Overnight Reversal and the Asymmetric Reaction to News

Thomas Dangl* Stefan Salbrechter†

first draft, December 20, 2022

Abstract

News released overnight has a significant directional impact on individual shares' opening prices, i.e., the market tends to open higher (lower) when news with positive (negative) sentiment is published. However, the market opening is not fully efficient due to over- or underreactions of market participants to the news, resulting in a predictable pattern of returns on the following trading day. In particular, we find that large daytime returns followed by overnight news with strong sentiment lead to a predictable return reversal during the subsequent trading day. This predictable reversal is present independent of the polarity of the news sentiment. Without overnight news, large previous-day returns only have marginal predictive power.

*Vienna University of Technology, Theresianumgasse 27, A-1040 Vienna, Austria, e-mail: Thomas.Dangl@tuwien.ac.at

†Vienna University of Technology, Theresianumgasse 27, A-1040 Vienna, Austria, e-mail: Stefan.Salbrechter@tuwien.ac.at

1 Introduction

We show that overnight news, i.e., news released during times when stock markets are closed, has a clear directional impact on the opening share price at the subsequent trading day. Overnight news with positive sentiment predicts a high opening price and overnight news with negative sentiment predicts a low opening price. This opening price is, however, not fully efficient in the sense that returns during the subsequent trading day are predictable. When there is no company relevant overnight news, predictability can hardly be detected.

Idiosyncratic returns of S&P 500 constituents reveal that investors do not simply over- or underreact to overnight news but that inefficiency is asymmetric. News releases after market close, which confirm the previous day's open-to-close return, i.e., good news after a positive open-to-close return or bad news after a negative open-to-close return, tend to come with an overshooting opening price on the next day. This overshooting reverses over the trading day in a predictable way. When news after market close opposes the previous day's open-to-close return, i.e., bad news after a positive open-to-close return or good news after a negative open-to-close return, the opening price does not fully reflect the new information. The return on the next trading day tends to make up this deficit and so it extends the direction of the overnight news release, which, again, results in a reversal relative to previous day's open-to-close return. In the absence of company-relevant overnight news, the opening price is –on average– efficient and we do not detect *exploitable* predictability of returns on the following trading day.

We determine news sentiment with a BERT-based language model, (see Dangl and Salbrechter, 2021), which we train, strictly out-of-sample, on a dataset of 4 million financial news articles released between 1996 and 2020.[1,2]

Our contribution to the literature is threefold. First, as described above, we document the impact of overnight news sentiment on the market opening price and report a mispricing that leads to a predictable return reversal. The reaction to news sentiment

[1]This corresponds to a total of 466 million words.

[2]We thank Refinitiv for providing us with the dataset.

is apparently asymmetric, depending on the direction of the previous day's return in relation to news sentiment. Extending Boudoukh et al. (2019), who disregard news sentiment and find that the presence of overnight news increases the variance of overnight returns, we are able to measure the directional impact of news on the opening price and predict *occurrence*, *direction*, and *magnitude* of inefficient market opening that translates into a subsequent return reversal. In the absence of company specific overnight news, subsequent-day returns can hardly be predicted.

Second, we re-investigate the attention effect reported by Barber and Odean (2008) and Berkman et al. (2012), stating that increased investor attention (indicated by large absolute previous-day returns) leads to elevated prices at market opening followed by a reversal during the trading day. We detect this effect unconditional on news releases, however, in the absence of overnight news this effect is magnitudes smaller than the impact of news sentiment on asset prices. While the attention effect predicts that large previous-day returns lead to positive overnight returns, we report a dominant news-driven effect, suggesting a strong interaction between news sentiment and asset returns.

Third, we present a simple trading strategy that exploits overnight reversal by taking a long (short) position in the opening auction of stocks that experienced exceptionally negative (positive) idiosyncratic returns on the previous trading day only if we observe overnight news. Before transaction costs, the long/short strategy generates an average return per trade of 27.79 bps.

The remainder of this paper is composed as follows. In Section 2 we review the related literature, in Section 3 we describe the data sources and the performed data preprocessing steps and in Section 4 we briefly explain our BERT-based language model. In Section 5.1 we document the directional impact that overnight news has on (contemporaneous) overnight returns and in Section 5.2 we describe the return reversal observed in the subsequent daytime period. We run linear regressions in Section 5.3, in Section 5.4 we study the impact of news released during market opening hours and in Section 5.5 we investigate the influence of news topics. We present an out-of-sample backtest in Section 5.6 and in Section 6 we conclude.

2 Literature Review

Does financial news move stock prices? Boudoukh et al. (2019) studies this research question and finds that financial news has a significant and measurable impact on stock prices. Authors focus on detecting relevant news articles, i.e., news that move stock prices, from a stream of Dow Jones Newswire articles. Therefore, the authors utilize state-of-the-art text analysis tools to identify firm-relevant news articles and measure their impact on overnight and daytime returns by analyzing return volatilities. What they find is a strong (contemporaneous) link between the release of relevant news articles and elevated return volatility. The idiosyncratic variance thereby explained by public information accounts for approximately 49.6% (12.4%) of the total overnight (daytime) variance. Authors, however, do not determine news sentiment and therefore cannot make conclusions about the directional impact that these news has on overnight and daytime returns. We therefore determine news sentiment in such a way that we can also draw conclusions about the directional impact of this news.

Beside Boudoukh et al. (2019), Greene and Watts (1996), Moshirian et al. (2012) and Jiang et al. (2012) also study the impact of overnight news on asset prices and volatility. The fact, that 95% of all earnings are reported outside of the regular U.S. trading hours makes the focus on overnight news even more relevant (Jiang et al., 2012; Michaely et al., 2014). Greene and Watts (1996) studies the impact of earnings announcements, released during trading and non-trading hours, on the NYSE and the NASDAQ exchange. In order to measure abnormal returns after earnings announcements, the authors implement a trading strategy where they go long (short) in assets that beat (miss) the analysts forecasts in earnings per share. They find that the opening price contains most of the price response. Since investors have more time to evaluate the news when the market is closed, the opening is usually more informative in comparison to the price response when earnings are announced during market opening hours. Moshirian et al. (2012) arrives at similar conclusions by studying the impact of overnight corporate announcements on the opening price for Australian Securities Exchange (ASX) listed stocks. The authors find that information asymmetry is reduced when overnight news is published, leading to a more efficient determination of the equilibrium price, while stock prices adjust quickly to released overnight announcements. The price response takes place to a great extent during the pre-opening period and the first fifteen minutes after market opening. Jiang et al. (2012) examines price reactions triggered by earnings announcements that are published during non-trading hours. The authors document that during after-hours trading, which is primarily performed by institutional investors, price reaction shows a high degree of informational efficiency. In this study we confirm the large impact that information released overnight has on individual shares opening price. In addition, however, we also find a predictable pattern that realizes during the subsequent trading day. Thus we argue that the opening price is not perfectly efficient but is exposed to investor over- and underreactions. Berkman et al. (2012) states that investors are more likely buyers of stocks that attract their attention. As a proxy for investor attention the authors consider the squared previous day returns. They argue that at days of high investor attention, retail investors tend to herd into stocks at market opening leading to elevated overnight returns, which in turn leads to a reversal during the subsequent trading day. Thus, the authors document an inefficient market opening, an overreaction, that reverses during the subsequent trading session. In this study, we confirm the existence of this attention effect. In addition, we show that the inefficiency caused by investor attention is much smaller than the inefficiency caused by the interplay of previous day returns and overnight news sentiment.

Other related research papers that examine the impact of financial news on the stock market using sentiment analysis include Antweiler and Frank (2004); Bollen and Mao (2011); Kelly et al. (2019); Loughran and McDonald (2011); Tetlock (2007); Uhl et al. (2015), among others.

3 Data and Data Preprocessing

We consider a total of 1122 constituents that are listed in the S&P 500 from 1996 to 2020. Also, we use daily open and close prices as well as payout- and split-adjusted close prices from Refinitiv Datastream. From adjusted close prices we calculate corresponding same-day adjusted open prices for each asset i as

$$p_{i,t}^{adj.open} = \frac{p_{i,t}^{open}}{p_{i,t}^{close}} \times p_{i,t}^{adj.close}, \tag{1}$$

where $p_{i,t}^{open}$ and $p_{i,t}^{close}$ are the open and the close price of asset i on day t, respectively, and $p_{i,t}^{adj.close}$ is the payout- and split-adjusted Datastream close price on that day. We calculate simple close-to-close returns $r_{i,t}$ from adjusted prices (total returns) and dissect them into overnight returns $r_{i,t}^{c}$, when markets are closed (close$_{(t-1)}$-to-open$_{(t)}$ total returns), and returns during market activity $r_{i,t}^{o}$ (open$_{(t)}$-to-close$_{(t)}$ total returns), as shown in Figure 1. Then we calculate the idiosyncratic return components relative to the market model, where βs are calculated from weekly returns over a rolling window of two years. The further analysis of this paper is fully based on idiosyncratic returns. When we use $t-1$ open-to-close returns as predictive variable, we use z-scores $z_{i,(t-1)}$, calculated dividing idiosyncratic open-to-close returns, $r_{i,(t-1)}^{o}$ by the daily return volatility estimated over a rolling window of 6 month.

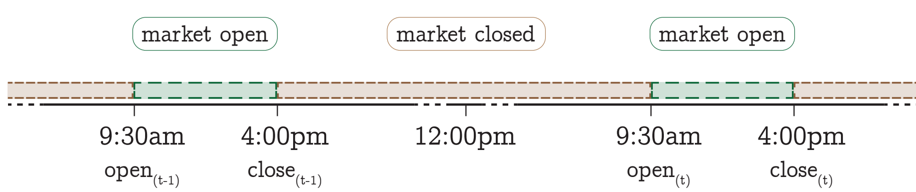

Figure 1: Market opening and market closing hours.

The financial news data is provided by Refinitiv (formerly Thomson Reuters). This comprehensive dataset contains news published between January 1996 to February

2020.[3] Each news article is tagged with metadata containing ticker codes of the companies mentioned in the news. After matching news to the set of S&P 500 companies, we find 812 unique ticker codes in the news metadata. As we focus on company-specific news articles, we restrict our data to news articles that contain either a company name or a ticker code in the headline. The content of these articles is usually more relevant to the targeted company than other, more general news. Then we feed each news article into a data cleaning pipeline, where the text is converted to lowercase and cleaned by removing all numbers, punctuation marks and brackets, so that only letters remain. In addition, irrelevant data such as the author's contact information, e.g. email addresses, phone numbers and hyperlinks, are also removed.

The release of Thomson Reuters financial news often occurs over several stages. First, a news alert is published which is followed by a news-break 5 to 20 minutes later. This is comprised of a headline and a short text. Another 20 to 30 minutes later, a news update is published with additional information. Further updates may be released successively as the story develops. In some cases, updates are released even days after the original news event. Consequently, using only the last updated status of a news article does not meet our need for a proper timing of the release of information. Our objective therefore is to use those versions of news articles that appear as early as possible and contain as much information as possible. As with the return data, we distinguish between news released during stock market closing hours and news released during stock market opening hours. If a news article is published during stock market closing (opening) hours and is then followed by several updates into the next trading session, we only consider the last update published before the market open (close). For the case when multiple news articles about the same company are published either during the stock market closing or opening hours, we combine them into a single news document. By doing so, we arrive at a total of 164,523 overnight and 109,952 daytime company-related news documents used in this study. An excerpt of news articles including their predicted sentiment is shown in Appendix F.

