PROBABILITY
& PARTNERS

News Sentiment and Corporate Bond yields

By Svetlana Borovkova and Zhiyu Zhang

Abstract

How company-specific news affect bonds issued by that company? This is the question we answer in this paper.

Using Refinitiv News Analytics and an extensive dataset of over 6000 corporate bonds of large US companies, we show that increasing positive sentiment of company-related news leads to a decrease in bond yields, indicating higher investor confidence. When sentiment deteriorates, this affects bond yields to a larger extent, meaning that, as in equities, more credence is given to negative news by bond market participants.

We employ regression models to demonstrate these effects on a company level, and show that companies with lower credit ratings are more likely to be affected by changes in news sentiment. Furthermore, simple sentiment-based bond trading strategies show improved performance over the bond benchmark. Finally, we note that news sentiment can be used as an effective risk overlay, to avoid losses on bond portfolios.

1 Introduction

Sentiment in news and social media is a type of alternative data which is increasingly used as a signal in quantitative investing and trading strategies. For equities and equity indices, it has been repeatedly demonstrated that adding sentiment as a signal improves portfolio performance: it has a potential to generate alpha and to significantly reduce risk. However, there is practically no evidence on the impact of news sentiment on the performance of corporate bonds. With this paper, we aim to fill this gap. We explore the relationships between news sentiment and the yield spreads of US corporate bonds, using Refinitiv News Analytics and a rich dataset encompassing 6000 bonds of over 600 companies over the past 12 years.

Numerous studies have been conducted on the role news sentiment plays in equity markets, and sentiment-based signals are commonly used by trading firms and asset managers. Numerous papers by Borovkova et al. ((Borovkova, Garmaev, Lammers, & Rustige, 2016), (Borovkova & Lammers, 2018), (Borovkova & Mahakena, 2015), (Borovkova & Reiniers, 2021)) have explored various ways sentiment can add value in terms of return and risk, for equity and commodity portfolios: for example, by using it as a systemic risk indicator, in sector rotation or multifactor strategies. A recent study by (Dangl & Salbrechter, 2021), who also used Refinitiv News Analytics, has shown that financial news carry information that is not immediately reflected in equity prices, and news is largely priced-in within one day.

Although the interaction between news sentiment and equity returns has been explored to a great extent, the impact of sentiment in bond markets is much less understood. Evidence to that end is overdue, as bond investing attracts a lot of capital and is a crucial part of a well-diversified portfolio, especially during current volatile times.

At the time of writing, the stock market barely recovered from the crash induced by COVID-19 and is now under the influence of current global turmoil. The year-to-date return of S&P 500 index is a disappointing -13.31% and that of STOXX Europe 600 is -9.40%. Not everyone can bear such a downside. For more conservative investors, fixed-income instruments such as government and corporate bonds provide a better alternative. Fixed-income securities are characterized by their ability to provide a steady flow of cash, as long as the issuer does not default. Sovereign bonds of developed market are normally considered risk-free, but their return is unsatisfactory. The average level of 1-year Treasury yield in 2021 was only 0.2%.

Corporate bonds, on the other hand, generate better returns, while still having much lower risk

than equities. The U.S. Corporate AAA Effective Yield last year was around 1.8%, which is tenfold of the Treasury yield. Being less volatile than stocks, corporate bonds have adequate liquidity and diversity, so that investors have the freedom to construct diversified portfolios and trade at any frequency.

One of the few papers on this subject: that of (Smales, 2016) - has shown that, for banks, there is a significant negative relationship between sentiment in news and changes in CDS spreads, and the relationship is asymmetric with negative news inducing a stronger effect than positive news. We are not limiting ourselves to a particular sector but investigate this relationship for corporate bonds of companies that are constituents of the S&P500 index. More precisely, here we investigate the following questions:

- Is there a significant relationship between sentiment in news, as measured by Refinitiv News Analytics, and corporate bond yield spreads?
- Is the relationship asymmetric, so that negative news have stronger effect on the yield spread?
- Does the extent to which news sentiment influence yield spread depend on the properties of a bond (credit rating, sector, etc.)?
- Can sentiment-based signals be incorporated in bond investing and what is the effect of them on the performance of bond portfolios?

