Beauty Contests around News Releases

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March 2023

Abstract

This paper examines the impact of beauty contest driven higher order beliefs on stock returns upon news releases. Consistent with higher order beliefs, in the short-term, overpriced stocks become less overpriced on days with low sentiment news, but they become much more overpriced when high sentiment news is released. The asymmetric impact of high and low sentiment news in overpriced stocks and the lack of an impact on underpriced stocks is driven by more positive news being released in recent years, investors paying more attention to overpriced stocks, and short sale constraints.

JEL Classification: G11; G12; G14; G15; G41
Keywords: News releases, Mispricing, Beauty contest, Higher order beliefs, Low latency trading

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[1] We are grateful to the participants in the following conferences and seminars: the 2022 Global AI Finance Research Conference (GAFRC), KAFA brownbag seminar, Case Western Reserve University, and KAIST, as well as Sungjune Pyun (GAFRC discussant) and Sahn-Wook Huh (KAFA brownbag seminar discussant). All remaining errors are our own.

Classical asset pricing theories are based on rational representative agents. However, the heterogeneity in investor beliefs, including biased beliefs, has become an important focus of research in recent years with a surge in empirical and theoretical work on understanding the formation of investor beliefs. One source of biased beliefs is the concept of the "beauty contest" proposed by Keynes (1936) to explain price fluctuations in equity markets.[2] In fact, beauty contests lead to higher order beliefs, when investors try not to predict the expected return and not even the beliefs of other investors about expected returns but the beliefs of other investors about what they believe about the beliefs of others to be.[3] Cespa and Vives (2015) develop a model where short-termism of investors leads to beauty contest behavior. Allen, Morris and Shin (2006) have argued that models with higher order beliefs overweight public information and that investors will focus more on short-run price movements. Schmidt-Engelbertz and Vasudevan (2022) develop a model to show that higher order beliefs lead to a hump-shaped pattern of return expectation following the arrival of news with the initial return expectation in the direction of the news followed by a subsequent expectation of a reversal. In this paper we will study the impact of the beauty contest driven higher order beliefs on returns of underpriced and overpriced stocks in the context of information shocks, i.e., earnings announcements and other news releases.

Unconditionally, announcements with good (bad) news should initially result in higher (lower) stock returns as investors trade based on their predictions of the reactions of others (who also predict the reaction of others) to the news. Also, unconditionally, overpriced (underpriced) stocks should have lower (higher) returns to the extent that markets are informationally efficient. However, the conditional reactions of overpriced and underpriced stocks to good and bad news can depend on whether it is the degree of

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[2] *"Investment based on genuine long-term expectation is so difficult to-day as to be scarcely practicable. He who attempts it must surely lead much more laborious days and run greater risks than he who tries to guess better than the crowd how the crowd will behave…"* page 157 in Keynes (1936).

[3] A number of papers have examined heterogenous beliefs and higher order beliefs including Harrison and Kreps (1978), Harris and Raviv (1993), Kandel and Pearson (1995), Banerjee and Kremer (2010), Allen, Morris, and Shin (2006), Bacchetta and van Wincoop (2008), Makarov and Rytchkov (2012), Cespa and Vives (2015), and Schmidt-Engelbertz and Vasudevan (2022).

mispricing or the higher order beliefs that prevails.

We obtain earnings announcement dates from Compustat and the dates and timing of news releases from RavenPack. Using the 11 mispricing signals from Stambaugh, Yu, and Yuan (2012) (henceforth SYY) to identify underpriced and overpriced stocks, the first set of our findings is as follows. On days without earnings announcements or other news releases, overpriced stocks earn lower returns. Unconditionally, returns are higher on news days and on earnings announcement days. These results are as expected. However, we also find that on average overpriced stocks earn higher returns on news days and lower returns on earnings announcement days. Thus, for overpriced stocks, mispricing is corrected on earnings announcement days while it is exacerbated on news days.

We then measure the information content of earnings announcement by the standardized unexpected earnings (SUE), and that of news by the RavenPack sentiment score (SENT). When SUE is high, underpriced stocks earn higher returns. On days with low sentiment news, overpriced stocks earn lower returns as both the overpricing and low news sentiment serve to reduce prices. These results are again as expected. However, we also find that with high sentiment news being released, overpriced stocks earn even higher returns, implying that the impact of higher order beliefs on returns dominates that of the overpricing. Therefore, the short-run reaction is that overpriced stocks become more overpriced upon the receipt of high sentiment news and this increases the distance between market price and fundamental value, thereby, reducing price efficiency. On the other hand, low sentiment news decreases overpricing and increases price efficiency.[4]

We test the impact of the beauty contest driven higher order beliefs by examining the trading behavior of high frequency or low latency traders (HFTs or LLTs) who have become an important part of financial

[4] These results are robust to (i) using signals from 95 anomalies studied by McLean and Pontiff (2016) to determine the degree of mispricing, (ii) using the SYY method of ranking to categorize underpriced or overpriced stocks, (iii) using only reputable news sources such as the Dow Jones Newswire, and (iv) using three days around each earnings announcement or news release rather than just the day of the announcement or release.

markets and comprise a large fraction of the trading volume in recent years. We find that the exacerbation of overpricing on news days is predominantly driven by LLTs who quickly react to news in the direction of its sentiment, i.e., with more intense low latency trading (LLT) activity on news release days, positive sentiment news leads to larger positive returns, and negative sentiment news leads to larger negative returns. While this result is unexpected because a large literature has shown that LLT improves the price discovery and market efficiency, it is consistent with higher order beliefs, such that the LLT algorithms are set up to react fast and trade in the direction that is expected of other market participants, i.e., LLTs act to quickly incorporate the return expectations into prices.

In addition, the impact of high sentiment news on overpriced stocks is at least twice as high as the impact of low sentiment news. Also, there is no impact of news on underpriced stocks. These results could be due to the following reasons. Investors pay more attention (as measured by the number of unique IP addresses that download firms' 10-K filings) to overpriced stocks than to underpriced ones, resulting in larger return reactions to news in overpriced stocks, both to positive and negative sentiment news. The number of news releases with positive sentiment is greater than that of news with negative sentiment. Finally, we use the SEC's SHO pilot program to provide causal evidence that short sale constraints impede the decline in prices, especially for underpriced stocks, when negative sentiment news is released. All of these factors – more attention paid to overpriced stocks by investors, larger reactions to news for overpriced stocks, more positive news produced, and short sale constraints – together lead to our finding that overpriced stocks become significantly more overpriced upon the release of high sentiment news while there is no impact of news on underpriced stocks. But why are there more articles with a positive sentiment than with a negative sentiment, especially in recent years?

Solomon (2012) documents that external investor relations (IR) firms generate more positive sentiment coverage for their clients by fostering and promoting positive press releases, leading to increased returns around news release days. Using a stock-level monthly proxy for IR activity, we show that overpriced stocks with higher IR activity earn higher returns on days with news releases and on days with positive sentiment news releases. Thus, the creation and fostering of firm-level positive news articles (possibly by IR firms) can lead to overpriced firms becoming even more overpriced, which results in an increase in the discrepancy between market price and fundamental value and a decrease in price efficiency. But why don't investors account for the IR activity in their investment decisions and correct this overpricing? The return expectations caused by the beauty contest driven higher order beliefs suggest that as short-term investors, e.g., LLTs, try to predict the behavior of others, they would "rationally" buy the overpriced stocks, at least in the short run, upon the release of high sentiment news.[5]

Our findings are different from those in Engleberg, McLean, and Pontiff (2018) (henceforth EMP) who find that overpriced stocks earn lower returns upon the release of news. Importantly, EMP findings imply an improvement in price efficiency upon the release of news while our results imply a deterioration in price efficiency. EMP employ the Dow Jones News Archive database (instead of RavenPack) for their news source over the sample period of 1979-2013. We are able to replicate the EMP result that overpriced stocks earn lower returns upon the release of news, when using the Dow Jones News Archive database over their sample period of 1979-2013. However, even with the Dow Jones News Archive database over the period 1979-2013, we still find that high sentiment news in the case of overpriced stocks leads to significantly higher returns and thus an exacerbation of existing overpricing. The question then is this – what causes the dramatic change over our sample period of 2000-2019 when overpriced stocks become even more overpriced upon the release of news? Over time, there has been an increase in the number of news releases and, further, the growth in positive sentiment news has been greater than negative sentiment news. More importantly, the rise of fast traders (i.e., LLTs) in recent years amplifies the impact of beauty

[5] Harrison and Kreps (1978) have suggested that investors would be willing to purchase overpriced stocks if they expect to be able to sell these stocks at even higher prices to others.

contest driven higher order beliefs on returns on news release days. These facts combined with finding that more attention is paid to overpriced stocks and their larger return reactions to news releases, explains the difference in our results from those in EMP.

In sum, the increase in prices of already overpriced stocks could be driven by the return expectations of investors who purchase overpriced stocks when positive sentiment news is released to earn short-term profits. The return impact of news releases is larger for overpriced stocks as investors pay more attention to these stocks and moreover positive news releases have become more prevalent in recent years possibly due to the increased IR activities. These findings shed light on the return impact of investors' biased expectations.

2. Data

To quantify the stock-level mispricing at the beginning of each month, we rely on the 11 cross-sectional mispricing signals studied in Stambaugh, Yu, and Yuan (2012).[6] These mispricing signals have been shown by prior studies to predict the cross-section of future stock returns. As in EMP, we define our stock-level mispricing variable, i.e., *MISP*, at the beginning of each month as the difference in number of long-side and short-side anomaly portfolios that each stock belongs to and we form long-side and short-side portfolios by sorting stocks into quintile portfolios by each mispricing signal.[7] Note that *MISP* is a relative underpricing measure, i.e., stocks with higher value of *MISP* are more underpriced in the cross-section at the beginning of each month. *MISP* remains the same throughout all days in that month.

We obtain earnings announcement dates from the Compustat quarterly file. For a firm that reports earnings after the close of the market, we use the next trading day as the announcement day. We define

[6] We construct the 11 mispricing signals of SYY following their methodology based on the variables available from the CRSP, Compustat, and I/B/E/S databases.

[7] In a robustness check, we employ an alternative definition of *MISP* following Stambaugh, Yu, and Yuan (2012), denoted $MISP^{AR}$, and repeat our tests with $MISP^{AR}$. We find that our test results and conclusion are robust to using $MISP^{AR}$. The results are presented in the Appendix Table A.3.

$EARN_{i,t}$ as an indicator variable for earnings announcement days: $EARN_{i,t}$ = 1 when firm *i* announces earnings on day *t* and $EARN_{i,t}$ = 0 otherwise. We measure the information content of earnings announcement by the standardized unexpected earnings (*SUE*). For firms covered by I/B/E/S, $SUE_{i,t}$ is calculated as the actual earnings per share (EPS) minus the median of all outstanding analyst EPS forecasts before the announcement, scaled by the stock price at the end of the fiscal quarter *q* that relates to the earnings announcement. For firms not covered by I/B/E/S, we measure $SUE_{i,t}$ by the seasonally-adjusted EPS change (EPS_q – $EPS_{q\text{-}4}$) divided by the stock price at the end of the fiscal quarter *q*. In addition, we winsorize *SUE* at -1 and 1 to mitigate potential effects of outliers and set *SUE* = 0 for non-earnings days, when $EARN_{i,t}$ = 0.

We obtain news-related variables from the RavenPack News Analytics database, which provides not only the date and time but also the novelty and relevance scores of each news story. Following Dang, Moshirian, and Zhang (2015) and Chordia, Lin, and Xiang (2021), we include only the news stories that have the novelty and relevance scores of 100. We define $NEWS_{i,t}$ as an indicator variable for news release days: $NEWS_{i,t}$ = 1 if firm *i* has at least one news story released on day *t* and $NEWS_{i,t}$ = 0 otherwise. To measure the information content of news, we define $SENT_{i,t}$ as the average sentiment score of all news articles about firm *i* released on day *t*. Specifically, $SENT_{i,t}$ = (average of ESS – 50)/50, where ESS is the sentiment score for each news article assigned by RavenPack. $SENT_{i,t}$ ranges from -1 to 1 and we assign $SENT_{i,t}$ = 0 for non-news days, when $NEWS_{i,t}$ = 0. Higher values of $SENT_{i,t}$ thus indicate more positive news articles about firm *i* released on day *t*.

We merge the news- and earnings-related variables with daily stock returns and monthly *MISP* variable to investigate whether and how mispricing returns change on news release days and earnings announcement days and how the changes are affected by the information content of these events. The sample period is January 2000 through December 2019 and is restricted by the availability of the news-related variables (*NEWS* and *SENT*) from RavenPack. We exclude low-priced stocks with prices less than $5 per share at the beginning of each month. The sample contains over 28.6 million stock-day observations.

2.1. Summary statistics

In our sample, news release days are much more frequent than earnings announcement days, and there are some overlap between the news days and the earnings days. Specifically, Panel A of Table 1 shows that among 5,845,200 news release days in total, 185,119 (3.17%) are also earnings announcement days. These descriptive statistics are similar to those reported in Engelberg et al. (2018) who study the sample period from January 1979 to December 2013.

We also present in Panel B of Table 1 the summary statistics of three mispricing-related variables: the numbers of long-side (i.e., *Long*) and short-side (i.e., *Short*) anomaly portfolios that each stock belongs to and our stock-level mispricing measure (i.e., *MISP*), which is defined as *Long* minus *Short*. Panel C plots the histogram of *MISP*. Overall, these statistics show that the majority of stocks do not exhibit signs of mispricing, with the top or bottom quartile of the distribution having only one net buy or sell. But the fat tails of the distribution indicate that a significant proportion of the stocks may be mispriced.

3. Returns on information days

3.1. Returns on earnings announcement days and news release days

We first investigate how mispricing relates to returns in the following panel regression.

$$RET_{i,t} = \alpha + \beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times NEWS_{i,t} + \beta_4 EARN_{i,t} + \beta_5 NEWS_{i,t} + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $RET_{i,t}$ is the return of stock *i* on day *t*, $MISP_{i,t}$ is the mispricing score of stock *i* measured at the beginning of the calendar month to which day *t* belongs, and $EARN_{i,t}$ and $NEWS_{i,t}$ are, respectively, the indicator variables for earnings announcement day and news release day. Following Engelberg et al. (2018), $\boldsymbol{X}_{i,t}$ is a (column) vector of control variables that include daily returns, squared daily returns, and daily share trading volume over the past ten days (from days *t*-10 to *t*-1). In addition, calendar date fixed effects are included, and standard errors are clustered by day to account for the cross-sectional correlation in daily returns.

