other Market Participants

A third alternative explanation for our findings is that individual investors might be providing liquidity to meet the demand for immediacy from other informed market participants who trade before the news. Hendershot et. al (2014) show that institutional traders are such 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 to profit from their initial positions. In this view, when institutions with informational advantage reverse their orders after the news (i.e. sell their shares following good news), the price adjustment to the public news might be incomplete. When individual investors take the counter part of the trade (i.e. buy following positive news) to provide liquidity, then the trades of individual investors will predict future returns more significantly on positive news days. Once again, 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 informative about 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 if they do not observe a positive return and do not profit from their trades.

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[12] 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.

In order to examine whether our findings can be explained by this story, we replicate our findings of Table 4 by limiting our news sample to news events that are not accompanied by any significant return on the news days. To retain no return days, we group stocks into five groups based on the absolute value of the daily return on the news days and keep the stocks at the bottom two quintiles which are the stocks with news but no significant daily return. If the liquidity provision argument is true, then we expect to find no evidence of improvement in return predictability for individual trades on positive sentiment news days without any significant positive return.

The results are presented in table 7. According to the results, while the coefficient on OIB is not significant, the interaction between the OIB and positive news event indicator is positive and significant in both specifications. This finding suggests that the positive relation between net trading by individual investors and future returns is significantly larger for positive news events even if the news event is not accompanied by any significant return.

5. Information Uncertainty and Individual Investors' News Interpretation Ability

5.1. Market Level Uncertainty

Barrot, Kaniel and Srear (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 Srear (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 examine the ability of net individual investor trading to predict future returns on news days separately when VIX is higher than the median and when VIX is lower than the median over our sample period. [13] In particular, we repeat our analysis in Column VI of Table 4 and keep the daily time series of coefficient estimates on individual order imbalance (OIB) and its interactions with news type dummies obtained from daily cross sectional regressions where the dependent variable is abnormal future returns.[14] Recall that the results in Table 4 were obtained by taking the time series average of the daily cross sectional coefficients. Then, we regress each of these coefficients on a constant and a VIX dummy. The VIX dummy equals one if VIX is higher than the median value over the sample period and zero otherwise. For each coefficient estimate from column 6 of Table 4, the coefficient on the VIX dummy represents the change in net trading based return predictability on news days when VIX is high (equals one) and the constant represents the average coefficient in low uncertainty periods.

The results are presented in Table 8. For the coefficient on OIB, the VIX dummy has a negative but insignificant coefficient suggesting that the predictive ability of individual investors' trades is similar during times of high or low market uncertainty when they trade in stocks without any public news. On the other hand, when we examine the time series properties of the coefficient on the interaction between OIB and the positive news indicator, the coefficient on the VIX dummy is positive and highly significant. This suggests that individual traders'

[13] We also use the historical median (18%) of VIX following Boehmer, Jones, and Zhang (2016) and obtain similar results.
[14] We obtain similar results when we use the model in Column III of Table 4 where the dependent variable is future raw returns.

success in interpreting positive news is time varying and they are successful in analyzing positive news events only during times of elevated market uncertainty.[15] Another interesting finding in Table 8 is that, unlike unconditional results in Table 4, individual investors also successfully trade on neutral news days when the uncertainty in the market is high.

Overall, the results in Table 8 show that individual investors are more successful in interpreting public 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.

5.2. Firm Level Uncertainty

In this section, we focus on the firm level information uncertainty on stock information advantage of individual agents. When firms have 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.

We use the analyst coverage[16] to capture firm level information uncertainty.[17] We argue that firms with lower analyst coverage should have more information uncertainty and therefore, should provide better opportunities for investors to trade on the public news. Since the number of analysts following a firm is related to a firm's size and age, in order to ensure that our results are

[15] 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 VIX dummy is not significant when we regress positive, neutral or, negative news coefficients on a constant and the VIX dummy.

[16] In addition to the number of analysts, when we repeat our analysis using the dispersion among analyst forecasts, idiosyncratic volatility of returns, and cash flow volatility, we obtain similar results. The results are available upon request.

[17] See Hong, Lim, and Stein (2000) and Zhang (2006) for the use of analyst coverage and forecast dispersion, respectively, for firm specific information uncertainty.

not driven by firm size or age which arguably might also capture other aspects of a firm's information environment, we regress the natural logarithm of log (1+ number of analysts) on log of firm market capitalization and the number of days the firm is publicly traded in the market. We use the residual values from these daily cross sectional regressions.