[3] The dataset contains more than 40 million news items with exact timestamp of publication and complete tracking of update histories. We thank Thomson Reuters for providing the dataset.

4 Determining News Sentiment

Language models made a big leap forward with the publication of the transformer model (Vaswani et al., 2017) and the idea of transfer learning popularized with the publication of the BERT model (Devlin et al., 2018). Since then, language models grew steadily in size and are trained with increasing amounts of textual data. However, a model trained with all today's available data would introduce a look-ahead bias if applied in an historical context. A model would likely classify news articles dealing with a new virus variant discovered in China differently when also trained with text data containing all news stories and studies published during the recent pandemic. To rule out a look-ahead bias caused by the training data of the model, we train our own language model exclusively with historical news data. In order to be able to conduct an out-of-sample study over a period of 18 years, we retrain our model with new data every 2 years. The model we implement is a down-sized BERT-like model with a total of 18.95 million parameters.[4] This model is pre-trained exclusively on domain-specific Thomson Reuters financial news. Fine-tuning on the sentiment prediction task is performed on an annotated dataset with annotations automatically generated from the joint behavior of news stories and asset returns (z-scores) as described in Dangl and Salbrechter (2021).

5 Results

5.1 Overnight News and Overnight Returns

In this section we study the impact of overnight news on overnight returns thereby conditioning on news sentiment. Boudoukh et al. (2019) document that the release of overnight news is associated with a significant increase in contemporaneous overnight return variance. They do not consider news sentiment, hence, they study the non-directional effect of the sheer presence of overnight news. We classify news sentiment

[4] For a detailed description of the model architecture, hyperparameter choices and training settings see Dangl and Salbrechter (2021).

as positive, neutral, or negative and, thus, are able to identify the directional effect of overnight news on the overnight return. The market tends to open significantly higher (lower) if positive (negative) news is released. Figure 2 plots the idiosyncratic mean returns of stocks with positive (red) and negative (blue) overnight news together with the mean overnight return of firms for which no news is released (solid line) during the hours where the stock market is closed. Mean overnight returns are calculated over all observations with z-values of previous-day returns exceeding (falling below) the threshold values indicated on the abscissa of the plot. Specifically, negative news comes with an average overnight return of -101.42 bps (t-value = -41.39) while positive news come with an average return of 96.42 bps (t-value = 54.27) (see Table 1, Panel B and C).

Please note that the reported large predictive power of news sentiment on (contemporaneous) overnight returns can hardly be exploited by investors, since release occurs when the stock market is closed. The opening price (the overnight return) summarizes the aggregate reaction of investors to the news content and is, thus, a clear measure of how investors interpret the news. Sentiment classification is trained strictly out-of-sample. Consequently, we conclude that the sentiment assigned by the BERT-based model is a good representation of investors' news perception.

Results also indicate that previous-day returns are only weak predictors of overnight returns. Inspecting overnight returns of stocks without overnight news reveals the presence of the attention effect as reported by Berkman et al. (2012). I.e., unconditional on sentiment, large negative as well as large positive previous-day returns (allegedly creating attention) are followed by slightly positive overnight returns (investors tend to buy attention-grabbing stocks) in the range of 3.54 - 4.32 bps.[5] The directional effect of news sentiment is, however, many times larger and certainly dominates return figures. In particular, if attention is created by negative-sentiment overnight news, the opening price is not higher (as predicted by the attention effect) but significantly below the unconditional mean.

Figure 2 also reveals that the market reaction to positive as well as to negative

[5]See Table 1, Panel A (abs(z-value) ≥ 1.5).

sentiment news is influenced by previous-day returns. After days with extreme returns (z-values), the reaction to news sentiment seems to be mitigated. In Section 5.2 we identify the interplay of the z-value of previous-day returns and overnight news sentiment as a predictor of return reversal.

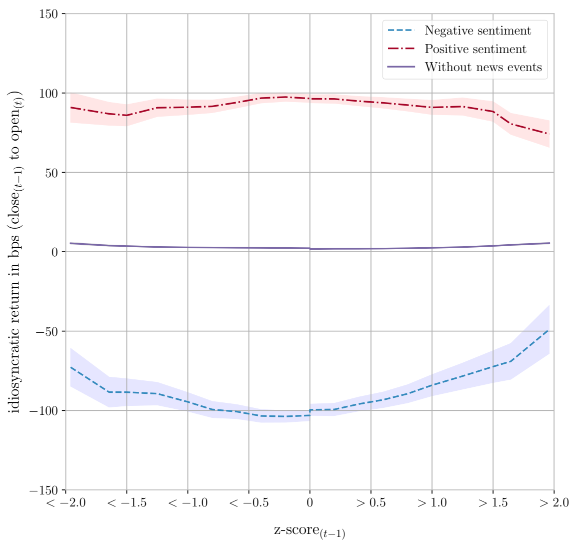

Figure 2: This plot shows the idiosyncratic mean returns in bps, measured from close$_{(t-1)}$ to open$_{(t)}$, conditional on both, the z-score at market close$_{(t-1)}$ and the predicted overnight news sentiment. The shaded area highlights the standard error of the returns. We consider all assets that are related to the published financial news articles and report the results over the time period from 2002 to 2020. For the correct interpretation of the results, it is important to note that we always consider all z-scores that are greater than > 0.0, > 0.5, > 1.0 etc. or smaller than < 0.0, < -0.5, < -1.0 etc.

z-score	≤ -1.645	≤ -1.5	≤ -1.0	≤ -0.2	≥ 0.2	≥ 1.0	≥ 1.5	≥ 1.645	(-∞, ∞)
Panel A: Without news events									
Mean	3.89***	3.54***	2.72***	2.36**	1.87*	2.49**	3.7***	4.32***	1.98**
SD	147.12	141.49	118.0	97.97	95.51	111.43	127.07	130.36	94.31
Std Err	0.49	0.42	0.23	0.11	0.11	0.22	0.37	0.43	0.07
t-value	7.87	8.43	11.75	21.64	17.33	11.34	9.95	10.09	29.39
Support	88,811	113,220	258,936	807,094	782,660	258,522	116,786	92,768	1,958,013
Panel B: Negative sentiment									
Mean	-88.42***	-88.47***	-94.57***	-103.75***	-99.35***	-84.07***	-72.36***	-69.05***	-101.42***
SD	476.29	465.51	431.71	410.12	409.48	438.1	479.03	493.18	407.63
Std Err	10.85	9.66	6.27	3.52	3.32	5.66	8.35	9.46	2.45
t-value	-9.32	-10.39	-15.95	-28.24	-25.3	-12.54	-7.19	-6.1	-41.39
Support	2,520	2,989	5,301	12,463	10,874	4,273	2,267	1,898	27,672
Panel C: Positive sentiment									
Mean	86.89***	85.94***	91.04***	97.45***	96.25***	90.92***	88.34***	80.56***	96.42***
SD	319.95	326.03	325.46	319.9	332.84	344.09	351.52	343.12	322.90
Std Err	7.26	6.73	4.68	2.78	2.78	4.5	6.26	6.67	1.78
t-value	11.97	12.77	19.45	35.01	34.65	20.2	14.1	12.08	54.27
Support	1,942	2,348	4,832	13,206	14,361	5,843	3,150	2,646	33,030

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1: Descriptive statistics of overnight returns measured from close$_{(t-1)}$ to open$_{(t)}$ (in bps) as displayed in Figure 2.

5.2 Overnight Reversal and the Asymmetric Reaction to News Sentiment

In this section, we discuss the impact of overnight news sentiment on subsequent daytime returns. Any predictability of subsequent daytime returns conditional on the overnight-news sentiment indicates that market open prices are not fully efficient after news is released. In contrast to the results documented in the previous section (contemporaneous overnight news and overnight returns), predictive information of overnight news can be exploited by entering a position in the opening auction.

We find a predictable reversal relative to the previous-day return which realizes during the trading day. This reversal is more pronounced the more extreme the previous-day return is. But this reversal is only present if overnight news is released. When extreme returns are followed by a night without company relevant news release, predictability is only marginal.

Figure 3 (a) and (b) illustrate the idiosyncratic returns conditional on $z_{i,(t-1)}$ and the overnight-news sentiment. Note, that in contrast to Figure 2 we aggregate the previous day's z-score $z_{i,(t-1)}$ into three subsamples according to it's value using the intervals

(-∞, -0.5], (-0.5, 0.5) and [0.5, ∞). This allows for easier interpretation as well as the use of statistical tests of the difference in mean and median returns in these buckets. Figure 3 (a) shows as in the previous section that overnight news sentiment strongly influences contemporaneous overnight returns, while the predictive power of $z_{i,(t-1)}$ is only weak. Figure 3 (b) shows the joint impact of $z_{i,(t-1)}$ and overnight news sentiment on the return of the subsequent trading day, $r^o_{i,t}$, i.e., the predictable reversal.

When the previous-day return is positive with $z_{i,(t-1)}$ above 0.5 and overnight news with strong sentiment–positive or negative–is released, we find a predictable reversal during the subsequent trading session, $r^o_{i,t} < 0$. Mean returns are -10.13 basis points when news sentiment is positive and -19.86 basis points when news sentiment is negative (with t-values of -3.98 and -5.03 respectively, see Table 2, Panel B and C). For negative previous-day returns with $z_{i,(t-1)}$ below -0.5 we detect again a predictable return reversal in the subsequent trading session, $r^o_{i,t} > 0$. Mean returns are 13.05 bps after news with positive sentiment and 10.87 bps after news with negative sentiment (with t-values of 4.68 and 2.56 respectively).

Without news release, if we solely condition on $z_{i,(t-1)}$, we observe an average open$_{(t)}$-to-close$_{(t)}$ return, $r^o_{i,(t)}$, of -4.03 bps if $z_{i,(t-1)}$ is above 0.5 and 0.67 bps if the z-score is below -0.5 (with t-values of -16.67 and 2.83 respectively, see Table 2, Panel A). Thus, in contrast to Berkman et al. (2012), who uses the squared return as a proxy for investor attention, we observe that the trading day reversal only exists after positive returns (z-scores). If the previous day's return is negative, the market tends to open slightly positive on average, but without a subsequent reversal.

Furthermore, if previous-day returns are comparably small (absolute z-values less than 0.5), we do not detect a significant reversal on the next trading day.