The results are reported in Panel A of Table 2. Prior research finds that due to short sale constraints, mispricing returns are mainly generated by the short leg of trades, i.e., stocks that are overpriced (Stambaugh et al. 2012). So, we estimate the regression model (1) for all stocks as well as for overpriced and underpriced stocks, separately. At the beginning of each month, we sort all stocks by *MISP*, and designate the bottom 30% and top 30% of stocks as overpriced stocks and underpriced stocks, respectively. In fact, we can see from the distribution reported in Panel C of Table 1 that *MISP* is negative in the bottom 30% and positive in the top 30%, suggesting that the designated overpriced stocks have at least one net sell signal and the designated underpriced stocks have at least one net buy signal. For expositional convenience, we divide $MISP_{i,t}$ by 100 and multiply $RET_{i,t}$ by 100 before estimating the model, implying that the coefficients of *MISP*, *MISP**EARN*, and *MISP**NEWS* are in basis points.

For the sample of all stocks, Column (1) of Panel A shows that *MISP* measured at the beginning of each month positively and significantly predicts the returns on non-information days during the month. While this could be due to positive returns to underpriced stocks or negative returns to overpriced stocks, Columns (2) and (3) show that, consistent with Stambaugh et al. (2012), it is the negative returns to overpriced stocks that drive the impact of *MISP* on the daily returns in Column (1). The coefficient on *MISP* is 0.996 (t-statistic = 8.08), suggesting that the daily negative return associated with one additional "sell" signal at the beginning of the month, is about one basis point on "normal" trading days with no information releases. Thus, unconditionally, overpriced stocks earn lower returns. The coefficient on the interaction term *MISP**EARN* is significantly positive at 4.798 (t-statistic = 7.25), and Columns (2) and (3) show that, compared to days without earnings announcements or news releases, overpriced stocks have a negative return that is almost eight times larger in magnitude on earnings announcement days. Therefore, earnings announcements lead to a significant reduction in overpricing and thus a large improvement in price efficiency.

On the other hand, in Column (1), the coefficient on *MISP*NEWS* is significantly negative at -0.967 (t-statistic = -7.62) and from Columns (2) and (3), we see that this is because overpriced stocks earn higher returns and they become even more overpriced upon the release of news. The negative coefficient on *MISP*NEWS* is surprising and inconsistent with Engelberg et al. (2018). In a later section, we will provide tests to reconcile these two results. Overall, the adjusted R^2 stays at fairly low levels of less than 1%, which is typical in regressions with daily returns as dependent variable.

In the regression model (1), to the extent that *MISP* captures the deviation between market price and fundamental value, the daily mispricing returns could be interpreted as the average amount of mispricing that is corrected (for earnings announcements) or exacerbated (for news). Positive (negative) coefficients on the interaction terms *MISP*EARN* (*MISP*NEWS*) indicate the convergence (divergence) between market price and fundamental value, and the magnitude of the coefficients reflects the speed of the convergence or divergence. The results in Panel A suggest that earnings announcements facilitate the convergence between price and value and improve price efficiency, while other news releases increase the divergence and hurt price efficiency. Note that in Column (1), the absolute coefficient of *MISP*EARN* is about 4.8 times that of *MISP*NEWS*, suggesting that earnings announcements correct the mispricing at 4.8 times the rate at which news releases exacerbate it.

The above results based on *EARN* and *NEWS* dummy variables reflect the impact of earnings announcements and news releases on stock returns. To further understand whether and how these effects vary with the information content of earnings announcements and news releases, we replace *EARN* and *NEWS* with earnings surprises and news sentiment, and estimate the following regression:

$$RET_{i,t} = \alpha + \beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times SUE_{i,t} + \beta_3 MISP_{i,t} \times SENT_{i,t} \; + \beta_4 SUE_{i,t} + \beta_5 SENT_{i,t} + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t} \,. \tag{2}$$

In equation (2), *SUE* is the standardized unexpected earnings (winsorized at -1 and 1), *SENT* is the average sentiment score (transformed to vary from -1 to 1) of all news articles released on news days, and all other variables are as previously defined. We set *SUE* = 0 for non-earnings announcement days when *EARN* = 0 and *SENT* = 0 for non-news release days when *NEWS* = 0. As shown in Panel B, *SUE* and *SENT* are both strongly and positively correlated with stock returns in all columns (i.e., for all stocks as well as overpriced and underpriced stocks), suggesting that these two proxies effectively capture the information content of earnings announcements and news releases. Turning to the interaction terms, the coefficient on *MISP*SUE* is significant only for the underpriced stocks, suggesting that the returns of underpriced stocks increase with the positive surprise in earnings announcements. In contrast, the coefficient on *MISP*SENT* is strongly negative only for the overpriced stocks, implying that, for overpriced stocks, news articles with a positive sentiment are associated with higher returns and more overpricing, and/or news articles with a negative sentiment are associated with lower returns and less overpricing. This observation motivates our next set of tests.

To estimate the differential impact of positive and negative sentiment news, we decompose the *NEWS* dummy into three dummy variables to separately measure the marginal effect of positive, negative and neutral news articles.

$$RET_{i,t} = \alpha + \beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times POSNEWS_{i,t} + \beta_4 MISP_{i,t} \times NEGNEWS_{i,t} + \beta_5 MISP_{i,t} \times ZERONEWS_{i,t} + \beta_6 EARN_{i,t} + \beta_7 POSNEWS_{i,t} + \beta_8 NEGNEWS_{i,t} + \beta_9 ZERONEWS_{i,t} + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where *POSNEWS* is an indicator variable for news days with positive average sentiment (*SENT* > 0).

Similarly, *NEGNEWS* and *ZERONEWS* are indicator variables for news days with negative (*SENT* < 0) and neutral sentiment (*SENT* = 0 and *NEWS* = 1), respectively. Panel C clearly shows that positive and negative news articles have a dramatically different impact on returns. In particular, Column (1) shows that the coefficient on *MISP*POSNEWS* is strongly negative at -4.737 (t-statistic = -30.18), while *MISP*NEGNEWS* has a strongly positive coefficient of 4.193 (t-statistic = 23.10). Columns (2) and (3) show that these results are mainly driven by overpriced stocks. Thus, overpriced stocks with positive (negative) news sentiment earn higher (lower) returns. In other words, overpricing is exacerbated by positive sentiment news, but it is reduced by negative sentiment news. In addition, we find that the averages of *POSNEWS* and *NEGNEWS* are 0.103 and 0.060, respectively, meaning that there are 72% more positive news days than negative news days in our sample. Combining them with the coefficients of *MISP*POSNEWS* and *MISP*NEGNEWS* suggests that for an average month, positive news days increase the return of a stock by an average of 0.488 (=4.737*0.103) basis points, while the negative news days decrease the return of a stock by an average of 0.252 (=4.193*0.06) basis points. Thus, the impact of positive news days on daily return is about twice that of negative news days and the net effect on news release days is the exacerbation of existing overpricing driven by positive news releases. This provides an explanation for why we obtained the negative and significant coefficient of *MISP*NEWS* in Panel A.

An important takeaway from the above analysis is that the regression based on the news day dummy variable (i.e. *NEWS*) as in equation (1), which is also the main research design adopted in Engelberg et al. (2018), can mask the important distinction between news articles with opposite sentiments, an issue that we will further explore in Section 5.4.

To assess the impact of the information content of positive and negative news days, we estimate the following panel regression, which accounts for the magnitude of the sentiment and allows the coefficients of the sentiment variable to vary between positive and negative news days.

$$RET_{i,t} = \alpha + \beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times SUE_{i,t} + \beta_3 MISP_{i,t} \times PSENT_{i,t} + \beta_4 MISP_{i,t} \times NSENT_{i,t} + \beta_5 SUE_{i,t} + \beta_6 PSENT_{i,t} + \beta_7 NSENT_{i,t} + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \quad (4)$$

where *PSENT* is the absolute value of the average sentiment of news articles published on a positive news day, and 0 otherwise. Similarly, *NSENT* is the absolute value of the average sentiment of news articles published on a negative news day, and 0 otherwise. Column (1) of Panel D shows that the coefficient on *MISP*PSENT* is strongly negative at -13.404 (t-statistic = -29.12), while *MISP*NSENT* has a strongly positive coefficient of 13.234 (t-statistic = 20.10). Columns (2) and (3) further show that this pattern is again found only amongst overpriced stocks. Therefore, overpriced stocks earn lower returns on days with negative sentiment news articles, but higher returns on days with positive sentiment news articles. The average values of *PSENT* and *NSENT* are 0.025 and 0.011, respectively. The coefficients of *MISP*PSENT* and *MISP*NSENT* suggest that an average positive news article increases the daily return of an overpriced stock by 0.335 (=13.404*0.025) basis points, while an average negative news article decreases the daily return of an overpriced stock by 0.146 (=13.234*0.011) basis points, implying that positive news articles have about a 2.3 times larger impact on daily mispricing return than negative news articles. Thus, the net effect of the information content of average news articles is the exacerbation of existing overpricing driven by positive news content, which provides an explanation for the negative and significant coefficient of *MISP*SENT* in Panel B.

Our results are mainly driven by overpriced stocks. Across all model specifications, the coefficients on *MISP* are significantly positive for overpriced stocks, while they are insignificant for underpriced stocks. For example, Column (2) of Panel A shows that the daily mispricing returns are about 1.724 basis points on non-information release days, which is more than 70% larger than that in Column (1). In addition, for overpriced stocks, the coefficients on the interaction terms in Column (2) show that mispricing returns significantly decrease on earnings announcements and negative news days but increase on positive news days. These patterns are all consistent with the full sample results in Column (1), but the magnitudes of the coefficient estimates are generally larger, suggesting that the effect of information releases on daily mispricing returns is stronger for overpriced stocks. In contrast, for underpriced stocks, Column (3) shows that the coefficients on various interaction terms (except for *MISP*SUE*) are mostly insignificant, suggesting that the mispricing signals do not have much impact on the daily returns of underpriced stocks on news release days (as opposed to earnings announcement days).

Next, we investigate whether and how higher order beliefs impact the daily return patterns.

3.2. Beauty contest and higher order beliefs

Allen, Morris and Shin (2006) have argued that when faced with higher order beliefs investors will focus more on short-run price movements and this can make the market price of an asset deviate from its fundamental value. More recently, Schmidt-Engelbertz and Vasudevan (2022) show that higher order beliefs can lead to a hump-shaped pattern of return expectation following the news arrival with the initial return expectation in the direction of the news followed by a subsequent reversal of expectation. In this section, we first examine the short-run impact of the news releases and then the subsequent reversal in the framework of beauty contest driven higher order beliefs.

3.2.1. Short-term continuation

We study the short-run impact of news releases on mispricing returns in the context of LLT. In recent years, the structure of the market has changed and technological advances have led to LLT with trade latency being reduced to milliseconds and even nanoseconds. LLT is driven by algorithms that react at very high frequencies. The LLTs aim to profit from short-run price movements by trading in the direction of expected price changes. This makes LLT a good setting to study the potential impacts of beauty contest driven higher order beliefs on stock returns on news release days. A large literature has argued that LLT has led to an improvement in (i) liquidity, (ii) market quality, (iii) price discovery, (iv) speed of information incorporation into prices, and (v) market efficiency.[8] Moreover, recent empirical evidence suggests that LLT leads to faster incorporation of fundamental information into prices not only in extremely high frequencies (e.g., at a millisecond frequency) but also in relatively low frequencies (e.g., at a daily frequency).[9] Unlike earnings announcements, other news releases are mostly unscheduled information events, the timing and content of which are largely unpredictable. Thus, it is unclear whether the positive effect of LLT on market reaction to earnings announcements also obtains for other news releases. So, we ask this question. How does LLT impact the market reaction to news releases?

Following Hasbrouck and Saar (2013) and Chordia and Miao (2020),[10] we define the daily LLT proxy as the number of time-weighted strategic runs as follows: for stock *i* on day *t*,

$$LLT_{i,t} = \frac{1}{2.34 \times 10^7} \sum_{j=1}^{N_{i,t}} T_{i,j,t}, \tag{5}$$

where $T_{i,j,t}$ is the time-in-force in milliseconds for the *j*th strategic run,[11] and $N_{i,t}$ is the total number of strategic runs. The total milliseconds in each trading day are 2.34×10^7.[12] The sample for the analysis in this section is restricted, by the availability of Nasdaq Historical TotalView-ITCH database used for calculating *LLT*, to Nasdaq-listed stocks with common shares, and starts in January 2008 and ends in December 2017.

[8] See, for instance, Chordia, Roll, and Subrahmanyam (2011), Hendershott et al. (2011), Carrion (2013), Hagströmer and Nordén (2013), Hendershott and Riordan (2013), Brogaard, Hendershott, and Riordan (2014), Chaboud et al. (2014), Conrad et al. (2015), and Chordia, Green, and Kottimukkalur (2018).
[9] For example, Chordia and Miao (2020), Bhattacharya, Chakrabarty, and Wang (2020), and Chakrabarty, Moulton, and Wang (2021) find that LLT activity is positively associated with the efficiency of market reaction to earnings announcements.
[10] Our choice of the strategic run measure by Hasbrouck and Saar (2013) is further supported by Chakrabarty, Comerton-Forde, and Pascual (2021) who employ proprietary data with known identities of actual HFTs and show that *LLT*, as measured in equation (5), outperforms seven other popular HFT proxies in identifying HFT activities.
[11] For the *j*th strategic run that has at least ten linked messages, we define the time-in-force (= $T_{i,j,d}$) as the time stamp of the last message minus the time stamp of the first message of the run.
[12] If a stock has no strategic run for a given day, the values for *T* and *N* are zero, producing *LLT* = 0. For more details about *LLT*, see Chordia and Miao (2020).

Table 3 presents the results. In Panel A, we regress the log-transformed *LLT* (= *Log(1+LLT)*) on the set of news variables. LLT activity increases on news days as compared to no news days and when positive or negative sentiment news is released as compared to zero sentiment news, indicating that news releases attract the investors with speed advantages. To examine the impact of *LLT* on stock returns on news release days, in Panels B through E, we interact *DLLT* with the news variables and *MISP* and add the three-way interaction terms into equations (1) to (4). *DLLT* is a daily dummy variable indicating stocks in the top decile of *LLT* on each day. In each panel, Column (1) presents the full sample results while Columns (2) and (3) present the results for overpriced and underpriced stocks, respectively.

In Panel B, the coefficient on *MISP*NEWS*DLLT* is insignificant although that of *MISP*NEWS* is significantly negative in Columns (1) and (2), which is consistent with Panel A of Table 2. In Panel C, Column (1) shows that the coefficients of *MISP*SENT*DLLT* and *MISP*SENT* are significantly negative at -20.31 (t-statistic = -13.11) and -14.28 (t-statistic = -27.82), respectively. Columns (2) and (3) indicate that it is mainly driven by overpriced stocks. These results imply that LLT significantly increases the prices of overpriced stocks when high sentiment news is released. To the extent that *LLT* is positively correlated with liquidity, the negative and significant coefficient of *DLLT* is consistent with the positive pricing of illiquidity level as in Amihud (2002) and Amihud and Noh (2021).