To test this idea, we repeat out analysis in Table 4 by adding a dummy variable, Res_Analyst, and its interaction with OIB and signed news event variables to our regression specification in columns III and VI. The dummy variable takes a value of if residual analyst following is below the median on a given day and zero otherwise. If individual investors have more interpretation advantage when firm specific information uncertainty is higher, then we expect to find a positive coefficient on the triple interaction with analyst coverage.

The results are presented in Table 9. According to the results, the coefficient on the interaction between analyst coverage, positive news event, and IOB is positive and is significant at 5% level. This suggests that the individual investors return predictability increases when firms are followed by fewer analysts. Indeed, individual investors seem to benefit from positive news mainly in firms which are followed by fewer analysts. Overall, these results are in line with the view that besides high market level uncertainty, individual investors benefit more from public news when firm specific uncertainty is higher.

6. Individual Investor Trading and Future Returns by News Categories

In this section, we examine the relation between individual trading order imbalance and news across different news categories. Besides the sentiment and relevance of the news items, Thomson Reuters also provides information on the category of the news. There are 74 categories provided by Thomson Reuters and if TR provides more than one news category code for the same news item, then we include these items in each category on the same date. Since, we find that individual investors can successfully process only positive news items, we retain only positive news items in our sample. This way, we can identify in which news categories the information is best processed by individual investors when the sentiment of the news is positive. Although there are a total of 74 news categories, in our final set of analysis, we have 59 news categories with enough number of observations left to perform our analysis.

To examine whether individual investors' information procession ability differs across different news categories, following Engelberg et. al. (2012), we run Panel regressions for each 60 news category where the dependent variable is 20 day returns following the news day and the main variable of interest is individual order imbalance IOIB. In our analysis, we include $Ln(MV)_{t-1}$, *Momentum*, $Return_t$, Returnt-1, and Returnt-2 as additional control variables and include firm fixed effects to account for a potential heterogeneity in the panel. The main variable of interest is *IOIB* and differences in the coefficient on this variable shows us how individual investors news processing ability varies across different news categories.

The results are presented in Table 10. According to the results while the relation between individual trading and future returns is positive in majority of the news categories, individual investors seem to successfully process information in 7 news categories. In particular, individual investors seem to better process information in news related to Corporate Results including tabular and textual reports, accounts, annual reports., Business Activities, the effect of domestic and government policies on the firm, dividends including dividend forecasts, internet related news stories, declarations and payments, international trade, and short term interest rates. These news items represent 45% of the total news by frequency count, suggesting that individuals possess superior information processing skills for almost half of the news items in our sample.

Arguably, the lack of significance for the remaining news types might be due to lack of power in these test since these news types are less frequently occurring in the sample.

As a final test, using a Fisher test of combined probability, we examine the cross sectional significance of the coefficient on IOIB across all news categories. According to the results, the statistic on Fisher tests statistics is XXX with a p value of XX suggesting that the coefficient on IOIB is significantly different than zero for the cross section of news categories.

7. Conclusion

In this paper, we examine the profitability of individual investors' trades around public firm specific news events. We find that individual investors' trades are significantly more profitable on days with positive public news. The association between retail order imbalances and monthly future returns increases roughly fourfold on days when the firm is covered in a news event with a positive tone. However, we find little or no evidence of incremental ability for retail trades to predict future returns on neutral or negative news event days. Moreover, individual investors cannot predict the news content and they are more successful in interpreting news during times of high 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 also explore potential alternative explanations such as retail traders providing liquidity to other investors, increase in firm visibility, or 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 are informed about future stock returns. However, our results and inferences are only limited to the retail orders executed on the New York Stock Exchange (NYSE) and cannot be generalizable 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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Table 1: Summary statistics

The sample includes 2,648,507 firm-day observations for 1,697 firms over the period April 1, 2004-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 $2 on a given day or CRSP share codes other than 10 and 11 (ordinary common shares) are eliminated. Panel A reports time series averages of daily cross-sectional summary statistics. Panel B reports firm-level summary statistics on proportion of days with various types of news events. Panel C reports day-level summary statistics on the number of firms and various types of news events on a given trading day. ***OIB*** is individual investor order imbalance and defined as the total number of stock *i* shares bought minus sold on day t across all individual investors in the sample, divided by the total CRSP volume in stock i on day t. ***Total Ind. Volume*** is the total number of stock *i* shares bought plus shares sold on day t, divided by the total CRSP volume in stock i on day t. ***Sentiment Score*** is the relevance weighted sentiment score across all news stories published on firm *i* on day t and varies between -1 and 1. *MV is* the market value of equity on day t-1; ***Momentum*** is cumulative raw stock returns over trading days t-63 through t-3; ***$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 (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: 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%