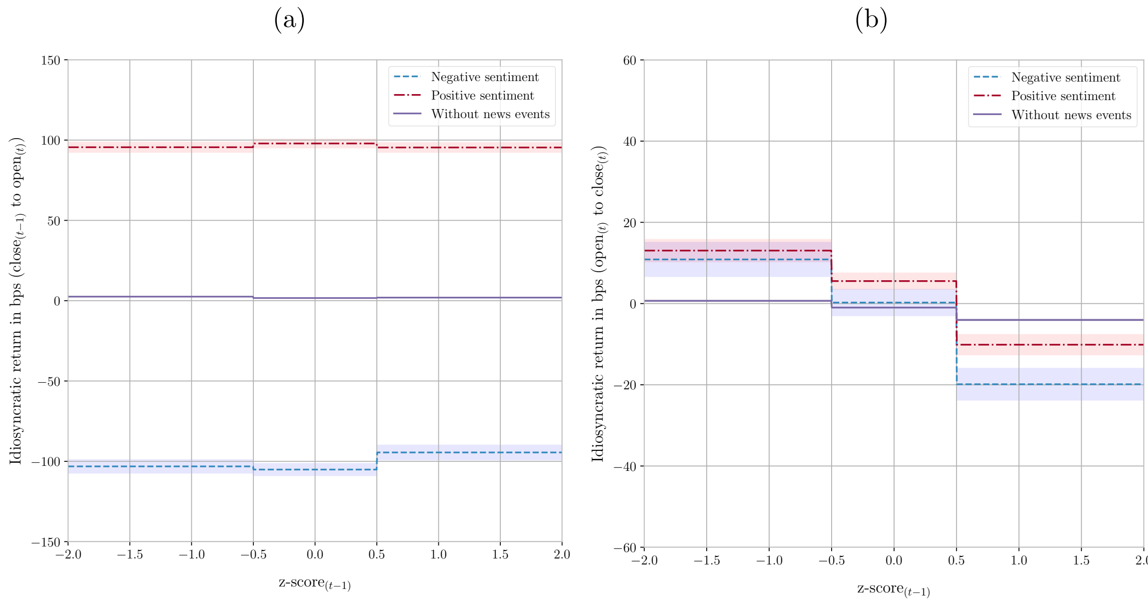

Figure 3: This plot shows the idiosyncratic mean returns in bps and the standard error, conditional on both, the z-scores measured at market close$_{(t-1)}$ and the predicted overnight news sentiment. We consider all assets that are related to the published financial news articles and report the results over the time period from 2002 to 2020. Figure (a) shows the idiosyncratic returns measured from close$_{(t-1)}$ to open$_{(t)}$, Figure (b) displays the idiosyncratic returns from open$_{(t)}$-to-close$_{(t)}$. The z-score subsamples we consider are the intervals: $(-\infty, -0.5], (-0.5, 0.5), [0.5, \infty)$.

	close$_{(t-1)}$ to open$_{(t)}$			open$_{(t)}$ to close$_{(t)}$		
z-score	$(-\infty$, -0.5]	(-0.5, 0.5)	[0.5, $\infty)$	$(-\infty$, -0.5]	(-0.5, 0.5)	[0.5, $\infty)$
Panel A: Without news events						
Mean	2.52***	1.66***	1.93***	0.67***	-0.99***	-4.03***
SD	103.55	83.92	99.97	176.05	153.09	176.65
Std Err	0.14	0.09	0.14	0.24	0.17	0.24
t-value	18.12	18.46	14.2	2.83	-5.96	-16.67
Support	553482	865875	538656	548654	857634	533999
Panel B: Negative sentiment						
Mean	-103.15***	-105.13***	-94.48***	10.87**	0.25	-19.86***
SD	411.92	397.24	416.09	406.84	334.46	350.54
Std Err	4.28	3.87	4.68	4.24	3.27	3.95
t-value	-24.08	-27.13	-20.2	2.56	0.08	-5.03
Support	9246	10510	7916	9196	10441	7870
Panel C: Positive sentiment						
Mean	95.54***	97.89***	95.39***	13.05***	5.54***	-10.13***
SD	318.06	324.97	324.62	269.14	232.26	260.42
Std Err	3.28	2.84	3.16	2.79	2.04	2.54
t-value	29.1	34.46	30.19	4.68	2.72	-3.98
Support	9387	13088	10555	9316	12988	10485
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 2: Descriptive statistics of overnight and daytime returns (in bps) as displayed in Figure 3.

In each of the subsamples formed on $z_{i,(t-1)}$, $(-\infty, -0.5], (-0.5, 0.5), [0.5, \infty)$, we group time t daytime returns into three groups: Observations that come after positive overnight news, observations after negative returns, and observations without related company-specific news.

As a robustness check and as an alternative test to the simple t-tests provided in Table 2, we use a Kruskal-Wallis test for differences in median returns. For each of the $z_{i,(t-1)}$ intervals, we test for differences in medians of $r^o_{i,(t)}$ conditional on the news sentiment (positive, negative, no-news) and find a significant variation in bucket medians.[6] We complement the Kruskal-Wallis test with a post-hoc Dunn's test, which tests for pairwise differences in medians. The result of the Dunn's test confirms predictability as diagnosed by t-tests, the corresponding p-values are shown in Table 3. When comparing the returns following positive or negative overnight news to the no news case, we observe that returns significantly deviate from the no news case when $z_{i,(t-1)}$ is large ($\text{abs}(z_{i,(t-1)}) \geq 0.5$). Moreover, the test shows that median returns after positive and negative news differ only when $z_{i,(t-1)}$ is positive. In the other subsamples, the difference is small, indicating that the actual news sentiment has only minor influence on daytime returns following overnight news.[7] If the previous day's z-score is small ($\text{abs}(z_{i,(t-1)}) < 0.5$), returns differ from the no news case only if positive news is released. In the case of negative news, the returns are not different from the case without news, indicating an efficient market in this case.

[6]The p-values of the Kruskal-Wallis test for the three buckets are: $p - value_{(-\infty,-0.5]} = 1.20e - 15$, $p - value_{(-0.5,0.5)} = 0.019$, $p - value_{[0.5,\infty)} = 2.12e - 15$.

[7]In contrast, for analyst forecast news, we observe a stronger impact of overnight news sentiment on daytime returns as shown in Section 5.5.

Z-score	$(-\infty$, -0.5]		(-0.5, 0.5)		$[0.5, \infty)$	
Sentiment	Negative	Positive	Negative	Positive	Negative	Positive
No News	0.041233**	0.000126***	0.885724	0.016725**	3.290547e-11***	0.001908***
Positive	0.209864		0.097544*		0.002795***	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: P-values of the Dunn's test for the cases of negative overnight news sentiment, positive overnight news sentiment and no overnight news for the three subsamples. As an adjustment for the p-values we use "holm", a step-down method using Bonferroni adjustments. The Dunn's test is performed over the full period from January 2002 to February 2020. A subperiod Dunn's test is provided in Appendix A.

At this point we want to provide a possible explanation for the underlying effects leading to the observed return reversal. Inefficiencies at market opening are likely caused by one or a combination of several behavioral biases, including confirmation bias (Nickerson, 1998), attribution bias (Daniel et al., 1998), and availability bias (Kahneman et al., 1982). People influenced by the confirmation bias tend to search for evidence that supports their prior beliefs while neglecting contradicting information. The attribution bias (biased self-attribution) let investors become overconfident when public information confirms their prior private views. If, on the other hand, new information contradicts their private views, they tend to underweight this news. Due to the availability bias, people tend to overweight recent and salient information which leads to the attention grabbing effect documented by Barber and Odean (2008).

In order to interpret the observed effects, consider the four cases: (1) positive z-score & positive news, (2) positive z-score & negative news, (3) negative z-score & positive news and (4) negative z-score & negative news. For case (1) we observe an overreaction to positive news at market open which then reverses during the trading day. This overreaction may be caused by investors seeking for confirmation of their prior believes (confirmation bias), or by confirmation of their private signals (attribution bias) by financial news. As $z_{i,(t-1)}$ is positive, we assume that their aggregate believes and private signals are also positive. If their prior believes or their private signals are confirmed by positive overnight news, they are more likely buyers at market open. Also, a combination of large previous day returns and salient overnight news increases investor attention which in turn also attracts more buyers (availability bias). This combined elevated buying pressure tends to results in an overreaction at market open which then tends to reverse during the following trading day. In case (2), however, investors tend to neglect (confirmation bias) or underweight (attribution bias) this contradicting information. This likely causes an underreaction at market opening. In addition, the availability bias induces buying pressure due to the salient information. This slightly elevates the opening price which in turn adds up to a strong reversal during the trading day.

In cases (3) and (4) $z_{i,(t-1)}$ is negative. Thus, we assume that investors' aggregate believes and private signals are also negative. In case (3), investors again tend to neglect or underweight the contradicting information. This causes an underreaction (reduced buying pressure) at market opening and a subsequent reversal in the positive direction. For case (4) we observe an overreaction to negative news at market open which then reverses (in the positive direction) during the trading day. This overreaction may be again influenced by the confirmation and attribution bias. If their prior believes or their private signals are confirmed by negative overnight news, they are more likely sellers at market open. The availability bias on the other hand should again induce buying pressure due to the salient information. This slightly elevates the opening price which in turn should lead to a slight reduction of the reversal in cases (3) and (4).

5.2.1 Event Study

The event study shown in Figure 4 displays the average price responses for the cases (1) to (4). We set the initial price to 100 and observe a time window of seven days including open (o) and close (c) prices. An event is triggered by $\text{abs}(z_{i,(t-1)}) \geq 0.5$ (tIc) followed by either positive or negative news articles published during market closing hours from $\text{close}_{(t-1)}$ to $\text{open}_{(t)}$ (to). From tIc to to a large price move in the direction of the news sentiment can be observed, as also shown in Figure 2. For the consecutive market open-to-close period (to to tc) declining prices can be observed in the case of positive z-scores, both for positive and negative news and increasing prices can be observed for negative z-scores, both for positive and negative news. Those results are in line with the observations in Figure 3.

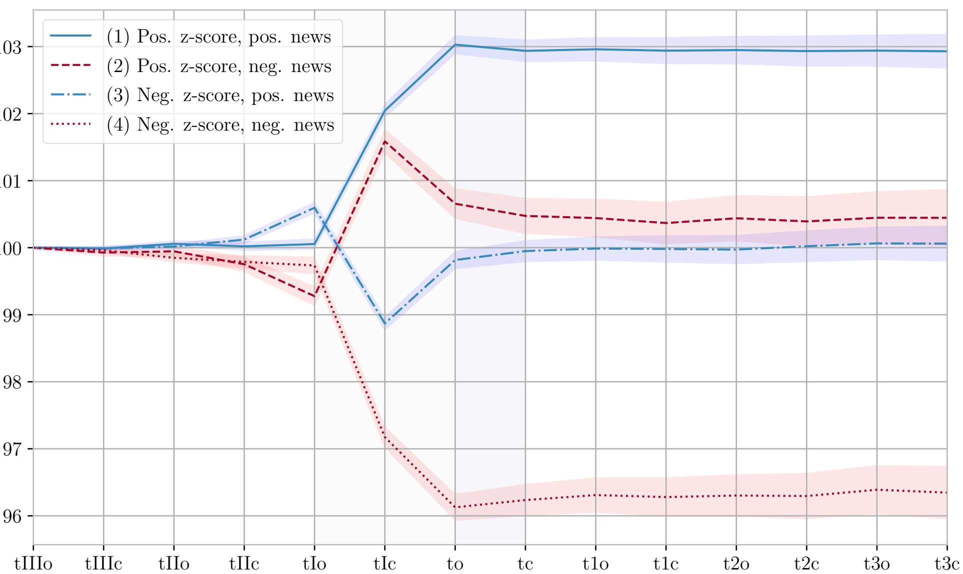

Figure 4: Event study showing the price response of the cases (1) to (4). Idiosyncratic daily returns are dissected into an overnight component (close-to-open) and into a daytime component (open-to-close). The returns are compounded starting with the close-to-open return three days prior to the news event *tIIIo* until the open-to-close return *t3c* three days after the news event. The z-scores are measured at *tIc* and the overnight news are released between *tIc* and *to*.