Panels D and E reaffirm that LLT significantly increases the prices of overpriced stocks when high sentiment news is released, while it significantly decreases their prices when low sentiment news is released. In Column (1) of Panel D, the coefficients on *MISP*POSNEWS*DLLT* and *MISP*POSNEWS* are -3.56 (t-statistic = -6.94) and -4.33 (t-statistic = -23.32), while those on *MISP*NEGNEWS*DLLT* and *MISP*NEGNEWS* are 5.28 (t-statistic = 8.39) and 4.23 (t-statistic = 20.12), respectively. In addition, the averages of *POSNEWS* and *NEGNEWS* in our LLT sample are 0.183 and 0.115, respectively, meaning that there are 59% more positive news days than negative news days in an average month. Combining these numbers with the coefficients of the double and triple interaction terms in Column (1) indicates that for stocks heavily followed by LLTs (with *DLLT* = 1), positive news days increase their returns by an average of 1.443 (= (4.331+3.555)*0.183) basis points, while negative news days decrease their returns by an average of 1.094 (= (4.230+5.281)*0.115) basis points. These are economically significant.[13] The impact of positive news days on mispricing return is about 1.32 times larger than that of negative news days and the net effect on news release days is the exacerbation of mispricing driven by positive news releases.

The main takeaway from Table 3 is that high LLT activity significantly amplifies the exacerbation of overpricing on positive news days and the mitigation of overpricing on negative news days. In other words, the impact of LLT on overpriced stocks is to move prices in the same direction as the underlying price changes, i.e., prices increase (decrease) for high (low) sentiment news. These results are consistent with O'Hara (2015) who argues that while LLTs trade faster upon the release of news, they do not unearth fundamental information. Also, for macroeconomic announcements, Chordia et al. (2018) show that LLTs react within milliseconds in the direction of the surprise. More importantly, given that computers are not subject to behavioral biases, this means that the algorithms are programmed to react to news and trade faster in the direction that other investors are expected to trade in, thereby, mimicking the bias caused by the beauty contest. Overall, our results are consistent with the idea in Schmidt-Engelbertz and Vasudevan (2022) that the short-term returns are in the direction of the information contained in news releases.

3.2.2. Reversals

Recall that Schmidt-Engelbertz and Vasudevan (2022) show that the impact of the higher order beliefs is nuanced and dynamic and the initial impact is reversed. Thus far, we have documented that

[13] They are about two times larger than those for stocks with *DLLT* = 0. For stocks with *DLLT* = 0, positive news days increase their returns by an average of 0.793 (= 4.331*0.183) basis points, while negative news days decrease their returns by an average of 0.486 (= 4.230*0.115) basis points.

news with a positive sentiment leads to more overpricing in already overpriced stocks in the short run. In this section, we examine whether this overpricing is reversed over time.

Our research design is based on the following regression of monthly returns on lagged mispricing and the counts of positive and negative news days in the lagged months:

$$RET_{i,m} = \alpha + \beta_1 MISP_{i,m-k} + \sum_{j=0}^{k} \beta_j^P MISP_{i,m-k} \times LPOSNEWS_{i,m-j} + \sum_{j=0}^{k} \beta_j^N MISP_{i,m-k} \times LNEGNEWS_{i,m-j} + \sum_{j=0}^{k} \gamma_j^P LPOSNEWS_{i,m-j} + \sum_{j=0}^{k} \gamma_j^N LNEGNEWS_{i,m-j} + \theta' \boldsymbol{X}_{i,m} + \varepsilon_{i,m}, \quad (6)$$

where $RET_{i,m}$ is stock i's return in month m, and $MISP_{i,m-k}$ is its mispricing score measured at the beginning of month m-k. $LPOSNEWS_{i,m-j}$ is the natural log of (1 + number of positive news days in month m-j), and $LNEGNEWS_{i,m-j}$ is the natural log of (1 + number of negative news days in month m-j). These two variables thus represent the number of positive and negative news coverage for stock i in month m-j. In addition to the key variables of interest, we also include lagged monthly return, market capitalization, book-to-market ratio, the Amihud (2002) illiquidity measure, and idiosyncratic volatility as control variables in $\boldsymbol{X}$. Month fixed effects are included and standard errors are clustered by month to account for the cross-sectional correlation in monthly returns. We estimate equation (6) separately for k = 0, 1, 2, 3 to test the ability of lagged *MISP* to predict the returns of current month m and how this return predictability varies over time. The results are reported in Table 4.

Column (1) shows that *MISP* measured at the beginning of the month positively predicts the stock return at the end of the month. For overpriced stocks, the monthly return increases with the number of positive news days and decreases with the number negative news days during the month, as evidenced by the negative coefficient on *MISP**LPOSNEWS* and positive coefficient on *MISP**LNEGNEWS*, both of which are highly significant. This result thus reaffirms our previous finding with daily returns that negative news tends to reduce, while positive news tends to increase the existing overpricing. When k = 1, Column (2) shows that, in contrast to the negative coefficient on $MISP_{m-1}*LPOSNEWS_{m}$, the coefficient on the one month lagged $MISP_{m-1}*LPOSNEWS_{m-1}$ is significantly positive, suggesting that there is some reversal of the initial exacerbation of overpricing due to the positive sentiment news. However, the coefficient of $MISP_{m-1}*LPOSNEWS_{m}$ is -0.334 while that of $MISP_{m-1}*LPOSNEWS_{m-1}$ is 0.08, implying that only 24% of the initial increase in overpricing is corrected one month later. When $k = 2$, Column (3) implies that about 38% of the initial increase in overpricing is corrected over the next two months with an equal amount of reversal occurring in each month. Column (4) with $k = 3$ indicates that there is no impact of news releases on mispricing returns beyond the subsequent two months. Therefore, while there is some reversal, over 60% of the overpricing exacerbation still remains two months after the release of positive sentiment news that caused the initial exacerbation. While Schmidt-Engelbertz and Vasudevan's (2022) model predicts that the initial impact of the bias driven by the beauty contest is reversed, we do not see a significant reversal.

4. Unexplained return patterns

Now we focus on return patterns that seem incongruous with the higher order beliefs. These include, (i) why is the return impact of news on overpriced stocks larger for the high sentiment news than for the low sentiment news, (ii) why is the impact of news on overpriced stocks larger than that on underpriced stocks, and (iii) why is there no impact of news on underpriced stocks? In the subsequent sections, we attempt to answer these three questions.

4.1. Production of positive versus negative news

Recall from the discussion following equations (3) and (4) that the impact of positive sentiment news on returns is at least twice as large as that of negative news. In this section, we ask why.

Managers are incentivized to withhold bad news and to engage external investor relations firms to facilitate the dissemination of good news (see, e.g., Kothari et al. 2009; Solomon 2012). We attempt to understand whether managers, external relations firms, or news media tend to produce news articles with positive sentiment even for overpriced stocks, and to investigate how this behavior affects the returns of overpriced stocks on positive news days.

Solomon (2012) shows that external investor relations (IR) firms generate more news coverage with positive sentiment for their clients by fostering and promoting positive press releases, leading to increased returns around news release days. Motivated by Solomon (2012), we examine the impact of IR activity on stock returns on news release days. IR activity by managers or external IR firms facilitates the production of a larger number of news articles with positive sentiment and/or news articles with stronger positive sentiment. We hypothesize that this increased positivity of news articles might drive overpriced stocks to become even more overpriced.

First, we construct a market-wide proxy for the average IR activity based on the news variables available from RavenPack. Specifically, for firm *i* in month *m*, we first calculate the difference in the number of news articles with positive and negative tone to quantify the net positive news coverage. Panel A of Figure 1 depicts the time-series of the cross-sectional average of this monthly net positive news coverage. There is a clear upward trend in the average net positive news coverage, especially, in recent years. Then, for firm *i* in month *m*, to obtain its normalized version, we scale the net positive news coverage by the total number of positive and negative news articles. Panel B of Figure 1 shows the time-series of the cross-sectional average of the normalized monthly net positive news coverage (by the total number of positive and negative news articles). These two graphs together indicate that the total number of news articles have increased over our 20-year sample period and, moreover, the growth rate for positive sentiment news articles is higher than that for negative sentiment news articles. These results suggest that firms have increased the release of positive sentiment news, possibly by hiring IR firms and that increased IR activity might be driving the exacerbation of overpricing on news release days.

Next, we construct a stock-level monthly proxy for IR activity as follows. For firm *i* in month *m*, we first calculate the number of news articles with positive sentiment minus the number of news articles with negative sentiment over the preceding three-month period that ends in month *m-1*, i.e., three-month net positive news coverage. We then run a cross-sectional regression of the three-month net positive news coverage on the averages of *SENT* and firm size (=log of daily market capitalization) over the same three-month estimation period and obtain the residual. The idea is to remove the impact of firm size (as larger firms have more news coverage) and the impact of the news sentiment (as investors are likely to react more to news with stronger sentiment) on our proxy for IR activity. This residual variable proxies for the impact of IR activity on the production of more positive news. Next, at the beginning of month *m*, we sort stocks by the residual into tercile portfolios, and assign $IR_{i,t} = 1$ if the residual value belongs to the top tercile and assign $IR_{i,t} = 0$ otherwise for stock *i* on each day *t* in month *m*. We update this stock-level IR proxy each month by moving the three-month estimation window forward by one month. We then interact *IR* with *MISP* and news variables and add the three-way interaction terms to equations (1) to (4). We expect the coefficient of the three-way interaction terms of *MISP*, *NEWS* (as well as *SENT*, *POSNEWS*, and *PSENT*), and *IR* to be negative and significant if IR firm activity drives how daily stock returns change on news release days. Table 5 presents the results.

The coefficient of *MISP*NEWS*IR* is negative and significant in Column (1). Similarly, the coefficient on the three-way interaction term *MISP*SENT*IR* is negative and highly significant in Column (2). The results imply that for overpriced firms with high IR activity, news sentiment exacerbates the mispricing of these stocks substantially more than for firms whose IR activity is lower. We also find that, consistent with our earlier tables, the coefficients of *MISP*NEWS* and *MISP*SENT* are all negative and highly significant. In Columns (3) and (4), we find that the coefficients on *MISP*POSNEWS*IR* and *MISP*PSENT*IR* are significantly negative. The coefficient on *MISP*NEGNEWS*IR* is significantly positive (while the coefficient on *MISP*NSENT*IR* is positive but insignificant), suggesting that in the presence of IR activity, negative sentiment news has an incremental negative effect on returns, possibly because with investors expecting the usual high sentiment news, the surprising arrival of low sentiment news moves prices more than usual. The return spread between positive and negative news days is even wider when IR activity fosters and promotes positive sentiment news.

In sum, the results support the idea that the increase in IR activity produces more positive news articles, and as a result, this exacerbates the overpricing on positive news release days.

4.2. Attention and market reaction to overpriced stocks

In this section, we investigate whether investor attention contributes to the impact of positive news days on returns. Specifically, we hypothesize that to the extent that overpriced stocks receive more investor attention, the market reaction to news releases for overpriced stocks will be stronger than that for underpriced stocks. Therefore, assuming that news releases for overpriced stocks and underpriced stocks have similar information content, the stronger market reaction of overpriced stocks suggest that on positive news release days, prices increase by a larger amount for overpriced stocks than for underpriced stocks, thus enlarging the relative mispricing in the cross-section. On the other hand, it also implies that on negative news release days, prices drop by a larger amount for overpriced socks than for underpriced stocks, thus reducing the relative mispricing in the cross-section. The asymmetric market reaction to news releases documented in Section 3.1, possibly driven by uneven allocation of investor attention between overpriced and underpriced stocks, could make the increased returns of overpriced stocks on positive news days the main driver of our findings.

To test our hypothesis, we first examine whether overpricing is associated with investors' download activity on the SEC's EDGAR website. Then, we test whether the strength of the market reaction to the content of news releases varies with the degree of stock mispricing.

4.2.1. Investor attention

Filings by firms of 10-K reports are an important source of information for investors. If overpriced stocks receive more investor attention, then there should be a higher download volume of 10-K reports immediately after they are released on SEC's EDGAR website. We examine the relation between stock-level mispricing and investor attention as follows:

$$Log\left(1 + Download_{i,m}\right) = \alpha + \beta_1 \times MISP_{i,m} + \beta_2 \times Log\left(MV_{i,m}\right) + \varepsilon_{i,m}, \tag{7}$$

where $Download_{i,m}$ is the number of unique IP addresses that download firm i's 10-K in month m. We count only downloads that are made within 7 days of each 10-K filing day to capture the timely search of information by investors. In addition, to measure investor attention more accurately, we exclude "robot downloads" from our sample, which are defined as IP addresses that access more than 30 firms' filings on a single day, because these downloads are mostly made by computer algorithms that constantly scan the EDGAR server and automatically download newly posted 10-K filings. $MISP_{i,m}$ is the mispricing score of firm i measured at the beginning of month m based on the 11 SYY anomaly signals. We control for firm size measured at the end of the previous month m-1, and include time and firm fixed effects to control for the impact of time trend or any time-invariant firm characteristics on EDGAR downloads. The standard errors are clustered by month. The sample period for this analysis is restricted to January 2003 through June 2017 as the SEC stopped updating the download data in June 2017. As Table 6 shows, the coefficient on *MISP* is significantly negative at -1.035 (t-statistic = -6.11), suggesting that the 10-K filings of underpriced stocks are downloaded significantly less often than those of overpriced stocks. This result is thus consistent with the idea that overpriced stocks tend to receive higher investor attention than underpriced stocks. This higher attention can lead to stronger market reactions to news releases, which we now formally investigate.

4.2.2. Stronger market reaction to news content of overpriced stocks

In this section, we assess the impact on returns in response to the sentiment of news releases for overpriced versus underpriced stocks. We use the following regression model to test whether the market reaction to news content of overpriced stocks is stronger than that of underpriced stocks:

$$RET_{i,t} = \alpha + \beta_1 \times SENT_{i,t} + \beta_2 \times SENT_{i,t} \times OP_{i,t} + \beta_3 \times OP_{i,t} + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \quad (8)$$

where $OP_{i,t}$ is an indicator variable for an overpriced stock, which equals 1 if $MISP_{i,t} < 0$ and 0 if $MISP_{i,t} > 0$, and $MISP_{i,t}$ is the mispricing score of stock *i* measured at the beginning of the month that day *t* belongs to. $\boldsymbol{X}_{i,t}$ includes the same set of control variables as in equation (1). We control for day fixed effects and the standard errors are clustered by day. Equation (8) is estimated using a sample that includes all news release days of mispriced stocks, i.e., stocks with $NEWS = 1$ and $MISP \neq 0$. Table 7 reports the results.