Panel B: Firm level statistics (1,697 Unique Firms)

% of Days with a	Mean	Std Dev	5^{th} Pctl	25^{th} Pctl	Median	75^{th} Pctl	95^{th} 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%

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Table 1 Cont'd.
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 2: Individual Investor Trading and Future Returns

This table reports time series averages of daily cross-sectional average abnormal and raw stock returns over the [1,20] for any given day t, order imbalance, firm size, and lagged raw returns for each tercile of daily individual investor order imbalance (OIB). Newey-West (1987) t-statistics are reported next to average future returns calculated using standard errors corrected for serial correlation with 20 lags.

	1	*2*		*3*		*4*	*5*	*6*
	OIB	***Raw Returns [1,20] in percent***		***Abnormal Returns [1,20] in percent***		***Firm Size ($Mil)***	***$Return_{t-1}$***	***$Return_{t-2}$***
OIB Tercile	**Mean**	**Mean**	**t-statistic**	**Mean**	**t-statistic**	**Mean**	**Mean**	**Mean**
T1	-0.0157	0.6480	1.21	0.1301	0.87	9,178	0.16%	0.13%
T2	-0.0010	0.7135	1.36	0.2200	1.54	8,723	0.04%	0.05%
T3	0.0070	0.9747	1.76	0.4588	2.69	6,851	-0.01%	0.01%
Test of difference: T3-T1		0.3267	6.53	0.3287	6.53			

Table 3: Regression analysis of individual investor trading around news events

This table reports coefficient estimates from the following panel data regressions:

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

where $OIB_{i\tau}$ is individual order imbalance in stock *i* on day τ. $News\ Event_{it}$ is a dummy variable that equals one if firm *i* is covered in a news story on day *t* and zero otherwise. 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 of the dependent variable, 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. In order to eliminate the effect of other news events, we require the firm to have a news event only on day *t*. The sample includes ordinary common shares of NYSE-listed stocks over the period April 1, 2004-December 31, 2011. Panel A reports coefficients for all news events while Panels B, C, and D report estimates for positive, negative, and neutral news events, respectively. 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. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Positive News Events

	Event time of the dependent variable					
	t-2	***t-1***	***t=0***	***t+1***	***t+2***	***After minus before***
Positive News Event$_t$	-0.012	0.012	0.027***	0.002	0.001	0.007
	(-1.36)	(1.43)	(3.19)	(0.20)	(0.16)	(0.41)
Return$_{t-1}$	-0.976***	-0.876***	-0.924***	-0.826***	-0.868***	-2.859***
	(-15.80)	(-14.21)	(-14.48)	(-13.14)	(-14.99)	(-25.87)
Return$_{t-2}$	-0.904***	-0.945***	-0.890***	-0.999***	-1.021***	-3.961***
	(-15.26)	(-14.77)	(-14.13)	(-17.24)	(-17.64)	(-35.82)
Observations	1,578,996	1,579,029	1,579,059	1,578,875	1,578,687	1,578,687
Number of Firms	1683	1683	1683	1683	1683	1683
Adjusted R^2	5.25%	5.21%	5.17%	5.18%	5.16%	0.06%

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Panel B: Negative News Events

	Event time of the dependent variable					
	t-2	***t-1***	***t=0***	***t+1***	***t+2***	***After minus before***
Negative News Event$_t$	0.014	0.006	-0.037**	-0.011	-0.015	-0.055*
	(0.88)	(0.37)	(-2.30)	(-0.69)	(-0.92)	(-1.79)
Return$_{t-1}$	-0.976***	-0.876***	-0.924***	-0.826***	-0.868***	-2.862***
	(-15.80)	(-14.21)	(-14.48)	(-13.14)	(-15.00)	(-25.89)
Return$_{t-2}$	-0.904***	-0.945***	-0.890***	-0.999***	-1.022***	-3.961***
	(-15.26)	(-14.77)	(-14.13)	(-17.25)	(-17.64)	(-35.82)
Observations	1,578,996	1,579,029	1,579,059	1,578,875	1,578,687	1,578,687
Number of Firms	1683	1683	1683	1683	1683	1683
Adjusted R^2	5.25%	5.21%	5.17%	5.18%	5.16%	0.06%