5.3 Regression Analysis

For the regression analysis we consider three predictive variables which are: (1) the z-score measured at market close $z_{(t-1)}$, (2) the overnight news sentiment[8] s_t and (3) the cross term $z_{(t-1)} \times abs(s_t)$. We regress (a) the idiosyncratic close$_{(t-1)}$-to-open$_{(t)}$ return and (b) the idiosyncratic open$_{(t)}$-to-close$_{(t)}$ return on these predictive variables. The regression results are presented in Table 4. Regression (a) shows that the overnight news sentiment has the greatest predictive power with a highly significant coefficient of 0.0108. Both the constant term and the cross term are significant as well, but with much smaller coefficients. The z-score of the previous close has no measurable impact on the opening price. The explained variance of this regression, R^2, is 2.19%. These results again show the large impact of overnight news on the opening price. For

[8]Note, that the sentiment score is a numeric variable ranging from -1 for negative sentiment to 1 indicating positive sentiment.

regression (b) we regress the idiosyncratic daytime return on the predictive variables and find that all coefficients are significant. The negative coefficient of $z_{(t-1)}$ indicates the existence of a slight reversal at daily frequencies. Furthermore, the coefficient of the overnight news sentiment is positive, while the coefficient of the cross term is negative. The significant cross term again underscores that overnight news sentiment, whether positive or negative, causes a reversal, irrelevant of the actual sentiment, due to investors over- and underreactions. This reversal is larger in magnitude for the combination of positive previous day's z-scores and negative overnight news. In regressions (c) to (e) we also control for (c) firm-fixed effects, (d) time-fixed effects and both, (e) firm and time fixed effects. We find that the results are robust after controlling for fixed effects.

	(a)	(b)	(c)	(d)	(e)
Const.	0.0002***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(25.164)	(-10.638)	(-10.638)	(-10.645)	(-10.643)
$z_{(t-1)}$	-0.0000	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(-1.017)	(-17.736)	(-17.881)	(-17.774)	(-17.921)
s_t	0.0108***	0.0003***	0.0003***	0.0003***	0.0003***
	(227.678)	(4.452)	(3.880)	(4.851)	(4.337)
$z_{(t-1)}$ x abs(s_t)	-0.0001***	-0.0005***	-0.0005***	-0.0005***	-0.0005***
	(-3.230)	(-9.055)	(-8.993)	(-9.045)	(-8.972)
Fixed effects	None	None	Firm	Date	Firm & Date
Observations	2,323,806	2,323,806	2,323,806	2,323,806	2,323,806
R^2	0.0219	0.0002	0.0002	0.0002	0.0002
F Statistic	17339.7211***	168.58***	168.82***	169.99***	170.14***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: This Table shows the results of the regression $r_t = \beta_0 + \beta_1 \times z_{(t-1)} + \beta_2 \times s_t + \beta_3 \times (z_{(t-1)} \times abs(s_t)) + \epsilon$. The dependent variables are (a) the idiosyncratic close-to-open return and (b) to (e) the idiosyncratic open-to-close return. The regression is performed over the full period from January 2002 to February 2020. In addition, regression (c) controls for firm fixed-effects, regression (c) controls for time fixed-effects (19 yearly time periods) and regression (e) controls for both time and firm fixed-effects.

5.3.1 Regressions over Subperiods

We perform the same regression as above over the three subperiods: 01/2002 to 12/2007, 01/2008 to 12/2009 and 01/2010 to 02/2020 (see Table 5). For open-to-close returns

(b) we note that the regression coefficients, as well as the R^2, are highest during the 2008 to 2009 financial crisis period. Furthermore, we observe that the coefficient of the cross-term (sentiment term) is larger (smaller) for the 2010 to 2020 period compared to the 2002 to 2007 period. Overall, the significance of the regression coefficients is strong.

	2002-2007		2008-2009		2010-2020	
	(a)	(b)	(a)	(b)	(a)	(b)
Const.	0.0003***	-0.0002***	0.0005***	0.0000	0.0000***	-0.0001***
	(26.4898)	(-10.2626)	(12.7150)	(0.6545)	(6.1106)	(-9.3683)
$z_{(t-1)}$	-0.0000***	-0.0002***	-0.0000	-0.0009***	0.0000**	-0.0001***
	(-3.7730)	(-8.9381)	(-0.3096)	(-16.1152)	(2.0379)	(-5.1588)
s_t	0.0109***	0.0007***	0.0133***	-0.0013***	0.0102***	0.0004***
	(127.7910)	(5.5920)	(57.6695)	(-3.5204)	(204.1787)	(6.1616)
$z_{(t-1)}$ x abs(s_t)	0.0003***	-0.0001	-0.0004**	-0.0019***	-0.0003***	-0.0003***
	(4.9931)	(-1.0504)	(-2.4884)	(-7.3597)	(-7.5418)	(-5.8074)
Observations	757,548	757,548	256,946	256,946	1,308,327	1,308,327
R^2	0.0215	0.0002	0.0128	0.0016	0.0309	0.0001
Adjusted R^2	0.0215	0.0002	0.0128	0.0016	0.0309	0.0001
Residual Std. Error	0.0108	0.0166	0.0191	0.0295	0.0090	0.0131
F Statistic	5542.7841***	39.2749***	1109.4759***	138.4413***	13907.4771***	36.7678***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: This Table shows the results of the regression $r_t = \beta_0 + \beta_1 \times z_{(t-1)} + \beta_2 \times s_t + \beta_3 \times (z_{(t-1)} \times abs(s_t)) + \epsilon$ over different periods. The dependent variables are (a) the idiosyncratic close-to-open return and (b) the idiosyncratic open-to-close return.

Figure 5 shows the realization of the daytime returns in these subperiods. During the 2008 to 2009 financial crisis period, we observe the largest magnitudes in daytime returns (see Figure 5c). These findings suggest that the intensity of the observed effects is amplified during periods of high uncertainty. For the pre-financial crisis period, we observe a reversal after positive z-scores ($0 < z_{i,(t-1)} < 1.0$) and positive news (case 1)[9] (see Figure 5b). However, with large positive z-scores, idiosyncratic daily returns tend to be positive in this sample. The most persistent effect we observe in all three subperiods is the underreaction to news that contradicts the direction of the previous day's returns, i.e., negative news after positive z-scores and positive news after negative

[9]We consider the four cases: (1) positive z-score & positive news, (2) positive z-score & negative news, (3) negative z-score & positive news and (4) negative z-score & negative news

z-scores (cases 2 & 3). Again we perform a Dunn's test (see Appendix A) for the different subperiods (Panel B to C) including a test for the entire period where we exclude the financial crisis period from 01/01/2008 to 31/12/2009 (Panel A). The test shows that the reversal of case (4) is driven by the financial crisis, as the reversal after a negative z-score and negative news is only significant during this period. However, the effects of cases (1) to (3) remain persistent after excluding the financial crisis period (see Appendix A, Panel A).

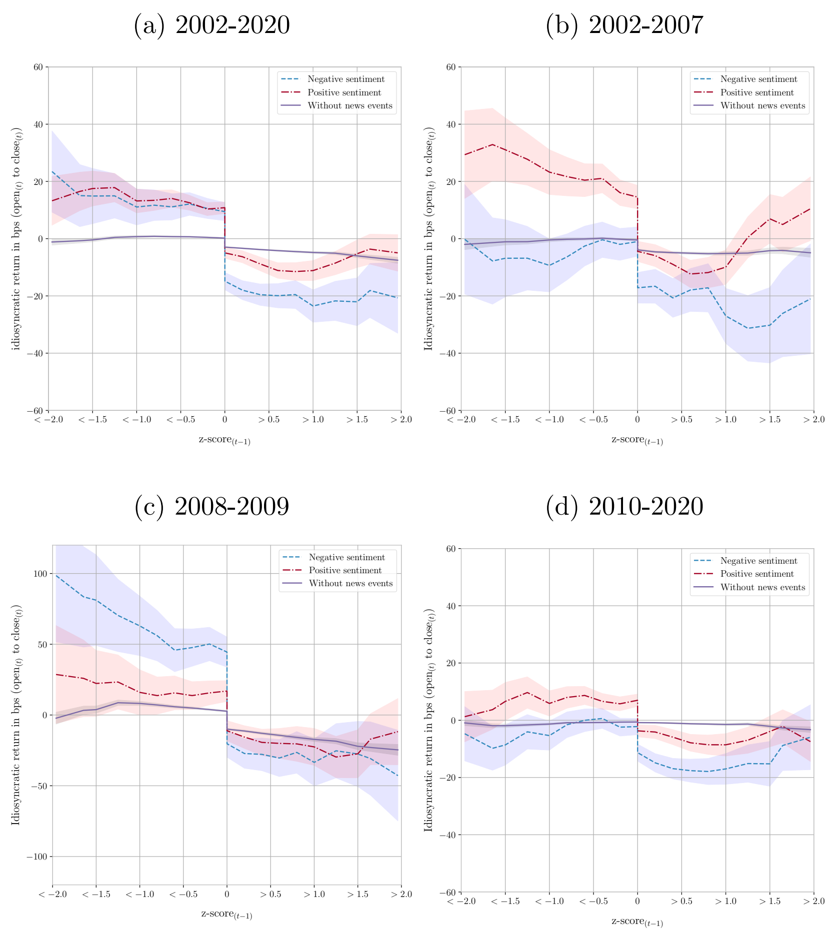

Figure 5: This plot shows the idiosyncratic mean returns in bps, measured from open$_{(t)}$ to close$_{(t)}$, conditional on both, the z-score at market close$_{(t-1)}$ and the predicted overnight news sentiment for different subperiods. The shaded area highlights the standard error of the returns. For the correct interpretation of the results, it is important to note that we always consider all z-scores that are greater than > 0.0, > 0.5, > 1.0 etc. or smaller than < 0.0, < -0.5, < -1.0 etc.

5.4 Daytime News and Overnight Returns

In this section, we examine the impact of news on asset returns for news articles published during the trading day. In particular, we investigate how well these news can explain both, idiosyncratic open$_{(t)}$-to-close$_{(t)}$ returns (daytime returns) as well as idiosyncratic close$_{(t)}$-to-open$_{(t+1)}$ returns (overnight returns). Therefore, we conduct a regression with the news sentiment as the only predictive variable and compare the results with the impact of overnight news. The results are summarized in Table 6.

First, we analyze how well news sentiment can explain returns over the same period, i.e., the extent to which daytime news explains daytime returns and the extent to which nighttime news explains nighttime returns (see Table 6 a and b). The explained variance, R^2 is 1.709% for the daytime period and 5.925% for the overnight period. Hence, the variance explained by financial news is 3.5 times larger in the overnight period than in the daytime period. Also, the coefficient of the sentiment term is closely twice as large for the overnight period relative to the daytime period (0.01081 vs. 0.00505). We argue that the reasons for this result are twofold. On the one hand, French and Roll (1986) find that volatility is higher during the day when the market is open than during the night when the market is closed.[10] On the other hand, Jiang et al. (2012) reports that 95% of firm relevant announcements are made outside the regular trading hours. Consequently, the impact of news published outside the regular trading hours has a more predictable impact on overnight returns since the volatility is lower during the overnight period and the news released during this period more likely affect stock prices. The opposite is true for daytime news.