The coefficient on *OP* is significantly negative suggesting that, unconditionally, overpriced stocks earn negative returns. The coefficient on *SENT* is positive at 1.301 (t-statistic = 102.10), indicating that news articles with higher sentiment earn higher returns for underpriced stocks when *OP* = 0. More importantly, the coefficient on *SENT*OP* is significantly positive at 0.698 (t-statistic = 37.19), indicating that the magnitude of market reaction to the sentiment of news increases by more than 50% for overpriced stocks. Thus, investors are more attentive to the information releases of overpriced stocks as shown in the previous subsection, and as a result, the prices of overpriced stocks increase (decrease) by a much larger amount on positive (negative) news days than those of underpriced stocks. This implies that for overpriced stocks, the stronger positive return on days that have positive sentiment news articles leads to the increase in deviation of market prices from fundamental values.

4.3. Short sale constraints

Short sale constraints could be another reason for why we do not see the lower returns in underpriced stocks when low sentiment news is released as well as the asymmetric impact of high versus low sentiment news in overpriced stocks. Further, the larger impact of positive sentiment news as compared to negative sentiment news in overpriced stocks could also be driven by short sale constraints.[14] We rely on the SEC's Reg SHO pilot program to draw causal inference on the impact of short sale constraints on the behavior of mispricing returns on news release days.[15] Specifically, we estimate the following panel regression model, where the key variables in equation (3) are interacted with three indicator variables – *PILOT*, *POST*, and *PILOT*POST* – to implement a difference-in-differences research design.

$$RET_{i,t} = \alpha + \theta_1 \times (\beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times POSNEWS_{i,t} + \beta_4 MISP_{i,t} \times NEGNEWS_{i,t} + \beta_5 EARN_{i,t} + \beta_6 POSNEWS_{i,t} + \beta_7 NEGNEWS_{i,t}) + \theta_2 \times PILOT_i \times (\beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times POSNEWS_{i,t} + \beta_4 MISP_{i,t} \times NEGNEWS_{i,t} + \beta_5 EARN_{i,t} + \beta_6 POSNEWS_{i,t} + \beta_7 NEGNEWS_{i,t}) + \theta_3 \times POST_t \times (\beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times POSNEWS_{i,t} + \beta_4 MISP_{i,t} \times NEGNEWS_{i,t} + \beta_5 EARN_{i,t} + \beta_6 POSNEWS_{i,t} + \beta_7 NEGNEWS_{i,t}) + \theta_4 \times PILOT_i \times POST_t \times (\beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times POSNEWS_{i,t} + \beta_4 MISP_{i,t} \times NEGNEWS_{i,t} + \beta_5 EARN_{i,t} + \beta_6 POSNEWS_{i,t} + \beta_7 NEGNEWS_{i,t}) + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t} \,. \tag{9}$$

The sample for this test includes only the constituent stocks of the Russell 3000 index as of June 2004. Since the pilot program effectively ran from May 2, 2005 to July 6, 2007, the sample period starts on January 1, 2000 and ends on July 6, 2007. Following Chu, Hirshleifer, and Ma (2020), $PILOT_i$ is an indicator variable that equals 1 if stock *i* was selected for the SEC's pilot program under Regulation SHO (Release No. 50104) and listed on NYSE or Amex, and 0 otherwise. $POST_t$ is another indicator variable which equals 1 for day *t* between May 2, 2005 and July 6, 2007, and 0 otherwise. The coefficients on the interaction terms *PILOT*POST*MISP*POSNEWS* and *PILOT*POST*MISP*NEGNEWS* thus capture the causal effects of loosening the short sale constraints on stock returns on news release days. As reported in Panel A of Table 8, the coefficient of *PILOT*POST*MISP*NEGNEWS* is significantly positive at 3.208 (t-statistic = 2.07), indicating that the relaxation of short sale restrictions results in a stronger correction

[14] Miller (1977) has argued that some investors have optimistic beliefs and their trades could lead to persistence in overpricing, if short sale constraints impede the incorporation of pessimistic beliefs into prices.
[15] Stocks randomly selected into the pilot program are exempted from the tick test requirement for short selling, providing a quasi-experiment setting. See Chu et al. (2020) for further details about the Reg SHO pilot program.

of overpricing on negative news days. Moreover, we see from Panel C that incremental negative returns obtain for underpriced stocks when negative sentiment news is released. This suggests that the absence of negative returns for underpriced stocks in Table 2 when negative sentiment news is released could be due to short sale constraints. For overpriced stocks in Panel B, the coefficient of *PILOT*POST*MISP*NEGNEWS*, while positive, is statistically insignificant. This provides a hint of the impact of short sale constraints on overpriced stocks when negative sentiment news is released. The coefficient on *PILOT*POST*MISP*POSNEWS* is negative for overpriced stocks. This result is not unexpected because our previous results show that positive news articles tend to exacerbate existing overpricing by pushing prices further away from fundamental value. To the extent that buy orders are submitted on positive news days, short sale constraints are unlikely to be binding and thus have a limited impact on stock returns.

In sum, we find that short sale constraints do impede the correction of overpricing when negative sentiment news is released, but they do not impact the exacerbation of overpricing observed on positive news days.

5. Robustness

5.1. Three-day event window

When estimating how earnings announcements and news releases affect mispricing returns, we made the assumption that the event dates are accurate and that market reaction is complete within the same day of information release. In this section, we relax this assumption and use a three-day event window to measure the market impact. Specifically, we code $EARN_{i,t} = 1$ if firm i makes an earnings announcement in a three-day window $[t-1, t+1]$, and $NEWS_{i,t} = 1$ if a news article about firm i is released on day t-1, t, or t+1. All other earnings and news variables, including *SUE*, *SENT*, *POSNEWS*, *NEGNEWS*, *ZERONEWS*, *PSENT*, and *NSENT*, are defined in a similar manner. The results are reported in the Appendix Table A.1. While the coefficients on *MISP* are comparable to those in Table 2 across all model specifications, the coefficients on the interaction terms between *MISP* and the earnings and news variables are all significantly smaller. This change is expected because while the wider event window is more robust to slight measurement errors in event dates, it also attenuates the estimated market impact of the events by averaging out the effect over three days. But more importantly, the patterns of mispricing returns on news days of Table 2 are all preserved. Positive and negative news releases continue to exhibit the opposite impact on daily returns and price efficiency.

5.2. News source

Drake et al. (2017) find that information intermediaries are not created equal – the coverage by professional intermediaries, such as Dow Jones Newswires, is associated with positive capital market effects but the coverage by nonprofessional intermediaries, such as nonfinancial websites or blogs, tend to hinder price discovery. In addition, Kogan et al. (2021) argue that falsely promotional articles about firms in social media platforms can temporarily boost firms' stock prices and trading volume by retail investors around article release days. Motivated by these studies, we examine whether the negative effect of positive news articles on price efficiency might be caused by low quality new articles that may contain misleading information. Specifically, we repeat the tests in equations (1) to (4) with two reliable subsamples of news sources. The first subsample consists of news articles that are from the news sources with Source Rank = 1 and complete news articles with News Type = Full Article as coded by RavenPack. The second subsample contains RavenPack news articles obtained only from the Dow Jones Newswire.[16]

Results based on the two refined subsamples of news articles are presented in Appendix Table A.2. We find that the effect of news days on mispricing returns documented earlier with all news articles remains robust for these subsets of high-quality news sources. The coefficients of *MISP*NEWS*,

[16] In the same spirit as our focusing on the news sources that have high credibility, Kogan et al. (2021) also argue that the news articles from the Wall Street Journal and New York Times are unlikely to be affected by fraud on social media platforms such as SeekingAlpha.com.

*MISP*SENT, MISP*POSNEWS*, and *MISP*PSENT* are all negative while those on *MISP*NEGNEWS* and *MISP*NSENT* are positive. The magnitude and statistical significance of these coefficients are comparable to those in Table 2. Thus, the exacerbation of stock mispricing on news release days prevails even among the most credible news sources, and it is unlikely to be driven by false information generated by news sources with low credibility.

5.3. Alternative mispricing measure

In this section, we test whether our results are sensitive to using alternative measures of stock-level mispricing. Specifically, following Stambaugh et al. (2012), we define $MISP_{i,t}^{AR}$ based firm i's average percentile ranking of the 11 SYY signals measured at the beginning of the month which day t belongs to. For the ease of interpretation, $MISP_{i,t}^{AR}$ is defined to range between -1 to 1 by transforming the raw percentile ranking, which ranges from 0 to 1, by $MISP_{i,t}^{AR} = 2 \times Ranking - 1$. To be consistent with Table 2, we define $MISP^{AR}$ as a measure of relative underpricing, meaning that stocks with higher values of $MISP^{AR}$ are more underpriced. One potential advantage of $MISP^{AR}$ over *MISP* in Table 2 is that $MISP^{AR}$ reflects the direction as well as the strength of each anomaly signal for a given stock, while *MISP* captures the direction, but not the strength, of the signal. Repeating the tests with this alternative mispricing measure $MISP^{AR}$, we confirm that our main findings remain qualitatively the same. As Appendix Table A.3 shows, while the magnitudes of the coefficients are not directly comparable with those in Table 2 because the construction of *MISP* is different, the signs of the coefficients in Appendix Table A.3 are generally consistent with those in Table 2. In particular, the coefficients of $MISP^{AR}$*NEWS*, $MISP^{AR}$*SENT*, $MISP^{AR}$*POSNEWS*, and $MISP^{AR}$*PSENT* are all negative and highly significant, while those of $MISP^{AR}$*NEGNEWS* and $MISP^{AR}$*NSENT* are positive and highly significant. Thus, once again, positive sentiment news articles tend to exacerbate the mispricing of overpriced stocks and negative sentiment articles tend to correct it. We thus conclude that the negative effect of positive news articles on price efficiency is not specific to how mispricing is measured.

5.4. Reconciling with Engelberg, McLean and Pontiff (2018)

Our analysis thus far shows that the daily anomaly returns of overpriced stocks in the subsequent month are significantly higher on news release days, implying that non-earnings news releases slow down the price discovery process. This result, however, appears to be contrary to the findings in Engelberg et al. (2018, hereafter EMP) that news facilitates the correction of existing mispricing as the anomaly returns for overpriced stocks are lower on news release days in their sample. In this section, we investigate the underlying reasons for this discrepancy between our results and those in EMP.

5.4.1. Choice of mispricing signals

EMP measure stock-level mispricing using a much broader set of 97 return predictors, compared to our mispricing measure based on the 11 SYY signals. To examine whether the choice of the empirical proxy for stock-level mispricing is responsible for the different results, we rerun the regressions (1) to (4) in Panels A through D, using an alternative measure of *MISP* based on the anomalies included in EMP.[17] The results in Column (1) of Table 9 show that choice of the anomalies used to calculate *MISP* does not drive the difference in the results. In Panel A, the coefficient of *MISP*NEWS* remains significantly negative, although the magnitude of the coefficient and its t-statistic are both smaller than those in Table 2. In Panel B, the coefficient of *MISP*SENT* is also negative and highly significant. Finally, Panels C and D show that the increase in returns of overpriced stocks on news release days is driven by news articles with positive sentiment. These patterns are all consistent with those reported in Table 2 and suggest that our finding that positive news impedes the price efficiency of overpriced stocks is not specific to the 11 SYY mispricing signals, but generalizable to those extracted from a broader set of firm characteristics.

[17] We obtain these return predictors from Chen and Zimmerman's Open Source Asset Pricing website at https://www.openassetpricing.com/. We drop Merger and SEO from the 97 anomalies used in EMP and employ the remaining 95 anomaly signals to calculate our *MISP* because the Merger and SEO data are not available in Chen and Zimmerman's dataset.

5.4.2. Choice of news sources

Another research design difference between our analysis and that in EMP is that we use RavenPack database to identify news releases days and to measure the sentiment of news stories, while EMP use Dow Jones News Archive database.[18] If there are systematic differences in the coverage of news articles between these two news databases, the results obtained with one database may fail to replicate those from the other. To examine this possibility, we re-estimate equations (1) to (4) using the Dow Jones News Archive database for the sample period of January 2000 to December 2019. Specifically, we define $NEWS_{i,t}$ = 1 if there is at least one news article in the Dow Jones News Archive database about firm *i* published on day *t*, and 0 otherwise. We measure the sentiment of a news article by its net tone, which is calculated as the difference between the number of positive words and the number of negative words, divided by the total number of words in the news article.[19] Our measure of the information content of a news day, $SENT_{i,t}$, is calculated as the average net tone of all news articles about firm *i* released on day *t*. $SENT_{i,t}$ ranges between -1 and 1. The results are reported in Column (2) of Table 9. In Column (2) of Panel A, the coefficient on the interaction term *MISP*NEWS* is positive but statistically insignificant, which is in contrast to the significantly negative coefficient in Column (1) and suggests that the difference in news coverage between the two news databases might affect the estimated effect of average news days on how mispricing changes. However, consistent with the results in Column (1), Column (2) of Panel B shows that the coefficient on *MISP*SENT* is significantly negative, and Panels C and D also show that the coefficients on *MISP*POSNEWS* and *MISP*PSENT* are significantly negative, and those on *MISP*NEGNEWS* and *MISP*NSENT* are significantly positive. Therefore, the opposing effects of

[18] The news variables constructed using Dow Jones News Archive database can be different from those constructed using Dow Jones Newswire classified by RavenPack since these two databases are different in news coverage and in how news sentiment is measured.
[19] The positive and negative words are obtained from Loughran and McDonald's master dictionary, which is available at https://sraf.nd.edu/loughranmcdonald-master-dictionary/

positive and negative sentiment news articles on mispricing returns continue to hold for the Dow Jones News Archive Database sample and are not sensitive to how the sentiment of the news stories are measured.