Continued on the next page

Table 3 Cont'd.
Panel C: Neutral News Events

	Event time of the dependent variable					
	t-2	***t-1***	***t=0***	***t+1***	***t+2***	***After minus before***
Neutral News Event$_t$	0.007	0.024***	-0.009	-0.013**	-0.022***	-0.066***
	(1.11)	(3.86)	(-1.39)	(-2.08)	(-3.48)	(-5.61)
Return$_{t-1}$	-0.976***	-0.876***	-0.924***	-0.825***	-0.866***	-2.852***
	(-15.80)	(-14.21)	(-14.48)	(-13.12)	(-14.96)	(-25.81)
Return$_{t-2}$	-0.904***	-0.944***	-0.889***	-0.998***	-1.022***	-3.963***
	(-15.26)	(-14.76)	(-14.11)	(-17.22)	(-17.65)	(-35.84)
Observations	1,578,996	1,579,029	1,579,059	1,578,875	1,578,687	1,578,687
Number of Firms	1683	1683	1683	1683	1683	1683
Adjusted R^2	5.25%	5.21%	5.17%	5.18%	5.16%	0.06%

Table 4: Regression analysis of the cross-sectional relation between daily individual order imbalance, monthly returns, and news

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

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

$Return_{i;t+1,t+20}$, is compounded returns over trading days *t+1* through *t+20*. *Models I, II,* and *III* use buy and hold raw stock returns (in percent) as the dependent variable while models *IV, V,* and *VI* use buy and hold abnormal returns (raw return minus CRSP value weighted index return). The sample includes 2,648,507 firm-day observations for 1,697 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 (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)$_{t-1}$*, *Momentum*, *Return$_t$*, *Return$_{t-1}$*, and *Return$_{t-2}$*. Definitions for control variables are provided in Table 1. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variable: Raw returns [1,20]						***Dependent Variable: Abnormal returns [1,20]***					
	I		**II**		**III**		**IV**		**V**		**VI**	
	Coeff.	***t-stat***	***Coeff.***	***t-stat***	***Coeff.***	***t-stat***	***Coeff.***	***t-stat***	***Coeff.***	***t-stat***	***Coeff.***	***t-stat***
Intercept	1.457	(1.23)	1.437	(1.20)	1.432	(1.19)	0.932	(1.02)	0.912	(0.99)	0.908	(0.98)
OIB	4.454***	(4.44)	4.987***	(5.26)	4.434***	(4.42)	4.456***	(4.44)	5.000***	(5.27)	4.437***	(4.42)
News Event	-0.053	(-0.78)					-0.054	(-0.79)				
OIBxNews Event	1.955	(0.80)					2.017	(0.83)				
Negative News Event			-0.220**	(-2.57)	-0.228***	(-2.66)			-0.223***	(-2.60)	-0.230***	(-2.69)
Neutral News Event			-0.077	(-0.96)	-0.077	(-0.96)			-0.078	(-0.96)	-0.078	(-0.97)
Positive News Event			0.045	(1.02)	0.046	(0.99)			0.044	(1.00)	0.044	(0.97)
OIBxNegative News Event					-24.63	(-1.13)					-24.083	(-1.11)
OIBxNeutral News Event					2.399	(0.87)					2.47	(0.89)
OIBxPositive News Event					22.323***	(3.35)					22.028***	(3.30)
Ln(MV)$_{t-1}$	-0.058	(-0.97)	-0.056	(-0.93)	-0.056	(-0.93)	-0.057	(-0.96)	-0.056	(-0.92)	-0.055	(-0.91)
Momentum	0.731	(1.37)	0.724	(1.36)	0.72	(1.36)	0.731	(1.37)	0.723	(1.36)	0.72	(1.35)
Return$_t$	-2.603***	(-2.65)	-2.658***	(-2.72)	-2.710***	(-2.75)	-2.590***	(-2.63)	-2.644***	(-2.70)	-2.696***	(-2.73)
Return$_{t-1}$	-1.297	(-1.34)	-1.344	(-1.39)	-1.347	(-1.40)	-1.288	(-1.33)	-1.334	(-1.38)	-1.337	(-1.38)
Return$_{t-2}$	-0.636	(-0.66)	-0.633	(-0.66)	-0.681	(-0.71)	-0.625	(-0.65)	-0.622	(-0.65)	-0.669	(-0.70)
Adj R^2	4.58%		4.59%		4.65%		4.58%		4.59%		4.66%	

Table 5: Individual investor trading, future returns, and news: Longer holding period