In the following sections, we address issues such as the data we use in our investigation, methodology and various models that are used to answer the above questions, as well as describe the obtained results. But for an impatient reader, here we already will outline our main findings:

- There exists a significant negative relationship between news sentiment and corporate bond yield spread, with sentiment leading by approximately one day. Change in the news sentiment Granger-causes the change in yield spread.
- This relationship is asymmetric. Event study shows that negative news induces more significant response in yield spread.
- The impact of sentiment change on yield spread vary with a company's credit rating. The lower rated a company is, the more likely its yield spread is widened by a drop in the news sentiment. No obvious difference in this relationship is found among different sector.
- Portfolios of corporate bonds whose media sentiment is improving, outperform the benchmark, even for monthly rebalancing. Avoiding those bonds with declining sentiment also improves bond portfolio performance.

2 Data exploration

Our universe of corporate bonds covers the constituents of **S&P 500 Bond Index** as of December 2021. The S&P 500 Bond Index measures the performance of corporate dept issued in the U.S. by companies (and their subsidiaries) in the S&P 500 index[1]. It consists of a total of 5945 bonds issued by 657 companies, with credit ratings ranging from AAA to B (investment grade: AAA/AA/A/BBB and high yield: BB/B). Both the corporate bond data and news sentiment

[1] S&P 500 Bond Index Methodology, October 2021. https://www.spglobal.com/spdji/en/documents/methodologies/methodology-sp-500-bond-index.pdf

data concerning the bond issuers were collected for the time period January 2010 - December 2021, at the daily frequency.

We used the bond index constituents as of December 2021 because the data was collected at that moment, and historical constituent information of this bond index is not easily available. Additionally, the bond index only came into existence in 2015, but we needed data before year 2015 to obtain more robust outcomes. The inevitable consequence of this selection is survivorship bias - none of the bonds included in this research have a record of default, nor did any of the bond issuers go bankrupt. Thus, we missed a proportion of data points with high yield (because of the possibly low credit-worthiness of issuers) and low sentiment values, which could suppress the amplitude of real impact of sentiment on corporate bonds. Another thing worth noting is that a low-rated company usually does not stay in its credit rating group for long. It either moves up in rating or drops out of the index. This is another aspect that we could not account for, since it is difficult to track the credit rating of over 600 companies more than 10 years back. The overall effect would be the yield spread data reported here has a downward bias, due to lower credit risk. This is likely to downplay our results on the asymmetry of the sentiment-yield relationship, since declining sentiment would likely to result in more pronounced escalation of yield spread.

2.1 News sentiment data

The news sentiment data was provided by the Refinitiv News Analytics (formerly TRNA), which employs complex Natural Language Processing (NLP) algorithms that read and interpret all the real-time news items from Reuters Newswire and 80+ other sources. Powered by a unique computational linguistic processing system, news items are transformed into a format that can be directly consumed by algorithm trading schemes[2]. All the assets mentioned in a news item, specifically companies and commodities, are scored individually. Each time-labeled news item is characterized by the following attributes:

- **Asset ID:** The identifier of the company or commodity of interest, on an entity level.
- **Relevance:** A number between 0 and 1 which indicates how relevant the news item is to the company or commodity.
- **Sentiment:** The probabilities of the news item being positive, neutral or negative towards the company or commodity $sent^{pos}$, $sent^{neu}$ and $sent^{neg}$. These probabilities have to satisfy the condition that $sent^{pos} + sent^{neu} + sent^{neg} = 1$.
- **Novelty:** The number of news items with similar content that was previously published within a given time window, choice of which are 12 hours, 24 hours, three days, five days and seven days.
- **Volume:** The ex-post calculated number of repetitions of a certain news item after its first release, within a given time window. The choices for the time window are: 12 hours, 24 hours, three days, five days and seven days.