5.4.3. Sample period

Since we rely on RavenPack to identify news releases days and to measure the sentiment of news stories, our sample is restricted by the coverage of the RavenPack database, which starts in 2000. In contrast, EMP use the Dow Jones News Archive database to identify news days and therefore were able to start their sample period in June, 1979. One possibility for the discrepancy between their results ours could be that the average effect of news on returns evolves over time. This could be due to multiple factors including, e.g., the changes in the average quality of news stories, the efficiency of information dissemination channels driven by the advances in technology, and growing popularity of social media platforms. But more importantly, it could also be driven by changes in news sentiment over time. Since positive and negative news articles have an opposite impact on returns of mispriced stocks, the relative proportion of positive versus negative news days in a sample will determine the average effect of news release days and hence the sign of the coefficient on *MISP*NEWS*. In an effort to replicate the result in EMP, we use the Dow Jones News Archive database over the same sample period from June 1979 to December 2013 as in EMP.[20] Column (3) of Panel A shows that when *MISP* is calculated using the 95 return predictors used in EMP over their sample period, the coefficient of *MISP*NEWS* turns significantly positive at 0.308 (t-statistic = 4.55), suggesting that overpriced stocks earn lower returns on average news release days. This is consistent with the finding in EMP. We next examine the differential effect of positive and negative news days for this earlier sample period. Column (3) of Panel B shows that the coefficient

[20] For an additional robustness check, we also use the news dataset shared by Jeon et al. (2021), which covers Dow Jones' Factiva database for the sample period from 1980 to 1999, and find that our findings are robust. The dataset can be downloaded from https://www.dropbox.com/s/62lt6uq1t4n6gcr/MainData_Factiva_Public.zip?dl=0

on *MISP*SENT* is significantly negative. Further, Column (3) of Panels C and D shows that the coefficients on *MISP*POSNEWS* and *MISP*PSENT* are significantly negative, and those on *MISP*NEGNEWS* and *MISP*NSENT* are significantly positive. These results are consistent with our main finding reported in Table 2, that negative sentiment news articles tend to reduce overpricing, while positive sentiment news articles tend to increase overpricing. As in our 2000-2019 sample, not all news days reduce mispricing by correcting investors' biased expectations, and the net effect of news days on returns largely depends on the composition of news articles with positive and negative sentiment.

In sum, in our effort to reconcile our main finding with that in EMP, we find robust evidence that the release of positive sentiment news exacerbates the existing mispricing. Our results also suggest that the news-day dummy variable, *NEWS,* is unable to capture the heterogeneity of the content of news articles and thus can mask important differences between positive and negative sentiment news articles in affecting the returns of mispriced stocks.

5. Conclusions

We examine the impact of beauty contest driven higher order beliefs on returns of mispriced stocks around news releases. The beauty contest idea suggests that, unconditionally, news releases with high (low) sentiment should, in the short-term, result in higher (lower) stock returns as short-term investors trade based on their predictions of the reactions of others (who also predict the reaction of others) to the news. In the longer-term prices should reverse. This is what we find empirically although prices do not completely reverse.

Conditionally, when high sentiment news is released, overpriced stocks become significantly more overpriced, increasing the distance between their market prices and fundamental values and reducing price efficiency. Also, overpriced stocks become less overpriced when low sentiment news is released. In the case of underpriced stocks, there is no impact of either high or low sentiment news. We provide evidence that the asymmetric impact of high and low sentiment news for overpriced stocks and the lack of a return impact on underpriced stocks to news could be driven by short sale constraints, more positive news being generated, more attention being paid to overpriced stocks by investors, and the larger impact of news for overpriced stocks.

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Table 1: Summary Statistics

This table presents various summary statistics of the sample, which includes all US domestic common stocks with stock prices above $5 from January 2000 to December 2019.

Panel A: Earnings Announcements and News Release Days

	News Day		Total
Earnings Day	No	Yes	
No	22,677,120 (79.11%)	5,660,081 (19.75%)	28,337,201 (98.85%)
Yes	143,571 (0.50%)	185,119 (0.65%)	328,690 (1.15%)
Total	22,820,691 (79.61%)	5,845,200 (20.39%)	28,665,891 (100%)

Panel B: Summary Statistics of *MISP* Variables

	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
Long	1.607	1.639	0	0	1	3	10
Short	1.224	1.516	0	0	1	2	11
MISP	0.382	2.184	-11	-1	0	1	10

Panel C: Distribution of *MISP*

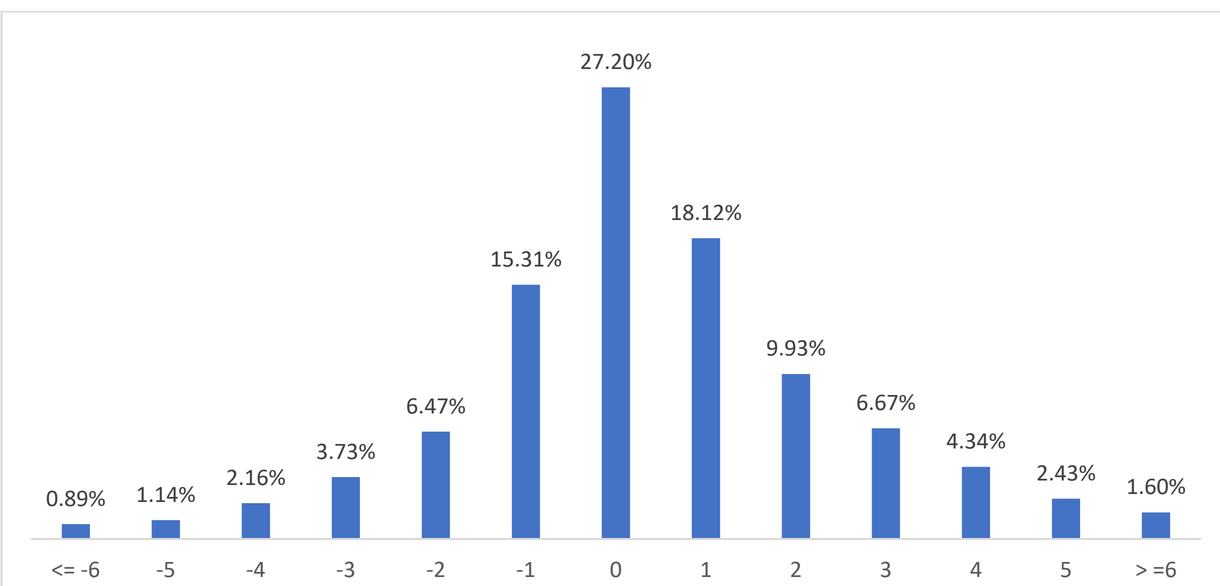


Table 2: Mispricing Returns on Earnings Days and News Days

This table presents the test results that examine how stock mispricing in the beginning of a month relates to daily returns on earnings announcement days and news release days during that month. We estimate each of the following panel regressions separately:

$$RET_{i,t} = \alpha + \beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times NEWS_{i,t} + \beta_4 EARN_{i,t} + \beta_5 NEWS_{i,t} + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \quad (1)$$

$$RET_{i,t} = \alpha + \beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times SUE_{i,t} + \beta_3 MISP_{i,t} \times SENT_{i,t} + \beta_4 SUE_{i,t} + \beta_5 SENT_{i,t} + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \quad (2)$$

$$RET_{i,t} = \alpha + \beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times POSNEWS_{i,t} + \beta_4 MISP_{i,t} \times NEGNEWS_{i,t} + \beta_5 MISP_{i,t} \times ZERONEWS_{i,t} + \beta_6 EARN_{i,t} + \beta_7 POSNEWS_{i,t} + \beta_8 NEGNEWS_{i,t} + \beta_9 ZERONEWS_{i,t} + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \quad (3)$$

$$RET_{i,t} = \alpha + \beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times SUE_{i,t} + \beta_3 MISP_{i,t} \times PSENT_{i,t} + \beta_4 MISP_{i,t} \times NSENT_{i,t} + \beta_5 SUE_{i,t} + \beta_6 PSENT_{i,t} + \beta_7 NSENT_{i,t} + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t}. \quad (4)$$

where $RET_{i,t}$ is the return of stock *i* on day *t*, and $MISP_{i,t}$ is the mispricing score measured at the beginning of the month which day *t* belongs to and it is based on the 11 anomaly signals of Stambaugh, Yu, and Yuan (2012). The higher *MISP* is, the more underpriced the stock is. In equation (1), $EARN_{i,t}$ is an indicator variable for earnings announcement days: *EARN* = 1 when earnings is announced on day *t* and *EARN* = 0 otherwise. $NEWS_{i,t}$ is an indicator variable for news release days: *NEWS* = 1 when a news is released on day *t* and *NEWS* = 0 otherwise. In equation (2), $SUE_{i,t}$ is the standardized unexpected earnings and defined as the actual EPS announced on day *t* minus the consensus forecast of the EPS, scaled by the stock price at the fiscal quarter end of the EPS. As the consensus forecast, we use the median of all earnings forecasts for each firm followed by security analysts or the actual EPS for the same fiscal quarter in the last fiscal year for each firm not followed by security analysts. We winsorize *SUE* at -1 and 1 to mitigate potential effects of outliers, and assign *SUE* = 0 for non-earnings days that have *EARN* = 0. $SENT_{i,t}$ is the average sentiment score of news articles released on day *t* and defined as (average of ESS-50)/50, where ESS is a sentiment variable from RavenPack. Thus, *SENT* ranges from -1 to 1 and we assign *SENT* = 0 for non-news days that have *NEWS* = 0. The higher *SENT* is, the more optimistic the average sentiment is. In equation (3), *POSNEWS*, *NEGNEWS*, and *ZERONEWS* are indicator variables for positive, negative, and neutral news contents, respectively. Specifically, *POSNEWS* = 1 if *SENT* > 0 and 0 otherwise; *NEGNEWS* = 1 if *SENT* < 0 and 0 otherwise; *ZERONEWS* = 1 if *SENT* = 0 and *NEWS* = 1, and 0 otherwise. In equation (4), *PSENT* is the absolute value of the average sentiment of the news articles publicized on positive news days and it is set to zero on negative news days. Similarly, *NSENT* is the absolute value of the average sentiment of the news articles publicized on negative news days and it is set to zero on positive news days. $\boldsymbol{X}_{i,t}$ is a (column) vector that contains three sets of control variables: the values of returns, volatility (return squared), and share trading volume over the past ten days before day *t*. Overpriced stocks are those in the bottom 30% of the *MISP* distribution and underpriced stocks are those in the top 30% of the *MISP* distribution. The sample period of the analysis is January 2000 through December 2019, which is restricted by the availability of RavenPack. The day fixed effects are included in estimating equations (1) to (4). For expositional convenience, we divide *MISP* by 100 and multiply *RET* by 100 before estimating equations (1) to (4). The standard errors of coefficients are clustered by day, and *t*-statistics are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Model (1)

	(1) All Stocks	(2) Overpriced Stocks	(3) Underpriced Stocks
MISP	0.996***	1.724***	0.209
	(8.08)	(6.18)	(1.42)
MISP x *EARN*	4.798***	13.323***	-1.016
	(7.25)	(6.61)	(-0.62)
MISP x *NEWS*	-0.967***	-1.008***	-0.143
	(-7.62)	(-3.00)	(-0.72)
EARN	0.044**	0.204***	0.179***
	(2.45)	(4.27)	(3.18)
NEWS	0.047***	0.044***	0.034***
	(7.95)	(4.73)	(4.30)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day
Num. of Obs.	28,665,891	8,526,782	7,405,942
Adj. R^2	0.004	0.003	0.003

Panel B: Model (2)

	(1) All Stocks	(2) Overpriced Stocks	(3) Underpriced Stocks
MISP	0.891***	2.072***	0.016
	(7.60)	(7.39)	(0.13)
MISP x *SUE*	6.749	-0.290	41.53**
	(1.35)	(-0.02)	(2.30)
MISP x *SENT*	-13.467***	-29.692***	0.339
	(-39.49)	(-25.38)	(0.52)
SUE	2.386***	2.313***	1.581***
	(19.01)	(6.04)	(2.88)
SENT	1.602***	1.299***	1.248***
	(108.13)	(44.87)	(49.31)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day
Num. of Obs.	28,665,891	8,526,782	7,405,942
Adj. R^2	0.008	0.008	0.007

Panel C: Model (3)

	(1) All Stocks	(2) Overpriced Stocks	(3) Underpriced Stocks
MISP	1.009***	1.722***	0.210
	(8.20)	(6.17)	(1.42)
MISP x *EARN*	4.208***	11.605***	-1.513
	(6.40)	(5.83)	(-0.92)
MISP x *POSNEWS*	-4.737***	-9.874***	-0.367
	(-30.18)	(-20.69)	(-1.49)
MISP x *NEGNEWS*	4.193***	10.475***	0.074

	(23.10)	(18.40)	(0.25)
MISP x *ZERONEWS*	-0.389***	-0.028	-0.140
	(-2.66)	(-0.06)	(-0.51)
EARN	0.027	0.163***	-1.513
	(1.49)	(3.46)	(-0.92)
POSNEWS	0.382***	0.287***	0.275***
	(57.18)	(23.81)	(28.31)
NEGNEWS	-0.488***	-0.369***	-0.361***
	(-58.08)	(-25.44)	(-30.96)
ZERONEWS	0.007	0.017	0.011
	(1.14)	(1.51)	(1.13)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day
Num. of Obs.	28,665,891	8,526,782	7,405,942
Adj. R^2	0.007	0.008	0.006

Panel D: Model (4)

	(1) All Stocks	(2) Overpriced Stocks	(3) Underpriced Stocks
MISP	0.924***	1.996***	0.040
	(7.81)	(7.15)	(0.30)
MISP x *SUE*	6.839	-0.251	41.606**
	(1.37)	(-0.02)	(2.31)
MISP x *PSENT*	-13.404***	-29.220***	0.350
	(-29.12)	(-19.66)	(0.41)
MISP x *NSENT*	13.234***	29.951***	-0.447
	(20.10)	(14.63)	(-0.36)
SUE	2.384***	2.311***	1.579***
	(19.00)	(6.03)	(2.87)
PSENT	1.512***	1.220***	1.180***
	(78.16)	(32.55)	(35.95)
NSENT	-1.802***	-1.477***	-1.394***
	(-63.26)	(-27.81)	(-29.61)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day
Num. of Obs.	28,665,891	8,526,782	7,405,942
Adj. R^2	0.008	0.008	0.007

Table 3: Impact of the LLT Activity on Mispricing Returns on News Days

This table investigates whether and how the low latency trading (LLT) activity affects the mispricing returns on news release days. Following Hasbrouck and Saar (2013), we measure LLT activity as the number of time-weighted strategic runs for stock *i* on day *t*,

$$LLT_{i,t} = \frac{1}{2.34\times10^7}\sum_{j=1}^{N_{i,t}} T_{i,j,t}, \tag{5}$$

where $T_{i,j,t}$ is the time-in-force in milliseconds for the *j*th strategic run, $N_{i,t}$ is the total number of strategic runs, and the total number of milliseconds available for each trading day is 2.34×10^7. Panel A reports the distribution of LLT activity on news days, using natural-log transformed variable *Log(1+LLT)* as the dependent variable in the regressions. Panels B to E report the impact of LLT activity on mispricing returns on news release days. *DLLT* is a dummy variable indicating the top decile of LLT for each calendar date. We interact *DLLT* with *MISP* and the news variables, add the three-way interaction terms into equations (1) to (4), and re-estimate them. The sample for this analysis contains Nasdaq-listed common stocks only and starts in January, 2008 and ends in December, 2017, which is restricted by the availability of *LLT*. For the other aspects of the tests, see the legend in Table 2. Day and firm fixed effects are included regressions in Panel A, and day fixed effects are included in regressions of Panels B to E. The standard errors of coefficients are clustered by day, and *t*-statistics are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: LLT Activity on News Days with $Dep.Var = Log(1 + LLT)$