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

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

$Return_{i;t+21,t+40}$, is compounded returns over trading days t+21 through t+60. Models I, II, and III use buy and hold raw stock returns as the dependent variable while models IV, V, and VI use buy and hold abnormal returns (raw return minus CRSP value weighted index return). The sample includes 2,648,507 firm-day observations for 1,697 unique NYSE listed stocks over the period April 1, 2004-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 (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. $\boldsymbol{X}$ is a vector of control variables and includes $Ln(MV)_{t-1}$, *Momentum*, $Return_t$, $Return_{t-1}$, and $Return_{t-2}$. 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]***			
	I		**II**		**III**		**IV**	
	Coeff.	***t-stat***	***Coeff.***	***t-stat***	***Coeff.***	***t-stat***	***Coeff.***	***t-stat***
Intercept	1.746	2.23	2.642	(1.64)	0.536	(2.67)	1.36	(1.10)
OIB	2.453	(1.58)	2.598*	(1.65)	2.438	(1.57)	2.600*	(1.66)
Negative News Event			-0.118	(-0.92)			-0.135	(-1.05)
Neutral News Event			-0.231**	(-2.07)			-0.241**	(-2.16)
Positive News Event			-0.058	(-0.76)			-0.065	(-0.86)
OIB x Negative News Event			35.396	(1.38)			32.45	(1.27)
OIBx Neutral News Event			-2.952	(-0.91)			-3.018	(-0.93)
OIBx Positive News Event			4.932	(0.61)			5.16	(0.64)
$Ln(MV)_{t-1}$			-0.08	(-1.02)			-0.074	(-0.94)
Momentum			1.033	(1.39)			1.055	(1.42)
$Return_t$			0.526	(0.41)			0.53	(0.42)
$Return_{t-1}$			0.994	(0.75)			1.002	(0.76)
$Return_{t-2}$			0.896	(0.72)			0.874	(0.70)
Adj. R^2	*0.04%*		4.00%		*0.04%*		4.00%	

Table 6: 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 2,648,507 firm-day observations for 1,697 unique NYSE listed stocks over the period April 1, 2004-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-statistic**
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 7: Individual investor trading and future returns on news days with low equity returns

This table reports results from estimating models III and VI in Panel A of Table 4 using only observations where the absolute stock return on any given day is in the bottom two quintiles of the cross-sectional distribution of absolute stock returns on that day. Column 1 uses buy and hold raw stock returns as the dependent variable while column 2 uses buy and hold abnormal returns (raw return minus CRSP value weighted index return). The sample includes 1,058,459 firm-day observations for 1,697 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 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. Definitions for control variables are provided in Table 1. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: Compounded raw returns [1,21]		***Dependent variable: Compounded abnormal returns [1,21]***	
	I		**II**	
	Coeff.	***t-stat***	***Coeff.***	***t-stat***
Intercept	1.477	(1.28)	0.954	(1.10)
OIB	2.970**	(2.01)	2.957**	(2.01)
Negative News Event	-0.118	(-1.11)	-0.121	(-1.13)
Neutral News Event	-0.009	(-0.12)	-0.01	(-0.13)
Positive News Event	0.028	(0.57)	0.028	(0.55)
OIB x Negative News Event	-297.989	(-1.40)	-297.866	(-1.40)
OIB x Neutral News Event	0.641	(0.13)	0.762	(0.16)
OIB x Positive News Event	41.450**	(2.54)	41.316**	(2.53)
$Ln(MV)_{t-1}$	-0.06	(-1.03)	-0.06	(-1.02)
Momentum	0.65	(1.22)	0.652	(1.23)
$Return_t$	-2.07	(-0.94)	-2.082	(-0.94)
$Return_{t-1}$	-1.098	(-0.92)	-1.097	(-0.91)
$Return_{t-2}$	-0.96	(-0.84)	-0.958	(-0.84)
Adj R^2	4.62%		4.62%	

Table 8: Market uncertainty and individual Investors' news interpretation ability

This table presents result from a time series regression of coefficient estimates on a constant and a VIX dummy. The coefficient estimates are obtained from daily cross sectional regressions in Model VI of Table 4 where the dependent variable is abnormal future returns**.** The VIX dummy equals to one if the VIX is higher than the median value over the sample period and zero otherwise. 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	5.291***	-25.055	-4.651**	2.152
	5.86	-1.41	-2.02	0.64
VIX Dummy	-1.650	1.890	13.790**	38.477***
	-0.86	0.04	2.59	3.05

Table 9: Firm level uncertainty and individual Investors' news interpretation ability