For the purpose of this research, we would like to concern ourselves mostly with the **Sentiment**. It is a common knowledge that media outlets can be biased and lacking consensus, rendering the sentiment probabilities $sent^{pos}$, $sent^{neu}$ and $sent^{neg}$ quite noisy and volatile. It is difficult to interpret these raw data or use them for the analysis. Hence, it is essential to process the data

[2]TRNA User Guide, 19 August 2019.

and extract the underlying de-noised sentiment signal. The methodology for this involves the application of Kalman filter, the computational detail of which is explained in e.g., (Borovkova & Mahakena, 2015). In short, the preprocessing steps can be summarised as:

1. Aggregate the news items for a certain company i on a daily basis.
2. Apply Kalman filter to extract the sentiment signal embedded in the noisy raw sentiment probabilities. The filtered probabilities are denoted as $\hat{sent}_{i,d}^{pos}$, $\hat{sent}_{i,d}^{neu}$ and $\hat{sent}_{i,d}^{neg}$, where d indicates the day.
3. Calculate the net company-specific daily sentiment as:

$$CS_{i,d} = \frac{\hat{sent}_{i,d}^{pos} - \hat{sent}_{i,d}^{neg}}{1 - \hat{sent}_{i,d}^{neu}} \tag{1}$$

The company-specific net news sentiment series $CS_{i,d}$ is then obtained. The values of $CS_{i,d}$ fall between -1 and 1. The more positive the number gets, the more optimistic the news item is towards the company, whereas a pessimistic sentiment is conveyed through a negative score. The market sentiment MS_d is the average of all the available company-specific sentiment scores over the index.

The level of media coverage for company depends on public interest and how influential the entity is. Among the 600+ companies investigated in this study, some very popular companies like Apple and Boeing are mentioned in approximately 20 news items per day on average. Other companies, e.g., Coca-Cola, though being an important part of the index, had just a few entries over the entire dataset. To obtain reliable daily sentiment values for individual companies, they have to have sufficient mentioning in news items. For that reason, restrict our analysis to the companies with sufficient media coverage, i.e., the average of 3 news items per day (among those are companies whose news flow is irregular, e.g., no news for many days, followed by heightened media attention during quarterly results announcements).

2.2 Corporate bond data

The historical corporate bond prices were downloaded from Refinitiv DataStream. The issuer of bonds can be identified with the same Asset ID as in the news sentiment data, which greatly enhances the efficiency of aligning bond and sentiment data. Besides the basic specifications of a bond, such as maturity, coupon rate and payment frequency, other relevant information is provided, e.g., whether the issuer is a financial institution or a corporate, and whether a bond has any option features.

We use Treasury yield of the same period as a reference, so that the macroeconomic component of prevailing interest rate is isolated from our bond yield. The data of Treasury yield rates are publicly available on the website of U.S. Department of The Treasury[3]. These rates are published for different maturities on each day, ranging from 1 month to 30 years, a total of 12 discrete data points. Treasury yields are not available for any maturity, for instance, 1.5 year, but might be needed for our analysis. So we fitted a Nelson-Siegel model of interest rate term structure (Nelson & Siegel, 1987) to each day's rates. A smooth curve is then obtained, which gives a fairly accurate approximation of Treasury yield term structure. An example of NS fitting is shown in Figure 1.