	(1)	(2)	(3)	(4)
NEWS	0.541***			
	(44.49)			
SENT		0.353***		
		(22.30)		
POSNEWS			0.601***	
			(42.75)	
NEGNEWS			0.604***	
			(47.67)	
ZERONEWS			0.299***	
			(37.10)	
PSENT				1.383***
				(40.75)
NSENT				1.616***
				(45.06)
Day Fixed effects	Yes	Yes	Yes	Yes
Firm Fixed effects	Yes	Yes	Yes	Yes
Num. of Obs.	7,442,851	7,442,851	7,442,851	7,442,851
Adj. R^2	0.091	0.003	0.098	0.042

Panel B: Model (1)

	(1) All Stocks	(2) Overpriced Stocks	(3) Underpriced Stocks
MISP	0.819***	2.863***	-0.014
	(3.65)	(4.05)	(-0.03)
MISP x *DLLT*	-0.152	-0.868*	0.089
	(-1.32)	(-1.84)	(0.42)
MISP x *EARN*	3.171***	16.909***	-0.986
	(2.67)	(4.53)	(-0.33)
MISP x *NEWS*	-0.764***	-1.267**	-0.076
	(-5.82)	(-2.56)	(-0.29)
MISP x *NEWS* x *DLLT*	0.027	2.173	-0.636
	(0.07)	(1.20)	(-1.27)
EARN	0.048	0.353***	0.129
	(1.50)	(3.98)	(1.20)
NEWS	0.057***	0.042***	0.037***
	(10.30)	(3.38)	(3.53)
NEWS x *DLLT*	-0.036***	0.059	-0.022
	(-2.72)	(1.46)	(-1.06)
DLLT	-0.015	-0.058***	-0.010
	(-1.06)	(-2.83)	(-0.87)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day
Num. of Obs.	7,442,851	2,128,804	2,291,232
Adj. R^2	0.006	0.004	0.009

Panel C: Model (2)

	(1) All Stocks	(2) Overpriced Stocks	(3) Underpriced Stocks
MISP	0.787***	2.893***	0.161
	(3.84)	(3.98)	(0.32)
MISP x *DLLT*	-0.128	-0.731	-0.035
	(-1.15)	(-1.59)	(-0.17)
MISP x *SUE*	95.644***	1.394	373.486***
	(5.93)	(0.04)	(2.66)
MISP x *SENT*	-14.276***	-25.291***	-2.189**
	(-27.82)	(-13.66)	(-1.98)
MISP x *SENT* x *DLLT*	-20.306***	-51.337***	1.404
	(-13.11)	(-6.54)	(0.65)
SUE	7.557***	4.395**	1.042
	(11.63)	(2.51)	(0.25)
SENT	1.732***	1.543***	1.393***
	(82.80)	(33.76)	(31.41)
SENT x *DLLT*	0.557***	0.074	-0.212**
	(10.73)	(0.43)	(-2.52)

DLLT	-0.057***	-0.087***	-0.040***
	(-4.90)	(-4.41)	(-4.27)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day
Num. of Obs.	7,442,851	2,128,804	2,291,232
Adj. R^2	0.013	0.012	0.017

Panel D: Model (3)

	(1) All Stocks	(2) Overpriced Stocks	(3) Underpriced Stocks
MISP	0.880***	3.186***	0.011
	(3.92)	(4.51)	(0.02)
MISP x *DLLT*	-0.179	-1.025**	0.079
	(-1.56)	(-2.18)	(0.37)
MISP x *EARN*	2.449**	14.198***	-1.387
	(2.09)	(3.88)	(-0.47)
MISP x *POSNEWS*	-4.331***	-8.394***	-0.636*
	(-23.32)	(-11.81)	(-1.71)
MISP x *NEGNEWS*	4.230***	8.083***	1.068**
	(20.12)	(9.94)	(2.54)
MISP x *ZERONEWS*	-0.262	-0.520	-0.062
	(-1.48)	(-0.80)	(-0.15)
MISP x *POSNEWS* x *DLLT*	-3.555***	-9.898***	-0.352
	(-6.94)	(-3.75)	(-0.55)
MISP x *NEGNEWS* x *DLLT*	5.281***	16.879***	-1.423*
	(8.39)	(5.96)	(-1.70)
MISP x *ZERONEWS* x *DLLT*	0.361	5.927***	-0.735
	(0.69)	(2.62)	(-0.71)
EARN	0.027	0.292***	0.096
	(0.85)	(3.35)	(0.90)
POSNEWS	0.412***	0.334***	0.309***
	(56.69)	(19.48)	(21.00)
POSNEWS x *DLLT*	0.022	-0.024	-0.102***
	(1.31)	(-0.43)	(-3.86)
NEGNEWS	-0.454***	-0.396***	-0.365***
	(-50.28)	(-20.05)	(-21.35)
NEGNEWS x *DLLT*	-0.171***	0.103	0.053
	(-8.23)	(1.64)	(1.56)
ZERONEWS	0.015***	0.013	0.013
	(2.72)	(0.79)	(0.84)
ZERONEWS x *DLLT*	-0.019	0.156***	0.015
	(-1.05)	(2.74)	(0.37)
DLLT	-0.011	-0.060***	-0.005
	(-0.78)	(-2.89)	(-0.46)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day

Num. of Obs.	7,442,851	2,128,804	2,291,232
Adj. R^2	0.012	0.012	0.015

Panel E: Model (4)

	(1) All Stocks	(2) Overpriced Stocks	(3) Underpriced Stocks
MISP	0.861***	2.999***	0.094
	(4.02)	(4.18)	(0.19)
MISP x *DLLT*	-0.194*	-0.814*	-0.034
	(-1.73)	(-1.75)	(-0.16)
MISP x *SUE*	95.694***	1.424	373.405***
	(5.94)	(0.04)	(2.66)
MISP x *PSENT*	-13.909***	-25.374***	-1.336
	(-21.67)	(-10.85)	(-0.94)
MISP x *NSENT*	14.838***	24.803***	3.862**
	(16.71)	(7.50)	(2.06)
MISP x *PSENT* x *DLLT*	-18.103***	-44.183***	0.711
	(-8.90)	(-4.13)	(0.27)
MISP x *NSENT* x *DLLT*	24.399***	63.547***	-3.022
	(8.83)	(5.61)	(-0.76)
SUE	7.555***	4.392**	1.045
	(11.63)	(2.51)	(0.25)
PSENT	1.711***	1.500***	1.360***
	(70.41)	(26.19)	(24.29)
PSENT x *DLLT*	0.474***	0.217	-0.224**
	(7.39)	(0.94)	(-2.13)
NSENT	-1.771***	-1.629***	-1.458***
	(-52.08)	(-19.70)	(-19.56)
NSENT x *DLLT*	-0.687***	0.195	0.206
	(-8.26)	(0.77)	(1.32)
DLLT	-0.049***	-0.085***	-0.035***
	(-4.03)	(-4.21)	(-3.52)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day
Num. of Obs.	7,442,851	2,128,804	2,291,232
Adj. R^2	0.013	0.012	0.017

Table 4: Post-news-day Mispricing Returns – Monthly Regressions

This table presents the test results that examine whether the mispricing exacerbation effect on news release days is reversed over time. We estimate the following monthly panel regressions:

$$RET_{i,m} = \alpha + \beta_1 MISP_{i,m-k} + \sum_{j=0}^{k} \beta_j^P MISP_{i,m-k} \times LPOSNEWS_{i,m-j} + \sum_{j=0}^{k} \beta_j^N MISP_{i,m-k} \times LNEGNEWS_{i,m-j} + \sum_{j=0}^{k} \gamma_j^P LPOSNEWS_{i,m-j} + \sum_{j=0}^{k} \gamma_j^N LNEGNEWS_{i,m-j} + \theta' \boldsymbol{X}_{i,m} + \varepsilon_{i,m}, \quad (6)$$

where $RET_{i,m}$ is the return of stock *i* at the end of month *m* and $MISP_{i,m-k}$ is its mispricing score measured at the beginning of month *m-k* based on the 11 SYY anomaly signals. $LPOSNEWS_{i,m-j}$ and $LNEGNEWS_{i,m-j}$ are, respectively, log(1 + number of positive news days) and log(1 + number of negative news days) in month *m-j* for firm *i*. The control variables in $\boldsymbol{X}$ include lagged monthly return, natural log of market capitalization, book-to-market ratio, natural log of Amihud's illiquidity measure, and idiosyncratic volatility estimated using the market model. Month fixed effects are included in estimating equation (6). The standard errors are clustered by month to account for the cross-stock correlation in monthly returns, and *t*-statistics are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Dependent Variable = RET_m			
	(1) $k = 0$	(2) $k = 1$	(3) $k = 2$	(4) $k = 3$
$MISP_{m-k}$	0.318***	0.266***	0.238***	0.209***
	(5.66)	(4.17)	(3.66)	(3.07)
$MISP_{m-k}$ x $LPOSNEWS_m$	-0.290***	-0.334***	-0.329***	-0.327***
	(-10.2)	(-14.15)	(-13.43)	(-12.86)
$MISP_{m-k}$ x $LNEGNEWS_m$	0.195***	0.166***	0.159***	0.156***
	(6.93)	(7.88)	(8.16)	(8.45)
$LPOSNEWS_m$	0.025***	0.026***	0.026***	0.027***
	(26.38)	(28.24)	(29.52)	(30.4)
$LNEGNEWS_m$	-0.016***	-0.015***	-0.016***	-0.016***
	(-18.52)	(-18.68)	(-18.73)	(-18.96)
$MISP_{m-k}$ x $LPOSNEWS_{m-1}$		0.080**	0.062**	0.066**
		(2.39)	(2.22)	(2.37)
$MISP_{m-k}$ x $LNEGNEWS_{m-1}$		0.018	0.022	0.027
		(0.77)	(0.98)	(1.21)
$LPOSNEWS_{m-1}$		-0.004***	-0.003***	-0.003***
		(-4.86)	(-4.34)	(-3.71)
$LNEGNEWS_{m-1}$		0.001	0.001	0.001

		(1.61)	(1.34)	(1.27)
$MISP_{m-k}$ x $LPOSNEWS_{m-2}$			0.063**	0.062**
			(2.46)	(2.50)
$MISP_{m-k}$ x $LNEGNEWS_{m-2}$			-0.039**	-0.037**
			(-2.05)	(-2.05)
$LPOSNEWS_{m-2}$			-0.003***	-0.003***
			(-5.94)	(-5.33)
$LNEGNEWS_{m-2}$			0.002***	0.002***
			(4.18)	(3.92)
$MISP_{m-k}$ x $LPOSNEWS_{m-3}$				0.027
				(1.49)
$MISP_{m-k}$ x $LNEGNEWS_{m-3}$				-0.021
				(-1.14)
$LPOSNEWS_{m-3}$				-0.003***
				(-6.9)
$LNEGNEWS_{m-3}$				0.003***
				(4.93)
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Month	Month	Month	Month
Num. of Obs.	1,217,293	1,210,657	1,204,077	1,197,577
Adj. R^2	0.116	0.117	0.119	0.120

Table 5: Mispricing Returns on Earnings Days and News Days

– Investor Relations Activities

This table repeats the mispricing return tests in Table 2 by interacting *MISP* and news variables with our monthly proxy for investor relations (IR) activities. We construct our stock-level monthly IR proxy as follows. For firm *i* in month *m*, we first calculate the number of news articles with positive sentiment minus the number of news articles with negative sentiment over the preceding three-month period that ends at month *m*-1, producing the "three-month net positive news coverage". We then run a cross-stock regression of the three-month net positive news coverage on the averages of *SENT* and firm size (=log of daily market capitalization) over the same three-month period, and obtain the residual. Finally, in the beginning of month *m*, we sort stocks by the residual into tercile portfolios, and assign $IR_{i,t} = 1$ if the residual value belongs to the top tercile and assign $IR_{i,t} = 0$ otherwise for stock *i* on each day *t* in month *m*. We update this IR proxy each month by moving the three-month estimation window forward by one month. We then add the three-way IR interaction terms with *MISP* and new variables to equations (1) to (4). For the other aspects of the tests, see the legend in Table 2. The sample period of our analysis is from January, 2000 to December, 2019. The day fixed effects are included in estimating equations (1) to (4). The standard errors of coefficients are clustered by day, and *t*-statistics are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
MISP	0.974***	0.907***	0.988***	0.931***
	(7.47)	(7.46)	(7.58)	(7.50)
MISP x *IR*	0.082	-0.022	0.080	0.005
	(1.13)	(-0.32)	(1.10)	(0.07)
MISP x *EARN*	4.760***		4.154***	
	(7.13)		(6.26)	
MISP x *NEWS*	-0.819***			
	(-5.87)			
MISP x *NEWS* x *IR*	-0.343**			
	(-2.25)			
EARN	0.034*		0.016	
	(1.88)		(0.88)	
NEWS	0.042***			
	(6.54)			
NEWS x *IR*	0.005			
	(1.25)			
MISP x *SUE*		6.537		6.623
		(1.31)		(1.32)
MISP x *SENT*		-12.172***		
		(-30.35)		
MISP x *SENT* x *IR*		-3.049***		
		(-5.19)		
SUE		2.375***		2.373***
		(19.03)		(19.03)
SENT		1.615***		
		(100.92)		
SENT x *IR*		-0.067***		
		(-4.40)		
MISP x *POSNEWS*			-4.418***	

	(1)	(2)	(3)	(4)
			(-24.58)	
MISP x *NEGNEWS*			3.824***	
			(18.90)	
MISP x *ZERONEWS*			-0.265	
			(-1.57)	
MISP x *POSNEWS* x *IR*			-0.583***	
			(-2.77)	
MISP x *NEGNEWS* x *IR*			0.846***	
			(3.17)	
MISP x *ZERONEWS* x *IR*			-0.347	
			(-1.62)	
POSNEWS			0.403***	
			(53.31)	
POSNEWS x *IR*			-0.057***	
			(-9.76)	
NEGNEWS			-0.494***	
			(-54.88)	
NEGNEWS x *IR*			0.020***	
			(2.84)	
ZERONEWS			0.006	
			(1.00)	
ZERONEWS x *IR*			-0.001	
			(-0.16)	
MISP x *PSENT*				-11.846***
				(-22.44)
MISP x *NSENT*				12.513***
				(16.06)
MISP x *PSENT* x *IR*				-3.729***
				(-5.00)
MISP x *NSENT* x *IR*				1.694
				(1.58)
PSENT				1.500***
				(71.57)
PSENT x *IR*				-0.011
				(-0.58)
NSENT				-1.883***
				(-59.06)
NSENT x *IR*				0.215***
				(7.95)
IR	-0.002	-0.005**	-0.002	-0.007***
	(-0.90)	(-2.15)	(-0.85)	(-2.84)
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Day	Day	Day	Day
Num. of Obs.	28,077,826	28,077,826	28,077,826	28,077,826
Adj. R^2	0.004	0.008	0.008	0.008