This table reports results from estimating models III and VI in Panel A of Table 4 including residual number of analysts following a firm and its interaction with individual order imbalance and news sentiment. Residual analyst following is the residual from regressing log (1+analyst following) on log of market capitalization and log of firm age (in days) using daily cross sectional Famam MAcBeth regressions. *Res_Analyst* is low residual analyst following which is a dummy variable set equal to 1 if the residual analyst following is below the median residual on a given day and zero otherwise. Column 1 uses buy and hold raw stock returns as the dependent variable while column 2 uses buy and hold abnormal returns (raw return minus CRSP value weighted index return). 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 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. Definitions for control variables are provided in Table 1. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: Compounded raw returns [1,21]		***Dependent variable: Compounded abnormal returns [1,21]***	
	I		**II**	
	Coeff.	***t-stat***	***Coeff.***	***t-stat***
Intercept	1.719	(1.36)	1.17	(1.18)
OIB	4.201***	(4.17)	4.248***	(4.17)
Res_Analyst	-0.223**	(-2.45)	-0.224**	(-2.46)
Negative News Event	-0.286***	(-2.87)	-0.286***	(-2.88)
Neutral News Event	-0.138*	(-1.92)	-0.139*	(-1.93)
Positive News Event	-0.024	(-0.43)	-0.025	(-0.46)
OIB x Negative News Event	146.904	(1.37)	146.839	(1.37)
OIB x Neutral News Event	6.885	(1.20)	7.035	(1.22)
OIB x Positive News Event	-0.839	(-0.08)	-1.241	(-0.11)
OIB x Negative News Event x Res_Analyst	-225.027	(-1.48)	-224.712	(-1.48)
OIB x Neutral News Event x Res_Analyst	-4.342	(-0.71)	-4.565	(-0.75)
OIB x Positive News Event x Res_Analyst	42.714**	(2.28)	42.079**	(2.23)
OIB x Res_Analyst	0.168	(1.22)	0.166	(1.21)
OIB x Neutral News Event x Res_Analyst	0.138*	(1.69)	0.137*	(1.67)
OIB x Positive News Event x Res_Analyst	0.149*	(1.69)	0.151*	(1.71)
Other Controls	Included		Included	
Adj R^2	4.78%		4.79%	

Table 9: Firm level uncertainty and individual Investors' news interpretation ability

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

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

Where $Return_{i;t+1,t+20}$, is compounded returns over trading days *t+1* through *t+20*. 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. *Only news events that are* classified as positiveare ncluded in the analysis. ***X*** is a vector of control variables and includes $Ln(MV)_{t-1}$, *Momentum*, $Return_t$, $Return_{t-1}$, and $Return_{t-2}$. The coefficients on these variables are included in the regression but are not presented in the table. In each regression we also control for firm fixed effects. Definitions for control variables are provided in Table 1. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

News Category	OIB	*t-stat*	N	Frequency	Adjusted R^2
Corporate Results Forecasts	2.36	(0.43)	10297	2.86%	0.073
Corporate Financial Results	11.956***	(3.13)	31324	8.69%	0.034
All Corporate Crisis	4.428	(0.90)	19312	5.36%	0.051
Debt Markets News	3.684	(0.78)	15139	4.20%	0.063
Stock Markets News	4.318	(0.47)	6342	1.76%	0.072
Major Breaking News	-5.538	(-0.62)	4866	1.35%	0.088
US Corporate Bonds	3.474	(0.66)	12631	3.50%	0.070
Mergers and Acquisitions	1.233	(0.34)	22023	6.11%	0.064
Macro News	8.11	(0.61)	4242	1.18%	0.126
Business Activities	9.694***	(3.96)	80024	22.19%	0.042
Corporate Analysis	67.422	(1.51)	696	0.19%	0.056
Hot Stocks	11.403	(1.00)	6270	1.74%	0.062
Regulatory Issues	-0.321	(-0.02)	3942	1.09%	0.105
Washington/US Govt. News	33.153*	(1.66)	2785	0.77%	0.147
Legislation	-2.059	(-0.38)	6517	1.81%	0.098
Fund Industry News	1.976	(0.24)	5921	1.64%	0.093
Broker Research and Recom.	1.082	(0.20)	17833	4.95%	0.060
Ratings	-5.808	(-0.98)	9278	2.57%	0.059
New Issues	11.914	(1.35)	4250	1.18%	0.124
Labour; (Un)employment	2.795	(0.29)	6892	1.91%	0.037
Management Issues/Policy	1.301	(0.21)	12587	3.49%	0.068
Domestic Politics	15.395**	(2.18)	6171	1.71%	0.132
Mortgage Backed Debt	21.771	(1.48)	1801	0.50%	0.073
Internet/World Wide Web	15.358***	(2.77)	14646	4.06%	0.051