Second, we analyze the impact of news on the subsequent period, i.e., we measure the impact of daytime news on subsequent overnight returns and the impact of overnight news on subsequent daytime returns. We find that neither the market closing nor the market opening price is fully efficient as the news sentiment still remains a significant predictor variable (see Table 6 c and d). However, the coefficient of the sentiment term is 60% larger for overnight news compared to daytime news (0.00024 vs. 0.00015).

[10] Our data also show this pattern (see Figure 9 in Appendix D)

Financial news released within a trading day are quickly incorporated into asset prices as Groß-Klußmann and Hautsch (2011) show. The authors examine the impact of company specific financial news on intraday trading activity using high frequency data and find a strong market response to relevant financial news within a window of 60 minutes prior and 120 minutes after the public arrival of news items. Hence, at market close news are already incorporated into asset prices to a great extent which is why the closing price has a higher degree of efficiency than the market opening price.

Furthermore, we analyze whether increased investor attention, due to the arrival of financial news, has an influence on returns on average. Therefore, we calculate the average return (constant term of the regression) for the same cases as above (Table 7 a to d), and also for the cases where no news is published, i.e., days where neither daytime nor overnight news is published (see Table 7 e and f). The results show that the average daytime return tends to be negative while the average overnight return tends to be positive (-1.5 bps vs. 1.6 bps).[11] In addition, we find that average daytime and overnight returns tend to be positive when news is published in the same period (Table 7 a and b) with mean returns of 1.20 bps and 5.80 bps respectively. Also, daytime and nighttime returns tend to be higher if news is released in the previous period (Table 7 c and d). The average overnight return is 113% (1.8 bps) larger if news is released in the preceding daytime period relative to the no news case (3.4 bps vs. 1.6 bps) and the average daytime return is 1.8 bps higher if news is released in the preceding overnight period (0.3 bps vs. -1.5 bps). Those results are in line with the findings of Berkman et al. (2012) who observes elevated overnight returns when investor attention in high. Our results suggest that the same is true for daytime returns when investor attention is increased due to salient overnight news.

[11] This result is consistent with the findings of Cooper et al. (2008). The authors find that the U.S. equity premium is determined entirely by overnight returns, which tend to be positive, while daytime returns tend to be zero or slightly negative.

	(a) daytime news & daytime returns	(b) overnight news & overnight returns	(c) daytime news & overnight returns	(d) overnight news & daytime returns
Const.	0.00039***	0.00022***	0.00035***	0.00003
	(5.59513)	(3.51179)	(8.71453)	(0.44073)
s_t	0.00505***	0.01081***	0.00015**	0.00024**
	(43.22846)	(100.86635)	(2.21665)	(2.34123)
Observations	107,388	161,525	105,297	160,198
R^2	0.01710	0.05926	0.00005	0.00003
Adjusted R^2	0.01709	0.05925	0.00004	0.00003
Residual Std. Error	0.02272	0.02521	0.01302	0.02366
F Statistic	1868.69975***	10174.02086***	4.91353**	5.48135**
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: This Table shows the results of the regression $r_t = \beta_0 + \beta_1 \times s_t + \epsilon$. The dependent variables are the idiosyncratic open-to-close (daytime) return and the idiosyncratic close-to-open (overnight) return. The regression is performed over the full period from January 2002 to February 2020.

	(a) daytime news & daytime returns	(b) overnight news & overnight returns	(c) daytime news & overnight returns	(d) overnight news & daytime returns	(e) no news & daytime returns	(f) no news & overnight returns
Const.	0.00012*	0.00058***	0.00034***	0.00003	-0.00015***	0.00016***
	(1.74412)	(8.95070)	(8.55154)	(0.57300)	(-12.48961)	(23.65438)
Observations	107,388	161,525	105,297	160,198	1,980,897	1,849,881
R^2	0.00000	-0.00000	-0.00000	0.00000	0.00000	0.00000
Adjusted R^2	0.00000	-0.00000	-0.00000	0.00000	0.00000	0.00000
Residual Std. Error	0.02292	0.02599	0.01302	0.02366	0.01651	0.00892
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 7: This Table shows the results of the regression $r_t = \beta_0 + \epsilon$. The dependent variables are the idiosyncratic open-to-close (daytime) return and the idiosyncratic close-to-open (overnight) return. The regression is performed over the full period from January 2002 to February 2020.

5.5 Impact of the News Topic

In this section, we examine how different news topics affect asset prices. Specifically, we consider the topics "analyst forecast" and "earnings report", i.e., we filter for news that are related to these topics.[12] Then we run regressions, as described in Section 5.3 for each subset of the news data. The results of the regressions are shown in

[12] In order to determine the news topic we use the Text2Topic approach as described in Dangl and Salbrechter (2021). This is done by computing topic loadings for each news article by calculating the cosine distance between all words in a news article and the predefined topic words using word vectors generated with word2vec.

Table 8. We find that the coefficient of the sentiment term is more than 4 times as large for analyst forecast news compared to general news (0.0013 vs. 0.0003). This causes quite a different pattern in open-to-close returns compared to the other subsets of news, as Figure 8 (a) shows. Analyst forecasts tend to cause return momentum since negative (positive) z-scores$_{(t-1)}$ tend to be continued with negative (positive) overnight and daytime returns. If we consider all news except analyst forecasts, see Figure 6 (c), we again observe a reversal which is stronger compared to the reversal observed in Section 5.2, since the contrarian effects attributable to analyst forecast news is eliminated. News marked as earnings reports show a strong reversal in the case of negative z-scores$_{(t-1)}$ and positive news, i.e., positive earnings surprises as Figure 6 (b) shows. This is also the case for positive z-scores and negative news, however, the effect disappears for z-scores greater than 1.5.

	(a)	(b)	(c)	(d)
Const.	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(-11.6554)	(-10.5624)	(-10.6178)	(-11.6332)
$z_{(t-1)}$	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(-16.6964)	(-16.5763)	(-17.6051)	(-17.8083)
s_t	0.0013***	0.0003***	0.0000	0.0003***
	(8.7235)	(3.2311)	(0.0645)	(2.9468)
$z_{(t-1)}$ x abs(s_t)	0.0004***	-0.0008***	-0.0008***	-0.0003***
	(3.9032)	(-9.1538)	(-13.1274)	(-4.3899)
Observations	2,099,597	2,122,527	2,226,202	2,203,272
R^2	0.0002	0.0002	0.0003	0.0002
Adjusted R^2	0.0002	0.0002	0.0003	0.0002
Residual Std. Error	0.0166	0.0169	0.0171	0.0168
F Statistic	120.9868***	139.5178***	199.2108***	127.4006***
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 8: This Table shows the results of the regression $r_t = \beta_0 + \beta_1 \times z_{(t-1)} + \beta_2 \times s_t + \beta_3 \times (z_{(t-1)} \times abs(s_t)) + \epsilon$ for the following news subsets: (a) analyst forecasts, (b) earnings reports, (c) all news except analyst forecasts, (d) all news except earnings reports. The dependent variable is the idiosyncratic open-to-close return and the regression is performed over the full period from January 2002 to February 2020.

(a) Analyst forecasts (b) Earnings reports

(c) All news except analyst forecasts (d) All news except earnings reports

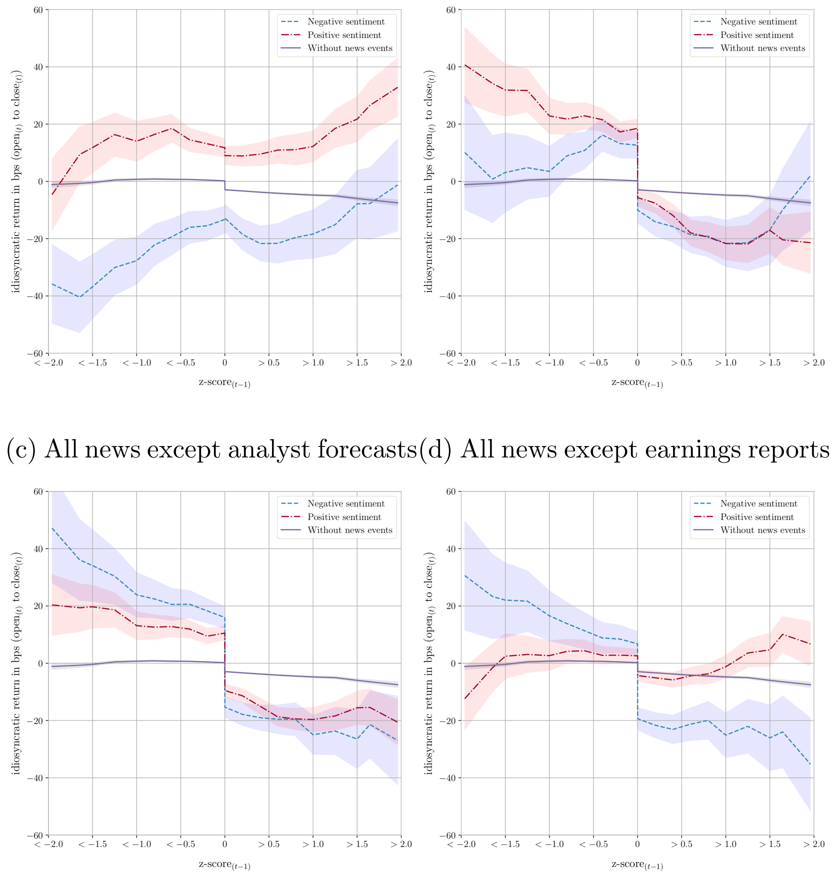

Figure 6: This plot shows the idiosyncratic mean returns measured from from open$_{(t)}$ to close$_{(t)}$ and the standard error, conditional on the z-scores measured at market close$_{(t-1)}$. We restrict the observations to news articles that are: (a) analyst forecasts, (b) earnings reports, (c) all news except analyst forecasts, (d) all news except earnings reports. The time period ranges from 2002 to 2020.

5.6 Backtest

To demonstrate that the observed effects are persistent and not solely driven by a small number of large impact events, we perform backtests utilizing the signals generated from financial news.

The trading logic we implement harnesses the inefficiencies caused by overnight news. We go long in stocks that either have a) positive overnight news of the topic analyst forecast and $z_{i,(t-1)} > 1.5$ or b) positive overnight news of the topic earnings report and $z_{i,(t-1)} <$ -1.0. In addition we short stocks with either c) negative overnight news of the topic analyst forecast and $z_{i,(t-1)} <$ -1.5 or d) negative news in combination with $z_{i,(t-1)} > 1.0$. This strategy is motivated by the findings of Sections 5.2 and 5.5. We enter trades at market open on day t and exit trades at market close on the same day. Moreover, the maximum weight is set to 100%, i.e., a maximum of 100% of the capital is invested in one asset within one trade,[13] portfolios are weighted equally.