Table 6: Mispricing and Investor Attention

– EDGAR Downloads of 10-K Fillings

This table presents the test result that examines the relation between stock-level mispricing and the level of investor attention proxied by a download volume of 10-K reports from SEC's EDGAR website. Specifically, we estimate the following panel regression:

$$Log\left(1 + Download_{i,m}\right) = \alpha + \beta_1 \times MISP_{i,m} + \beta_2 \times Log\left(MV_{i,m}\right) + \varepsilon_{i,m}, \quad (7)$$

where $Download_{i,m}$ is the number of unique IP addresses that download firm *i*'s 10-K in month *m*. We count only downloads that are made within seven days of each 10-K filing day to capture the timely search of information by investors. Robot downloads (IP addresses that download more than 30 firms' filings on a single day) are excluded from the count. *MISP* is defined as the difference in the number of long-side (i.e., *Long*) and short-side (i.e., *Short*) anomaly portfolios that each stock belongs to based on the 11 mispricing signals of Stambaugh, Yu, and Yuan (2012). *MISP* is measured at the beginning of month *m* and divided by 100. *MV* is the market value of equity at the end of the previous month *m*-1. The sample period is January 2003 through June 2017, which is restricted by the availability of *Download*. Month and firm fixed effects are included in estimating equation (7). The standard errors of coefficients are clustered by month, and *t*-statistics are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Log(1+DOWNLOAD)
MISP	-1.035***
	(-6.11)
Log(MV)	0.048***
	(4.06)
Fixed effects	Month / Firm
Num. of Obs.	61,667
Adj. R^2	0.898

Table 7: Market Reaction to News Sentiment

– Overpriced vs. Underpriced Stocks

This table presents the test result that examines whether the market reaction to news contents of overpriced stocks is stronger than that of underpriced stocks. Specifically, we estimate the following panel regression:

$$RET_{i,t} = \alpha + \beta_1 \times SENT_{i,t} + \beta_2 \times SENT_{i,t} \times OP_{i,t} + \beta_3 \times OP_{i,t} + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \quad (8)$$

where $OP_{i,t}$ is an indicator variable for an overpriced stock, which equals to 1 if $MISP_{i,t} < 0$ and 0 if $MISP_{i,t} > 0$, where $MISP_{i,t}$ is the mispricing score of stock *i* measured at the beginning of the month that day *t* belongs to. $SENT_{i,t}$ is the average sentiment score of news articles released on day *t*. $\boldsymbol{X}_{i,t}$ includes the same set of control variables as in equation (1). We estimate equation (8) using the sample that includes all news release days of mispriced stocks, i.e., stocks with $NEWS = 1$ and $MISP \neq 0$ and with day fixed effects included in the model. For more details of variable definitions, see the legend in Table 2. The sample period of our analysis is January, 2000 through December, 2019. The standard errors of coefficients are clustered by month, and *t*-statistics are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	RET
SENT	1.301***
	(102.10)
SENT x *OP*	0.698***
	(37.19)
OP	-0.041***
	(-4.87)
Control variables	Yes
Fixed effects	Day
Num. of Obs.	4,805,640
Adj. R^2	0.015

Table 8: Mispricing Returns on Earnings Days and News Days

– Short Sale Constraints

This table runs a mispricing return test similar to equation (3) in Table 2 by interacting the two variables (*PILOT* and *POST*) based on the SEC's Reg SHO pilot program, which effectively ran from May 2, 2005 to July 6, 2007. Specifically, we estimate the following panel regressions:

$$RET_{i,t} = \alpha + \theta_1 \times \left(\beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times POSNEWS_{i,t} + \beta_4 MISP_{i,t} \times NEGNEWS_{i,t} + \beta_5 EARN_{i,t} + \beta_6 POSNEWS_{i,t} + \beta_7 NEGNEWS_{i,t}\right) + \theta_2 \times PILOT_i \times \left(\beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times POSNEWS_{i,t} + \beta_4 MISP_{i,t} \times NEGNEWS_{i,t} + \beta_5 EARN_{i,t} + \beta_6 POSNEWS_{i,t} + \beta_7 NEGNEWS_{i,t}\right) + \theta_3 \times POST_t \times \left(\beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times POSNEWS_{i,t} + \beta_4 MISP_{i,t} \times NEGNEWS_{i,t} + \beta_5 EARN_{i,t} + \beta_6 POSNEWS_{i,t} + \beta_7 NEGNEWS_{i,t}\right) + \theta_4 \times PILOT_i \times POST_t \times (\beta_1 MISP_{i,t} + \beta_2 MISP_{i,t} \times EARN_{i,t} + \beta_3 MISP_{i,t} \times POSNEWS_{i,t} + \beta_4 MISP_{i,t} \times NEGNEWS_{i,t} + \beta_5 EARN_{i,t} + \beta_6 POSNEWS_{i,t} + \beta_7 NEGNEWS_{i,t}) + \gamma' \boldsymbol{X}_{i,t} + \varepsilon_{i,t}, \quad (9)$$

where $PILOT_i$ = 1 if stock *i* was included in the SEC's pilot order of Regulation SHO (Release No. 50104) and listed on NYSE or Amex, and $PILOT_i$ = 0 otherwise. $POST_t$ = 1 if day *t* is between May 2, 2005 and July 6, 2007, and $POST_t$ = 0 otherwise. The sample includes all constituent stocks of the Russell 3000 index as of June 2004, and the sample period is January 1, 2000 through July 6, 2007. For the other aspects of the test, see the legend in Table 2. The day fixed effects are included in estimating equation (9). The standard errors of coefficients are clustered by day, and *t*-statistics are reported in parenthesis.

Panel A: All Stocks

		x *PILOT*	x *POST*	x *PILOT* x *POST*
MISP	1.086***	-0.870***	-0.705**	0.428
	(4.04)	(-4.14)	(-2.31)	(1.53)
MISP x *EARN*	4.578***	-5.232*	-1.920	6.847
	(2.65)	(-1.86)	(-0.67)	(1.36)
MISP x *POSNEWS*	-4.602***	3.034***	1.050	-1.275
	(-9.32)	(3.74)	(1.60)	(-1.21)
MISP x *NEGNEWS*	6.595***	-5.007***	-2.719***	3.208**
	(8.31)	(-4.23)	(-2.76)	(2.07)
EARN	0.165***	0.095	-0.076	0.020
	(3.53)	(1.20)	(-1.01)	(0.15)
POSNEWS	0.471***	-0.204***	-0.082***	0.083***
	(33.07)	(-9.60)	(-4.25)	(2.97)
NEGNEWS	-0.964***	0.364***	0.537***	-0.187***
	(-37.39)	(11.40)	(17.39)	(-4.65)
PILOT	0.011			
	(1.09)			
PILOT x *POST*	0.001			
	(0.07)			
Control variables	Yes			
Fixed effects	Day			
Num. of Obs.	4,787,601			
Adj. R^2	0.006			

Panel B: Overpriced Stocks

		x *PILOT*	x *POST*	x *PILOT* x *POST*
MISP	0.681***	-0.245	-0.558**	-0.095
	(2.95)	(-1.26)	(-2.09)	(-0.36)
MISP x *EARN*	2.382	-5.890**	0.501	4.741
	(1.54)	(-2.21)	(0.20)	(1.01)
MISP x *POSNEWS*	-2.235***	2.149***	0.018	-1.699*
	(-5.93)	(3.42)	(0.03)	(-1.80)
MISP x *NEGNEWS*	5.056***	-2.245**	-2.998***	1.683
	(8.42)	(-2.37)	(-3.86)	(1.20)
EARN	0.236*	-0.256	-0.042	0.084
	(1.83)	(-1.18)	(-0.20)	(0.23)
POSNEWS	0.292***	-0.062	-0.008	-0.100
	(8.52)	(-1.13)	(-0.16)	(-1.31)
NEGNEWS	-0.650***	0.283***	0.328***	-0.100
	(-11.65)	(3.44)	(4.81)	(-0.91)
PILOT		-0.010		
		(-0.62)		
PILOT x *POST*		0.002		
		(0.11)		
Control variables		Yes		
Fixed effects		Day		
Num. of Obs.		1,976,784		
Adj. R^2		0.007		

Panel C: Underpriced Stocks

		x *PILOT*	x *POST*	x *PILOT* x *POST*
MISP	0.521***	0.019	-0.474***	0.155
	(4.12)	(0.08)	(-2.93)	(0.48)
MISP x *EARN*	4.669**	-2.931	-2.838	8.135
	(2.19)	(-0.65)	(-0.75)	(0.97)
MISP x *POSNEWS*	1.900**	-2.720*	-1.748*	2.862
	(2.50)	(-1.87)	(-1.95)	(1.53)
MISP x *NEGNEWS*	-0.197	-1.402	1.256	-4.172*
	(-0.19)	(-0.68)	(1.04)	(-1.67)
EARN	0.097	0.183	0.014	-0.261
	(0.66)	(0.59)	(0.05)	(-0.46)
POSNEWS	0.286***	0.078	-0.010	-0.105
	(5.66)	(0.82)	(-0.16)	(-0.88)
NEGNEWS	-0.615***	0.210	0.224***	0.219
	(-8.50)	(1.55)	(2.61)	(1.34)

PILOT	-0.007
	(-0.37)
PILOT x *POST*	-0.001
	(-0.03)
Control variables	Yes
Fixed effects	Day
Num. of Obs.	1,257,303
Adj. R^2	0.007

Table 9: Mispricing Returns on Earnings Days and News Days with the 95 Anomaly Signals from McLean and Pontiff (2016)

This table repeats the mispricing return tests in Table 2 by constructing the stock-level mispricing variable *MISP* using the 95 (out of 97) return predictors studied in McLean and Pontiff (2016). We obtain these 95 predictors from Chen and Zimmerman's Open Source Asset Pricing at https://www.openassetpricing.com/. They drop Merger and SEO variables due to lack of data from the original 97 predictors in McLean and Pontiff (2016). In Column (1), the news variables are constructed using RavenPack database, while in Columns (2) and (3), the same news variables are constructed using Dow Jones News Archive database. The sample periods are, respectively, January 2000 through December 2019 for Columns (1) and (2), and June 1979 through December 2013 for Column (3). In Columns (2) and (3), where Dow Jones News Archive database is used as the news source, $SENT_{i,t}$ is the average sentiment of all news articles released on day *t* for firm *i*, where the sentiment is calculated as (number of positive words – number of negative words)/total number of words based on Loughran and McDonald's master dictionary. We assign *SENT* = 0 for non-news days that have *NEWS* = 0. All other variables are defined as in Table 2 and see the legend in Table 2 for the other aspects of the tests. The standard errors of coefficients are clustered, and *t*-statistics are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Model (1)

	(1) RavenPack Database (Jan. 2000 ~ Dec. 2019)	(2) Dow Jones News Archive Database (Jan. 2000 ~ Dec. 2019)	(3) Dow Jones News Archive Database (Jun. 1979 ~ Dec. 2013)
MISP	0.414***	0.373***	0.467***
	(5.29)	(5.43)	(11.07)
MISP x *EARN*	2.410***	2.344***	2.056***
	(8.95)	(8.78)	(12.40)
MISP x *NEWS*	-0.136**	0.099	0.308***
	(-2.16)	(1.57)	(4.55)
EARN	0.075***	0.059***	0.160***
	(4.51)	(3.55)	(14.34)
NEWS	0.049***	0.091***	0.144***
	(9.44)	(19.32)	(28.22)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day
Num. of Obs.	28,643,730	28,643,644	43,664,459
Adj. R^2	0.004	0.004	0.007

Panel B: Model (2)

	(1) RavenPack Database (Jan. 2000 ~ Dec. 2019)	(2) Dow Jones News Archive Database (Jan. 2000 ~ Dec. 2019)	(3) Dow Jones News Archive Database (Jun. 1979 ~ Dec. 2013)
MISP	0.500***	0.370***	0.459***
	(7.21)	(5.36)	(10.46)
MISP x *SUE*	4.493**	10.667***	10.301***
	(2.17)	(3.63)	(6.95)
MISP x *SENT*	-4.466***	-28.831***	-32.42***
	(-35.37)	(-14.88)	(-19.50)
SUE	2.402***	4.222***	3.047***
	(18.48)	(14.57)	(26.35)
SENT	1.470***	5.482***	4.953***
	(111.63)	(40.26)	(42.71)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day
Num. of Obs.	28,643,730	28,643,644	43,664,459
Adj. R^2	0.008	0.004	0.008

Panel C: Model (3)

	(1) RavenPack Database (Jan. 2000 ~ Dec. 2019)	(2) Dow Jones News Archive Database (Jan. 2000 ~ Dec. 2019)	(3) Dow Jones News Archive Database (Jun. 1979 ~ Dec. 2013)
MISP	0.410***	0.379***	0.472***
	(5.24)	(5.52)	(11.18)
MISP x *EARN*	2.363***	2.232***	1.942***
	(8.83)	(8.38)	(11.74)
MISP x *POSNEWS*	-1.241***	-0.798***	-0.985***
	(-17.94)	(-10.46)	(-11.03)
MISP x *NEGNEWS*	1.499***	0.821***	1.161***
	(18.43)	(7.68)	(10.95)
MISP x *ZERONEWS*	-0.190***	-0.155*	-0.070
	(-2.56)	(-1.84)	(-0.95)
EARN	0.051***	0.070***	0.173***
	(3.10)	(4.23)	(15.45)
POSNEWS	0.343***	0.259***	0.360***
	(59.37)	(47.74)	(53.39)
NEGNEWS	-0.428***	-0.051***	-0.027***
	(-58.06)	(-7.35)	(-3.82)

ZERONEWS	0.011**	0.068***	0.186***
	(2.06)	(11.38)	(31.57)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day
Num. of Obs.	28,643,730	28,643,644	43,664,459
Adj. R^2	0.007	0.004	0.008