Table 10 Continued					
Reuters Exclusive News	-27.703	(-1.05)	633	0.18%	0.293
Press Digests	38.963	(0.74)	122	0.03%	0.108
Multi-Industry	7.01	(0.43)	5049	1.40%	0.083
Loans	4.225	(0.25)	2649	0.73%	0.106
Crime, Law Enforcement	-12.933	(-0.06)	238	0.07%	0.336
Terms of Bond Issues	28.527	(1.23)	853	0.24%	0.211
Interest Rates	-23.425	(-0.68)	314	0.09%	0.024
Government/Sovereign Debt	-21.671	(-0.49)	515	0.14%	0.138
Dividends	8.227^{**}	(2.09)	16672	4.62%	0.028
Judicial Processes/Court	-88.469	(-0.54)	411	0.11%	0.068
Initial Public Offerings	-7.744	(-0.66)	2679	0.74%	0.204
Eurobonds	32.078	(1.11)	383	0.11%	0.246
Credit Default Swaps	13.636	(0.27)	610	0.17%	0.211
Wholesale	9.178	(0.54)	4108	1.14%	0.048
International Trade	63.696	(1.56)	394	0.11%	0.182
Weather	-1.707	(-0.03)	190	0.05%	0.397
Bankruptcies	22.924	(0.25)	221	0.06%	0.133
Macro-Economics	-34.658	(-1.22)	1579	0.44%	0.108
Economic Indicators	-7.15	(-0.20)	844	0.23%	0.076
US Agencies	-81.772	(-0.94)	88	0.02%	0.259
Forex Markets	-59.279	(-1.07)	441	0.12%	0.085
Investment Grade Debt	-2.588	(-0.15)	1938	0.54%	0.049
Diplomacy, Int. Relations	11.795	(1.01)	1008	0.28%	0.222
Money Markets	28.406	(0.18)	132	0.04%	0.173
Disasters and Accidents	62.962	(0.81)	125	0.03%	0.294
Exchange Activities	28.04	(0.76)	645	0.18%	0.016
Lifestyle	-12.865	(-1.16)	6830	1.89%	0.075
Civil Unrest	68.241	(0.30)	56	0.02%	0.781
High-Yield Debt	10.7	(0.34)	2080	0.58%	0.076
Federal Reserve Board	-133.924	(-0.88)	137	0.04%	0.220
(Inter)national Security	-4.183	(-0.08)	1108	0.31%	0.158
Short-Term Interest Rates	264.677^{***}	(3.04)	53	0.01%	0.739
Equity-Linked Bonds	104.369	(0.88)	192	0.05%	0.146
Asset-Backed Debt	-6.46	(-0.38)	1131	0.31%	0.040
Reuters Summits	13.4	(0.22)	367	0.10%	0.281
Fisher test					
p-value					

Figures

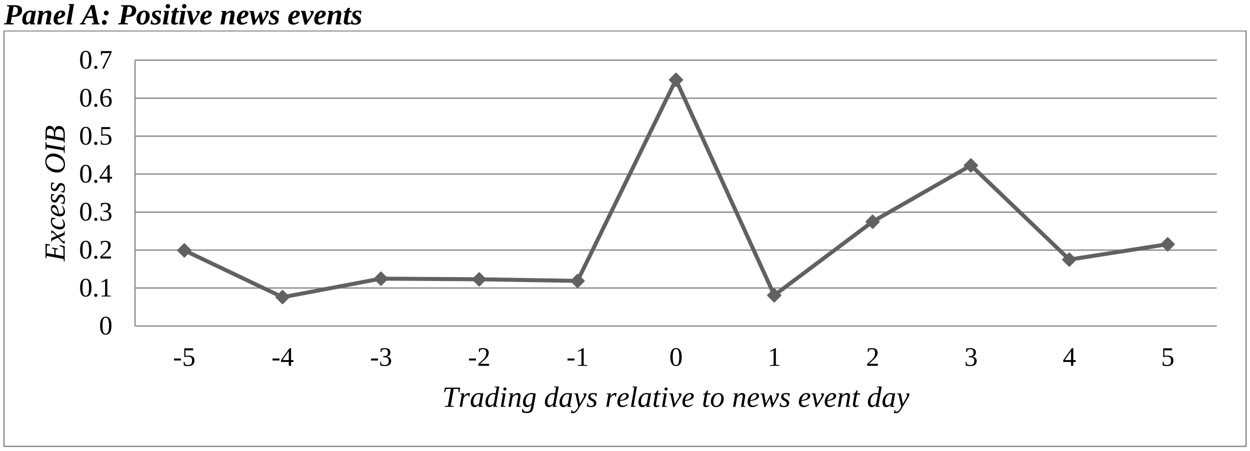
Figure 1: Excess order imbalance around news events