The cumulative portfolio return of this strategy is shown in Figure 7, the corresponding statistics are displayed in Table 9. This strategy generates a return per trade of 26.17 bps in the long leg and 28.55 bps in the short leg with an average number of 1.87 trades/week in the long leg and 3.94 trades/week in the short leg. This results in a Sharpe ratio of 0.73 (0.85) in the long (short) portfolio and a Sharpe ratio of 1.31 in the long/short portfolio. The winning rate is 52.10% for trades in the long leg and 54.54% for trades in the short leg, i.e., the return on each trade is positive (negative) in 52.10% (54.54%) of the time.

	Performance (%)	CAGR (%)	SD (%)	Sharpe Ratio	Max. Drawdown (%)	Max. Drawdown (days)	Avg. nr. of trades per week	Avg. portfolio return (bps)	Avg. return per trade (bps)	Winning trades (%)
S&P500 Total Return	247.53	7.36	18.32	0.40	-58.67	1353.00				
S&P500 Price Index	142.86	5.19	18.32	0.28	-60.08	1516.00				
Long	1332.71	16.40	22.60	0.73	-57.88	1134.00	1.87	26.58	26.17	52.10
Short	5668.83	26.02	30.44	0.85	-54.38	832.00	3.94	-23.87	-28.55	54.54
Long/Short	91162.63	47.52	36.38	1.31	-59.75	279.00	5.82	32.01	27.79	

Table 9: Descriptive statistics of the backtest shown in Figure 7.

[13]A maximum weight of 100% is of course an extreme setting, by choosing a lower value, the portfolio volatility can be significantly reduced which in turn results in higher Sharpe ratios (see Appendix B). We have chosen the maximum weight of 100% to make the return per trade and the daily portfolio returns comparable.

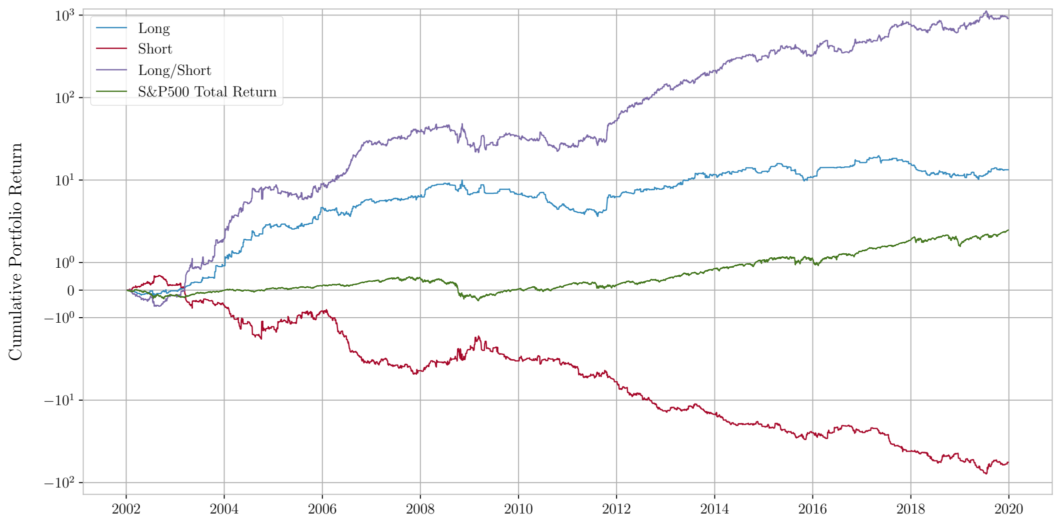

Figure 7: This figure shows the cumulative idiosyncratic returns of the long-, the short- and the long/short portfolio in comparison to the S&P 500 total return with transaction costs set to zero.

Table 9 reports the average daily portfolio return as well as the average return per trade. Most notably we observe that the average absolute return of the short portfolio is lower than the average return of all trades that enter the short portfolio. What this indicates is a tendency that the most profitable trades likely occur in clusters, i.e., on the same day. The equal weighting of returns then leads to an underweighting of these profitable trades. We examine this result in more detail by grouping returns according to the corresponding size of daily portfolios and compute descriptive statistics as shown in Table 10. Panel A shows the result for the entire period from 2002 to 2020, Panel B shows the results for the first subperiod from January 2002 to December 2009, and Panel C shows the results for the second subperiod from January 2010 to December 2019. We find that clustering occurs only for short trades and only in the first subperiod (Panel B). In this case, the return per trade and the winning rate increase quite substantially with increasing densities of trade signals and hence larger portfolio sizes. However, this pattern is not observed for returns of long trades in the first subperiod and also not for returns of long- and short trades in the second subperiod (Panel C).[14]

Assuming transaction costs of 10 basis points (20 bps per trade), which approxi-

[14]Returns that enter the long and the short portfolio tend to be distributed evenly across the entire sample period (see Figure 8 in Appendix C).

mates the average costs of large asset managers,[15] this strategy generates substantial excess returns in the first subperiod, but only minor excess returns in the second subperiod, presumably due to the increased efficiency of capital markets over the past decade.

	Long				Short			
Portfolio size	Avg. return per trade	SD	Winning rate	#Trades	Avg. return per trade	SD	Winning rate	#Trades
Panel A: Full Period, Jan 2002 to Dec 2020								
1	28.93 bps	2.99%	52.35%	831	-14.52 bps	3.15%	53.20%	1156
2	14.57 bps	3.09%	52.56%	430	-33.99 bps	3.39%	55.83%	1030
3	39.15 bps	3.24%	49.49%	198	-38.29 bps	2.93%	55.61%	597
> 3	26.64 bps	2.92%	52.51%	299	-33.66 bps	3.94%	54.09%	917
Panel B: Period Jan 2002 to Dec 2009								
1	45.69 bps	3.52%	56.37%	369	9.48 bps	3.63%	51.98%	531
2	51.81 bps	3.15%	56.33%	158	-67.17 bps	3.99%	57.68%	482
3	92.95 bps	3.55%	54.67%	75	-52.41 bps	2.95%	60.23%	264
> 3	3.04 bps	3.40%	45.33%	75	-44.93 bps	5.34%	52.63%	342
Panel C: Period Jan 2010 to Dec 2019								
1	15.53 bps	2.48%	49.13%	462	-35.02 bps	2.67%	54.24%	625
2	-7.23 bps	3.04%	50.37%	272	-4.93 bps	2.72%	54.20%	548
3	6.52 bps	3.01%	46.34%	123	-27.07 bps	2.91%	51.95%	333
> 3	34.57 bps	2.75%	54.91%	224	-26.97 bps	2.81%	54.96%	575

Table 10: We filter for trades that occur in portfolios of different sizes and report average returns per trade, standard deviations, winning rates and the number of trades.

6 Conclusion

In this study, we focus on information contained in financial news and its impact on the U.S. stock market. Previous research conducted in this area documents a quick response to news at the market opening (Boudoukh et al. (2019); Greene and Watts (1996); Jiang et al. (2012), among others). There is, however, a lack of literature analyzing the impact of overnight news by measuring news sentiment. We therefore train a modern BERT-based natural language model on the *Thomson Reuters* financial news database, which allows us to analyze the market reaction to news sentiment. We consider the U.S. market and a stock universe of S&P 500 companies. The interplay of previous-day returns with overnight news sentiment predicts *occurrence*, *direction*, and *magnitude* of an inefficient market opening, which in turn translates into a predictability of subsequent-day returns. In particular, we document a predictable return reversal of previous day returns on days

[15] Transaction costs of 10 bps are composed of bid-ask spreads, price impact and commissions as described in (Frazzini et al., 2018).

with company-relevant overnight news. When there is no overnight news, predictability is only marginal. This pattern comes from an asymmetric reaction of investors to news sentiment. Whenever overnight news sentiment confirms the direction of previous-day returns, the opening price tends to overreact to the news, a movement which is reverted on the subsequent day. When overnight news sentiment disagrees with the previous-day return, the market tends to under-react. A portion of the news content feeds into prices only during the subsequent day, resulting in a predictable return along the news sentiment. I.e., it also reverts the previous-day return. Hence, overnight news with strong sentiment predicts return reversal.

References

Antweiler, W. and Frank, M. Z. (2004). Is all that talk just noise? the information content of internet stock message boards. 59(3):1259–1294.

Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The review of financial studies*, 21(2):785–818.

Berkman, H., Koch, P. D., Tuttle, L., and Zhang, Y. J. (2012). Paying attention: overnight returns and the hidden cost of buying at the open. *Journal of Financial and Quantitative Analysis*, 47(4):715–741.

Bollen, J. and Mao, H. (2011). Twitter mood as a stock market predictor. 44(10):91–94.

Boudoukh, J., Feldman, R., Kogan, S., and Richardson, M. (2019). Information, trading, and volatility: Evidence from firm-specific news. *The Review of Financial Studies*, 32(3):992–1033.

Cooper, M. J., Cliff, M. T., and Gulen, H. (2008). Return differences between trading and non-trading hours: Like night and day. *Available at SSRN 1004081*.

Dangl, T. and Salbrechter, S. (2021). News sentiment and equity returns. *Available at SSRN*.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *the Journal of Finance*, 53(6):1839–1885.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Frazzini, A., Israel, R., and Moskowitz, T. J. (2018). Trading costs. *Available at SSRN 3229719*.

French, K. R. and Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of financial economics*, 17(1):5–26.

Greene, J. T. and Watts, S. G. (1996). Price discovery on the nyse and the nasdaq: The case of overnight and daytime news releases. *Financial Management*, pages 19–42.

Groß-Klußmann, A. and Hautsch, N. (2011). When machines read the news: Using automated text analytics to quantify high frequency news-implied market reactions. *Journal of Empirical Finance*, 18(2):321–340.

Jiang, C. X., Likitapiwat, T., and McInish, T. H. (2012). Information content of earnings announcements: Evidence from after-hours trading. *Journal of Financial and Quantitative Analysis*, 47(6):1303–1330.

Kahneman, D., Slovic, S. P., Slovic, P., and Tversky, A. (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge university press.

Kelly, B. T., Ke, Z. T., and Xiu, D. (2019). Predicting returns with text data. (2019-10):54.

Loughran, T. and McDonald, B. (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-ks. 66(1):35–65.

Michaely, R., Rubin, A., and Vedrashko, A. (2014). Corporate governance and the timing of earnings announcements. *Review of Finance*, 18(6):2003–2044.

Moshirian, F., Nguyen, H. G. L., and Pham, P. K. (2012). Overnight public information, order placement, and price discovery during the pre-opening period. *Journal of Banking & Finance*, 36(10):2837–2851.

Nickerson, R. S. (1998). Confirmation bias: A ubiquitous phenomenon in many guises. *Review of general psychology*, 2(2):175–220.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. 62(3):1139–1168.

Uhl, M. W., Pedersen, M., and Malitius, O. (2015). What's in the news? using news sentiment momentum for tactical asset allocation. *The Journal of Portfolio Management*, 41(2):100–112.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, 30.