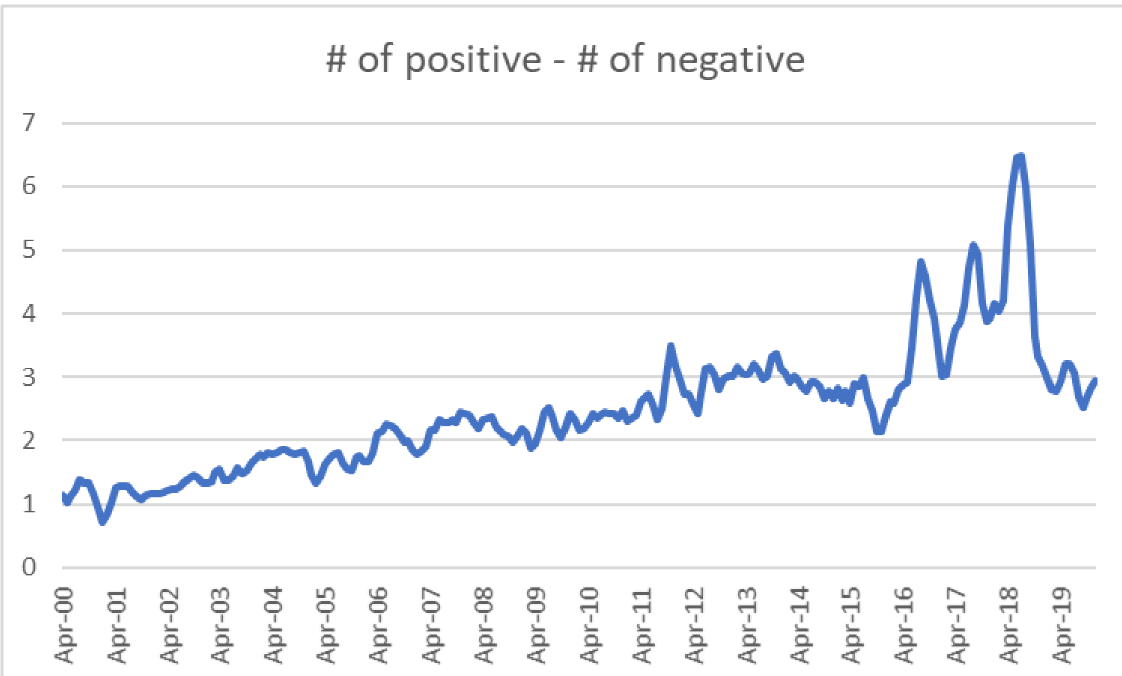
Panel D: Model (4)

	(1) RavenPack Database (Jan. 2000 ~ Dec. 2019)	(2) Dow Jones News Archive Database (Jan. 2000 ~ Dec. 2019)	(3) Dow Jones News Archive Database (Jun. 1979 ~ Dec. 2013)
MISP	0.453***	0.346***	0.455***
	(6.24)	(5.06)	(10.53)
MISP x *SUE*	4.546**	10.674***	10.262***
	(2.19)	(3.63)	(6.93)
MISP x *PSENT*	-3.839***	-15.380***	-22.579***
	(-20.63)	(-6.79)	(-8.46)
MISP x *NSENT*	5.787***	36.356***	37.498***
	(21.09)	(13.11)	(17.48)
SUE	2.399***	4.221***	3.046***
	(18.46)	(14.57)	(26.34)
PSENT	1.397***	6.277***	8.090***
	(82.59)	(39.06)	(41.25)
NSENT	-1.633***	-5.004***	-3.808***
	(-64.40)	(-24.39)	(-24.94)
Control variables	Yes	Yes	Yes
Fixed effects	Day	Day	Day
Num. of Obs.	28,643,730	28,643,644	43,664,459
Adj. R^2	0.008	0.004	0.008

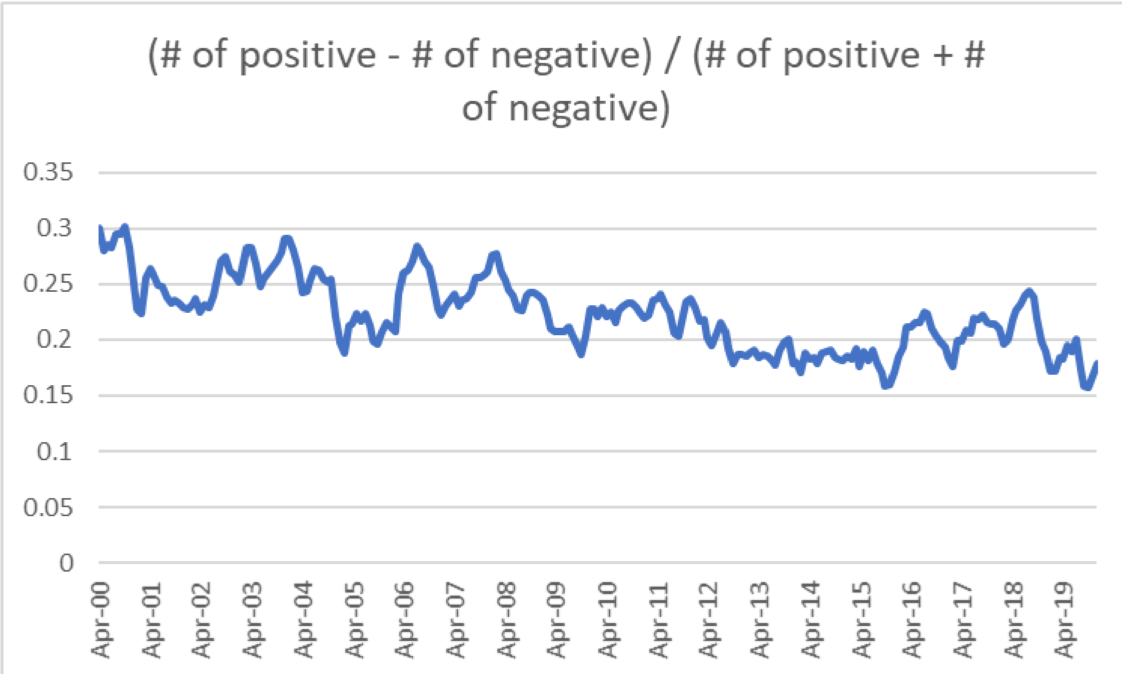
Figure 1: Time-series of One-month Net Positive News Coverage

This figure presents the time-series plots of cross-stock averages of one-month net positive news coverage (Panel A) and its normalized version (Panel B). For firm *i* in month *m*, to obtain the "one-month net positive news coverage", we first calculate the number of news articles with positive sentiment minus the number of news articles with negative sentiment. We then take the cross-stock average of the one-month net positive news coverage for month *m* and report its monthly time-series in Panel A. To obtain its normalized version, for firm *i* in month *m*, we scale the one-month net positive news coverage by the total number of news articles with positive or negative sentiment. We then take the cross-stock average of the normalized one-month net positive news coverage for month *m* and report its monthly time-series in Panel B.

Panel A: Cross-stock average of one-month net positive news coverage



Panel B: Cross-stock average of normalized one-month net positive news coverage



Internet Appendix – Beauty Contest around News Releases

by Tarun Chordia, Bin Miao, and Joonki Noh

March 2023

This appendix provides additional test results and associated materials for the paper entitled "Beauty Contest around News Releases" by Chordia, Miao, and Noh (2023).

Table A.1: Mispricing Returns on Earnings Days and News Days

– Three-day Event Window

This table repeats the mispricing return tests in Table 2 with a three-day event window to capture the price reaction to news releases. We code $EARN_{i,t}$ = 1 if firm *i* makes an earnings announcement in a three-day window [*t*-1, *t*+1], and $EARN_{i,t}$ = 0 otherwise. We code $NEWS_{i,t}$ = 1 if a news article about firm *i* is released on days *t*-1, *t*, or *t*+1, and $NEWS_{i,t}$ = 0 otherwise. All other earnings and news variables, including *SUE*, *SENT*, *POSNEWS*, *NEGNEWS*, *ZERONEWS*, *PSENT*, and *NSENT*, are defined in a similar manner. For the other aspects of the tests, see the legend in Table 2. The sample period of our analysis is from January, 2000 to December, 2019. The day fixed effects are included in estimating equations (1) to (4). The standard errors of coefficients are clustered by day, and *t*-statistics are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
MISP	1.094***	0.917***	1.112***	0.913***
	(7.65)	(7.76)	(7.77)	(7.47)
MISP x *EARN*	2.597***		2.270***	
	(8.35)		(7.33)	
MISP x *NEWS*	-0.797***			
	(-6.40)			
EARN	0.025***		0.013	
	(2.83)		(1.47)	
NEWS	0.030***			
	(4.81)			
MISP x *SUE*		1.229		6.404
		(0.62)		(1.28)
MISP x *SENT*		-6.585***		
		(-27.55)		
SUE		1.026***		2.419***
		(20.53)		(19.22)
SENT		0.898***		
		(95.76)		
MISP x *POSNEWS*			-2.449***	
			(-17.90)	
MISP x *NEGNEWS*			1.513***	
			(10.16)	
MISP x *ZERONEWS*			-0.409***	
			(-2.96)	
POSNEWS			0.185***	
			(28.53)	
NEGNEWS			-0.230***	
			(-30.85)	
ZERONEWS			-0.004	
			(-0.66)	
MISP x *PSENT*				-6.347***
				(-18.36)

MISP x *NSENT*				6.924***
				(13.45)
PSENT				0.850***
				(53.07)
NSENT				-1.011***
				(-43.46)
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Day	Day	Day	Day
Num. of Obs.	28,665,891	28,665,891	28,665,891	28,665,891
Adj. R^2	0.004	0.005	0.005	0.006

Table A.2: Mispricing Returns on Earnings Days and News Days

– News Sources with High Credibility

This table repeats the mispricing return tests in Table 2 with the two refined subsamples of news sources that have high credibility. For Panel A, we use the most credible news sources by selecting Source Rank = 1 and complete news articles by selecting News Type = Full Article, both of which are coded by RavenPack. For Panel B, we use news articles in RavenPack coming only from Dow Jones Newswire. For the other aspects of the tests, see the legend in Table 2. The sample period of our analysis is from January, 2000 to December, 2019. The day fixed effects are included in estimating equations (1) to (4). The standard errors of coefficients are clustered by day, and *t*-statistics are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: High Quality News Sources and Complete News Articles

	(1)	(2)	(3)	(4)
MISP	0.876***	0.896***	0.887***	0.946***
	(7.57)	(7.67)	(7.65)	(8.16)
MISP x *EARN*	4.755***		4.317***	
	(7.19)		(6.55)	
MISP x *NEWS*	-1.530***			
	(-8.65)			
EARN	0.042**		0.024	
	(2.32)		(1.32)	
NEWS	0.089***			
	(14.64)			
MISP x *SUE*		6.509		6.628
		(1.30)		(1.32)
MISP x *SENT*		-20.762***		
		(-28.65)		
SUE		2.382***		2.414***
		(19.01)		(19.21)
SENT		2.153***		
		(101.64)		
MISP x *POSNEWS*			-7.163***	
			(-24.31)	
MISP x *NEGNEWS*			4.570***	
			(17.79)	
MISP x *ZERONEWS*			0.066	
			(0.22)	
POSNEWS			0.664***	
			(77.77)	
NEGNEWS			-0.483***	
			(-54.29)	
ZERONEWS			-0.006	
			(-0.64)	
MISP x *PSENT*				-6.775***
				(-22.68)

MISP x *NSENT*				9.715***
				(18.87)
PSENT				0.638***
				(53.74)
NSENT				-0.877***
				(-38.90)
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Day	Day	Day	Day
Num. of Obs.	28,665,891	28,665,891	28,665,891	28,665,891
Adj. R^2	0.004	0.006	0.006	0.006

Panel B: Dow Jones Newswire

	(1)	(2)	(3)	(4)
MISP	0.914***	0.920***	0.924***	0.933***
	(7.82)	(7.87)	(7.90)	(7.97)
MISP x *EARN*	4.729***		4.214***	
	(7.15)		(6.39)	
MISP x *NEWS*	-0.857***			
	(-6.61)			
EARN	0.044**		0.017	
	(2.45)		(0.93)	
NEWS	0.052***			
	(8.66)			
MISP x *SUE*		6.398		6.164
		(1.28)		(1.23)
MISP x *SENT*		-13.87***		
		(-31.49)		
SUE		2.403***		
		(19.13)		
SENT		1.560***		2.418***
		(91.18)		(19.28)
MISP x *POSNEWS*			-4.370***	
			(-22.90)	
MISP x *NEGNEWS*			3.984***	
			(19.47)	
MISP x *ZERONEWS*			-0.323**	
			(-2.06)	
POSNEWS			0.367***	
			(48.44)	
NEGNEWS			-0.382***	
			(-41.06)	
ZERONEWS			0.002	
			(0.35)	
MISP x *PSENT*				-11.137***

				(-23.59)
MISP x *NSENT*				11.297***
				(17.50)
PSENT				1.086***
				(79.31)
NSENT				-1.114***
				(-50.24)
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Day	Day	Day	Day
Num. of Obs.	28,665,891	28,665,891	28,665,891	28,665,891
Adj. R^2	0.004	0.006	0.005	0.006

Table A.3: Mispricing Returns on Earnings Days and News Days

– An Alternative Definition of Stock-level Mispricing

This table repeats the mispricing return tests in Table 2 with an alternative definition of stock-level mispricing following the method of Stambaugh, Yu, and Yuan (2012). At the beginning of the month which day *t* belongs to, as a stock *i*'s measure of relative mispricing, we define $MISP_{i,t}^{AR}$ as 2*average percentile ranking-1 (ranging from -1 to 1), where we calculate the average percentile ranking (ranging from 0 to 1) of the 11 signals of Stambuagh et al. (2012). The higher $MISP^{AR}$ is, the more underpriced the stock is. For the other aspects of the tests, see the legend in Table 2. The sample period of our analysis is from January, 2000 to December, 2019. The day fixed effects are included in estimating equations (1) to (4). The standard errors of coefficients are clustered by day, and *t*-statistics are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
MISP	0.061***	0.062***	0.062***	0.062***
	(5.07)	(5.20)	(5.13)	(5.18)
MISP x *EARN*	0.484***		0.415***	
	(6.84)		(5.90)	
MISP x *NEWS*	-0.060***			
	(-4.63)			
EARN	0.055***		0.036**	
	(3.19)		(2.11)	
NEWS	0.044***			
	(7.57)			
MISP x *SUE*		0.188		0.198
		(0.39)		(0.41)
MISP x *SENT*		-1.444***		
		(-38.54)		
SUE		2.382***		2.380***
		(18.86)		(18.85)
SENT		1.571***		
		(107.58)		
MISP x *POSNEWS*			-0.471***	
			(-28.72)	
MISP x *NEGNEWS*			0.503***	
			(25.86)	
MISP x *ZERONEWS*			0.014	
			(0.86)	
POSNEWS			0.371***	
			(56.69)	
NEGNEWS			-0.477***	
			(-58.26)	
ZERONEWS			0.005	
			(0.97)	
MISP x *PSENT*				-1.393***
				(-27.80)

MISP x *NSENT*				1.505***
				(21.29)
PSENT				1.483***
				(78.03)
NSENT				-1.764***
				(-63.74)
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Day	Day	Day	Day
Num. of Obs.	28,050,508	28,050,508	28,050,508	28,050,508
Adj. R^2	0.004	0.008	0.007	0.008