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 includes 727,550 firm-day observations with news events for 1,697 firms over the period April 1, 2004-December 31, 2011 (1,953 trading days). The sample 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. 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

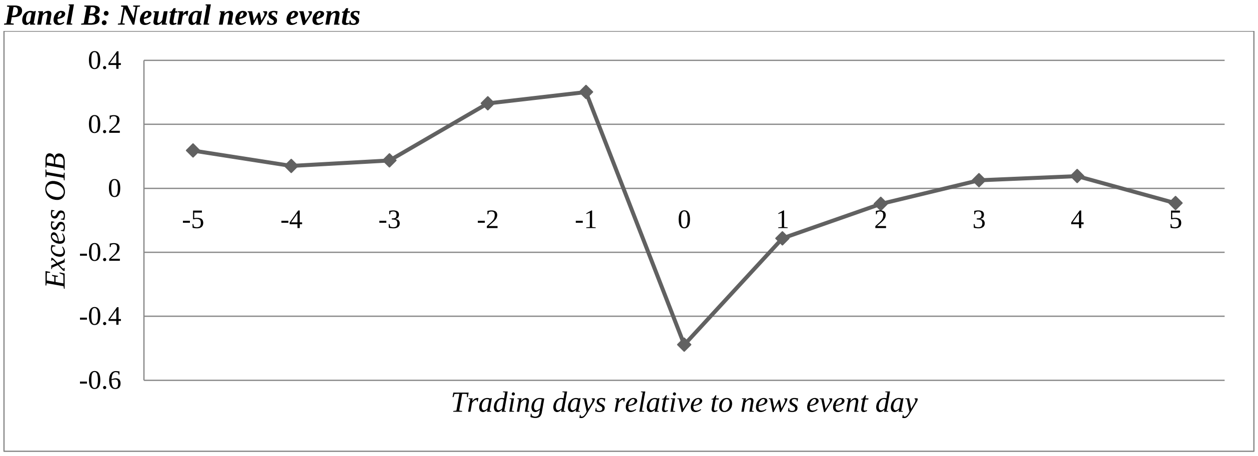


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Figure 1 Cont'd.
Panel C: Negative news events

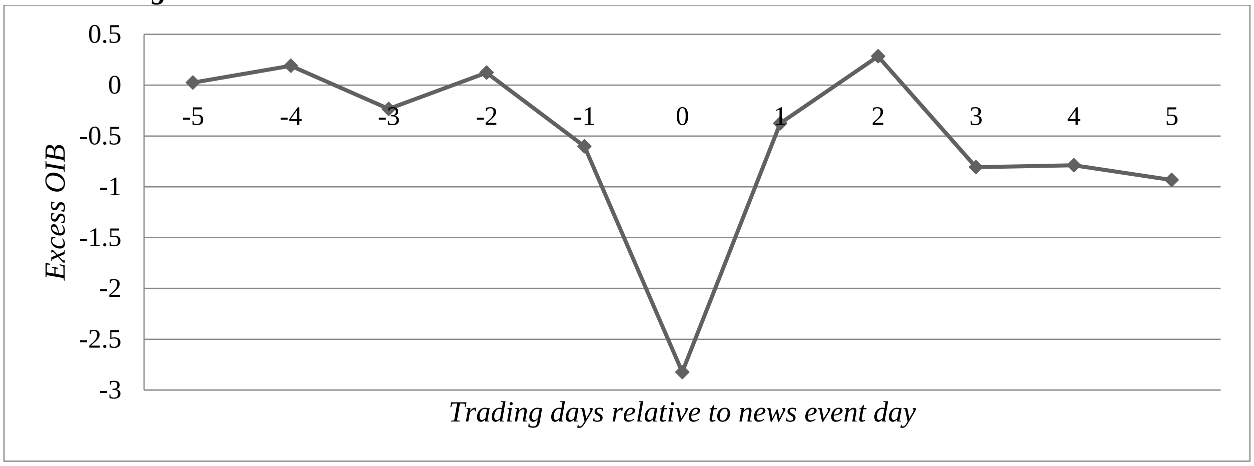

Figure 2: Stock liquidity around positive news event days

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.