Appendices

A Subperiod Dunn's Test

Z-score	$(-\infty, -0.5]$		$(-0.5, 0.5)$		$[0.5, \infty)$	
Sentiment	Negative	Positive	Negative	Positive	Negative	Positive
Panel A: Period 2002 to 2020, exlc. 2008 to 2009						
No News	0.459233	0.000431***	0.264434	0.010841**	2.219295e-10***	0.004286***
Positive	0.074001*		0.011481**		0.002547***	
Panel B: Period 2002 to 2007						
No News	0.932249	0.058648*	0.250728	0.161844	0.000152***	0.257995
Positive	0.213853		0.126007		0.035262**	
Panel C: Period 2007 to 2009						
No News	0.021630**	0.580282	0.203654	0.571911	0.024414**	0.377930
Positive	0.580282		0.643307		0.414816	
Panel D: Period 2010 to 2020						
No News	0.362556	0.005042***	0.632868	0.076837*	7.941048e-07***	0.009263***
Positive	0.293699		0.138845		0.026848**	
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 11: P-values of the Dunn's test for the cases of negative overnight news sentiment, positive overnight news sentiment and no overnight news for the three subsamples and multiple subperiods. As an adjustment for the p-values we use "holm", a step-down method using Bonferroni adjustments.

B Backtest - Descriptive Statistics

Table 12 shows the descriptive statistics of a backtest with the same trading strategy as described in Section 5.6, but with a limited maximum asset weight of 50%. Thus, if the portfolio consists of only one asset, 50% of the capital is allocated to the strategy, the remaining capital is allocated to the risk-free asset. This strategy achieves Sharpe ratios of 0.83 (1.20) for the long (short) portfolio and 1.60 for the long/short portfolio.

	Performance (%)	CAGR (%)	SD (%)	Sharpe Ratio	Max. Drawdown (%)	Max. Drawdown (days)	Avg. nr. of trades per week	Avg. portfolio return (bps)	Avg. return per trade (bps)	Winning trades (%)
S&P500 Total Return	247.53	7.36	18.32	0.40	-58.67	1353.00				
S&P500 Price Index	142.86	5.19	18.32	0.28	-60.08	1516.00				
Long	588.55	11.63	14.06	0.83	-37.11	988.00	1.87	16.58	26.17	52.10
Short	5212.65	25.43	21.17	1.20	-31.20	186.00	3.94	-20.77	-28.55	54.54
Long/Short	30669.80	38.65	24.09	1.60	-37.17	186.00	5.82	24.61	27.79	

Table 12: Descriptive statistics of a backtest with the trading strategy described in Section 5.6 and a maximum asset weight of 50%.

C Return Scatter-plots of the Backtest Strategy

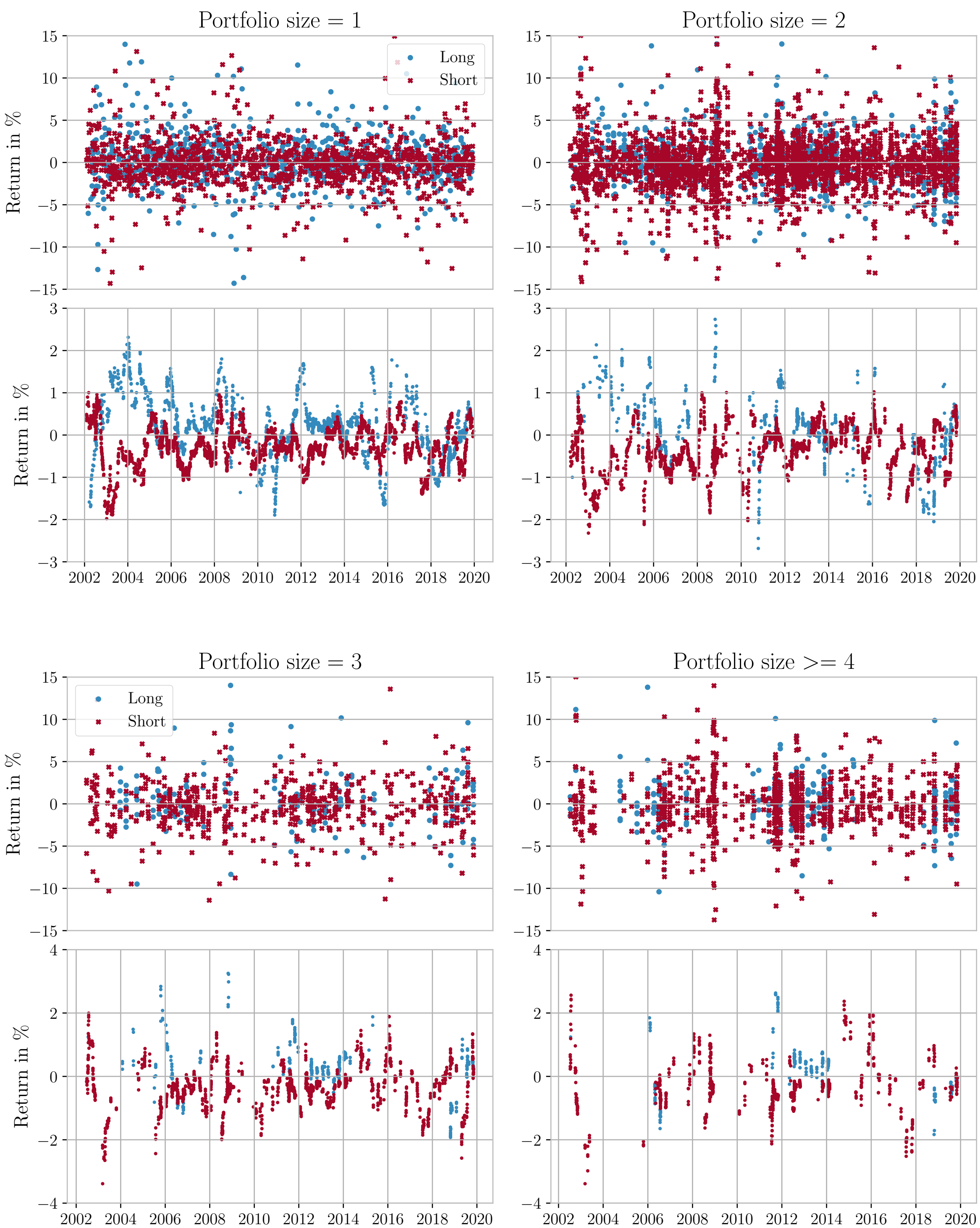

Figure 8: Realized idiosyncratic returns that enter the long- and the short portfolio, filtered for different portfolio sizes. The bottom graphs shows the return per trades averaged over a rolling window of a half year (127 trading days).

D Return Variance: Overnight vs. Daytime

Figure 9 shows the distribution of (a) idiosyncratic overnight returns associated with positive and negative overnight news and (b) idiosyncratic daytime returns associated with positive and negative daytime news. It can be observed that the negative sentiment distribution is centered towards a negative mean, while the positive sentiment distribution is centered towards a positive mean. This pattern is stronger in the case of overnight returns, as overnight news tend to have a larger impact on overnight returns than daytime news has on daytime returns. Figure 9 (c) shows the distribution of the idiosyncratic overnight and daytime returns observed over the period 2002 to 2020. This figure shows that on average, overnight returns have a smaller variance than daytime returns. French and Roll (1986) also finds that daytime volatility is larger than overnight volatility. The authors argue that this is due to a) active trading during market opening times based on private signals and b) pricing errors that occur during trading hours. Since no trading happens during the overnight period, the average variance is smaller during this period. However, if we exclusively observe overnight and daytime returns that are directly affected by the release of news with strong sentiment, either positive or negative, the variance of overnight returns is almost identical with the variance of daytime returns (Figure 9 (d)). In Appendix E we investigate in more detail the impact of news sentiment on return variances.

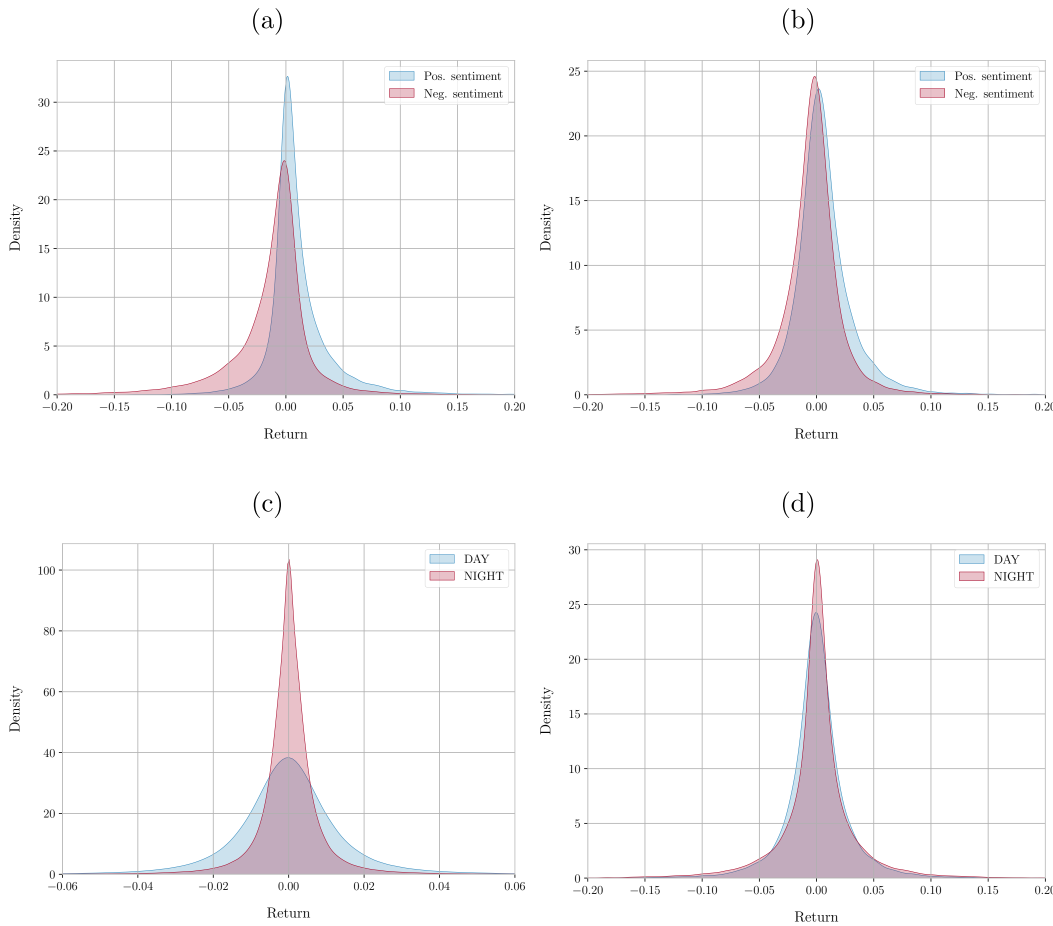

Figure 9: Density plots showing the distribution of (a) idiosyncratic overnight returns associated with positive and negative overnight news and (b) idiosyncratic daytime returns associated with positive and negative daytime news. Density plot (c) shows the distribution of all idiosyncratic overnight and daytime returns observed from 2002 to 2020 (Note the different scale on the abscissa!). Density plot (d) shows the distribution of overnight and daytime returns for observations where news with strong sentiment (*abs(sentiment)* $\geq$ *0.9*) is released in the overnight and in the daytime period, respectively.

E Volatility Analysis

In this study we find a strong link between news arrival and asset returns. In addition, we now also quantify the impact of news on the return variance for both, the overnight and the daytime period. Thereby, we follow a similar approach to Boudoukh et al. (2019). As a measure of return volatility we consider the squared z-scores.[16] The z-

[16]While Boudoukh et al. (2019) sort daytime and overnight returns into percentiles separately for each stock and year to control for cross-sectional variation in total returns, we do not split for individual stocks but consider z-scores instead of stock returns to control for the cross-sectional variation in returns.

scores are calculated over a rolling window of 6 month for the daytime period using open-to-close returns $r^o_{i,t}$ and for the overnight period using close-to-open returns $r^c_{i,t}$. The squared z-scores are then assigned into percentiles which are the 20% most extreme values, the moderate 40% and the smallest 40%. Moreover, we define strong news, i.e., news with a clearly positive or negative sentiment ($abs(sentiment) \geq 0.9$). Columns one to three of Table 13 report the change of the quantiles relative to the unconditional expectation.[17] Daytime effects are displayed in Table 13, Panel A. The data shows that large price changes are 35.65% more likely if news is published and 84.42% more likely if strong news is published. Moreover, Panel B shows that overnight news releases make extreme price changes in overnight returns even more likely. If news (strong news) is published, it is 80.23% (182.77%) more likely to observe large price changes.[18] In order to determine whether the return variance significantly differs between news arrival and no news arrival we perform a variance ratios test.[19] The variance ratio is reported in Table 13. We note that the variance ratio is significant in all cases, which means that the variance upon news arrival is significantly different from the variance observed upon no news arrival. Moreover, the variance ratio is larger during the overnight period. Specifically, for strong news the variance ratio is five times larger (17.26 vs. 3.45) in the overnight period compared to daytime period. This is partly due to the fact that important announcements with large price impacts, such as earnings announcements, are mainly published during stock market closing hours.[20] Furthermore, the fact that the average variance is smaller for the overnight period (Figure 9c), but almost identical to the daytime period when news is published (Figure 9d) also explains the larger variance ratios for the overnight period.

[17] For example, if 40% of the observations, conditioned on strong news, are in the extreme 20% percentile, then the reported change would be 100% $((0.4/0.2) - 1)$.

[18] In this study we only consider firm-relevant news articles, which are news articles where either the company name or the ticker code is mentioned in the headline. The use of relevant news articles explains why news without strong sentiment is also associated with large return volatility.

[19] As described by Boudoukh et al. (2019).

[20] Our data includes 22.957 earnings related news published overnight in contrast to only 6.851 earnings news published during trading hours. The increasing release of earnings reports during market closing hours is in line with the findings in the literature (see Jiang et al. (2012) and Michaely et al. (2014)).

		Extreme 20% (%)	Moderate 40% (%)	Low 40% (%)	Var Ratio	Support
Panel A: Daytime						
	Total	0.00	0.00	0.00	1.03***	3206603
	No News	-1.20	0.20	0.40	1.00	3102406
	News	35.65	-5.99	-11.84	1.97***	104197
	Strong News	84.42	-14.55	-27.66	3.45***	33787
	Strong News of Topic 1	94.97	-15.63	-31.86	3.11***	5452
	Strong News of Topic 2	142.12	-26.91	-44.15	4.81***	6410
Panel B: Overnight						
	Total	0.00	0.00	0.00	1.31***	3275806
	No News	-4.07	0.76	1.27	1.00	3117794
	News	80.23	-15.03	-25.08	7.37***	158012
	Strong News	182.77	-39.22	-52.17	17.26***	50437
	Strong News of Topic 1	159.35	-31.07	-48.60	7.31***	9811
	Strong News of Topic 2	238.68	-53.64	-65.70	22.29***	22775
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 13: We transform daily returns into z-scores and sort these z-scores into percentiles, the extreme 20%, moderate 40% and low 40% for (A) the daytime period (open-to-close) and (B) the overnight period (close-to-open). In the first three columns we report the conditional change of percentile counts relative to the unconditional expectation. The fourth column reports the variance ratio - the variance of returns conditional on news arrival relative to the variance of no news observations. News of topic 1 are analyst forecasts and news of topic 2 are earnings reports.

Figure 10 shows the squared z-scores sorted into deciles ranging from q1, containing the 10% lowest values to q10, containing the 10% most extreme price changes. If we do not filter for news, the counts for each quantile are evenly distributed with a slight decline for extreme values (No News). Those extreme price changes are observed to a large proportion if we condition on the arrival of news. Extreme price changes are most likely if we condition on earnings reports with a large sentiment score (Strong News of Topic 2).

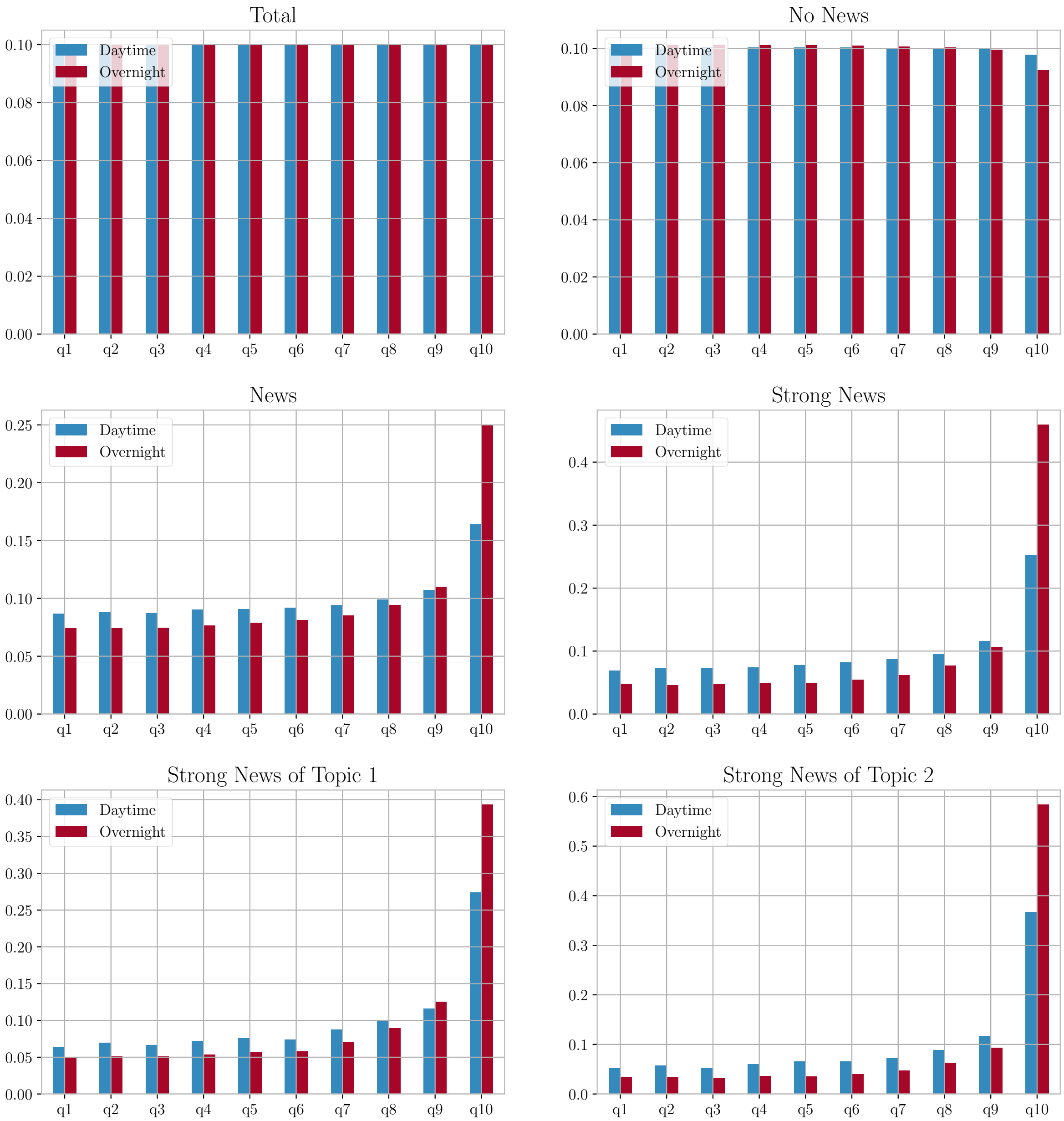

Figure 10: We sort the squared z-scores into deciles ranging from q1, containing the lowest values to q10, containing the most extreme price changes, separately for the daytime period and the overnight period. Strong news are news with a strong sentiment score (*abs(sentiment)* $\geq$ *0.9*).

F News Data Excerpt

Timestamp	Ticker	Sentiment
21.06.2002 09:29	XEL	-0.99
... morgan stanley said it cut its rating of electricity and natural gas company xcel energy inc to equal weight from overweight on friday citing uncertainty over earnings and dividends and its subsidiary nrg energy inc morgan stanley said in research note there is chance that xcel which traditionally considers its dividend in june could decide next week to reduce its payments to shareholders the investment firm also said that xcel is facing pressure from ratings agencies over its affiliate nrg morgan stanley forecast that recent decision by connecticut regulators means the company forecast could come down further xcel said on tuesday that decision by connecticut regulators to deny rate increase could cut its income by million month the firm also said xcel earnings per share could be diluted as it expects the company to issue equity xcel closed thursday at per share ...		
12.05.2003 08:42	HIG	-0.96
... insurer hartford financial services group inc on monday said it would cut jobs or about percent of its staff and boost its asbestos reserves by billion the company based in hartford connecticut said it had loss of billion or share for the first quarter largely because of the reserve addition in the year earlier quarter it had profit of million or share new york may insurer hartford financial services group inc on monday said it would cut jobs or about percent of its staff and boost its reserves for asbestos claims by billion the company also said it would beef up its balance sheet by raising billion through stock and debt offerings and would pull out of the property casualty reinsurance business it said it was already in talks to sell its hartre unit as result of the asbestos reserve worth billion after tax hartford said it lost billion or share in the first quarter in the year earlier quarter ...		
20.10.2009 08:12	AAPL	0.99
... jp morgan expects apple annual revenue growth story to trend deep into double digit territory jp morgan expects increasing revenue growth out of apple in driven by sustained momentum in mac and iphone jp morgan says except for apple most other it hardware peers will have upside potential more on bottom line versus topline lance knobel is guest columnist the views expressed are his own he is an independent strategy advisor and writer based in the united states his professional site is www lknobel com by lance knobel berkeley calif oct here how bullish steve jobs and his colleagues at infinite loop in cupertino feel after blowout september quarter...		
19.01.2012 20:04	INTC	0.99
... intel corp shares were up percent after the bell as it reported results revenue also meets expectations gaap eps cents shares up after earnings report san francisco jan intel corp forecast quarterly revenue in line with wall street expectations as shortage of hard drives disrupts pc production in market already hobbled by shaky economy and growing preference for tablets intel said revenue in the current quarter would be billion plus or minus million analysts on average had expected current quarter revenue of billion according to thomson reuters the world leading chipmaker said revenue in the fourth quarter was billion up percent and slightly higher than the billion expected ...		

Table 14: This table shows excerpts of news from the Thomson Reuters dataset along with the predicted news sentiment (positive: *sentiment* $\geq$ *0.95*, or negative: *sentiment* $\leq$ *-0.95*).