[3] https://home.treasury.gov

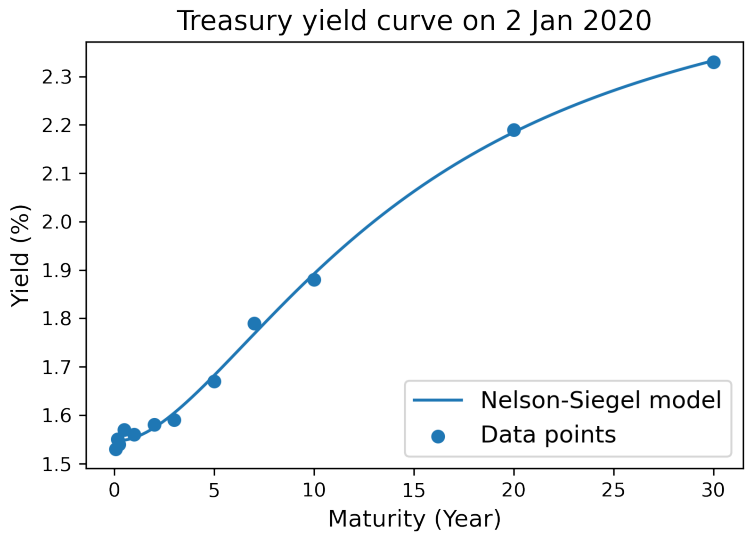

Figure 1: A sample of fitting Nelson-Siegel model to rates, January 2, 2020.

Subsequently, a bond's yield spread against Treasury yield can be calculated using the relationship:

$$P = C_1 e^{-[y(\tau_1)+YS]*\tau_1} + C_2 e^{-[y(\tau_2)+YS]*\tau_2} + \ldots + C_n e^{-[y(\tau_n)+YS]*\tau_n}, \tag{2}$$

where bond price P equals to the sum of all expected future payments C_k's, $k = 1, 2, \ldots, n$, discounted by its yield spread YS in addition to Treasury rate $y(\tau_k)$ of corresponding maturity τ_k. Company-level bond price and yield spread are simply the averages over all bonds issued by the company.

2.3 Exploratory data analysis

The descriptive statistics of all company-level daily bond yield spreads and news sentiment is shown in Table 1. For all companies, averages were first taken across the time period 2010-2020, and then cross-sectional means and standard deviations were calculated for groups of different credit ratings. The majority of our companies have ratings of either A or BBB, so that when equally weighted, the companies in these two credit groups will represent the general market.

As credit rating deteriorates, the average yield spread widens and volatility increases, as expected. The largest gap can be found between BBB-rated bonds and BB=rated, because that is the dividing point between investment-grade and high-yield. One exception is AAA-rated bonds, whose average yield spread is slightly higher than that of AA-rated bonds - this is due to only two companies belonging to this credit group, so a large uncertainty about the mean spread.

Regarding sentiment, we note that overall, the sentiment about S&P 500 companies and their subsidiaries is positive. An interesting observation is that highly-rated companies (AAA and AA) get rather neutral sentiment, and the most optimistic sentiments and were attributed to those whose credit ratings are in the middle. They also have higher standard deviations in sentiment, implying the swinging media's opinion about them. Companies with high credit

rating normally have few surprises and less news to inform the investors. At the same time, they grow at a much slower rate and offers less exciting updates on their development. On the contrary, the companies rated lower than AAA are much more adventurous, so that more growth and risk is expected and more news are generated in the course of their operation.

Table 1: Summary statistics of company-level daily bond yield spread and news sentiment during 2010-2021. The mean and standard deviation are all cross-sectional.

		Count	Mean yield spread (%)	Std. Dev. (%)	Mean sentiment	Std. Dev.
All		657	1.850	0.919	0.234	0.220
Credit ratings	*AAA*	2	1.021	0.03	0.000	0.051
	AA	15	0.981	0.311	0.010	0.190
	A	181	1.318	0.341	0.215	0.251
	BBB	368	1.771	0.572	0.242	0.196
	BB	67	3.047	0.923	0.291	0.231
	B	24	4.349	1.374	0.192	0.347

To give a bigger picture of the interplay between the yield spread and sentiment, the company-level data was aggregated on a weekly basis and plotted in the scatter plot in Figure 2. Companies from different credit groups are labeled with different colors, and the time period of interest was chosen to be during COVID-19 crisis, so that the distinction between groups is more visible. Log transformation was applied to the yield spreads for better visual representation.

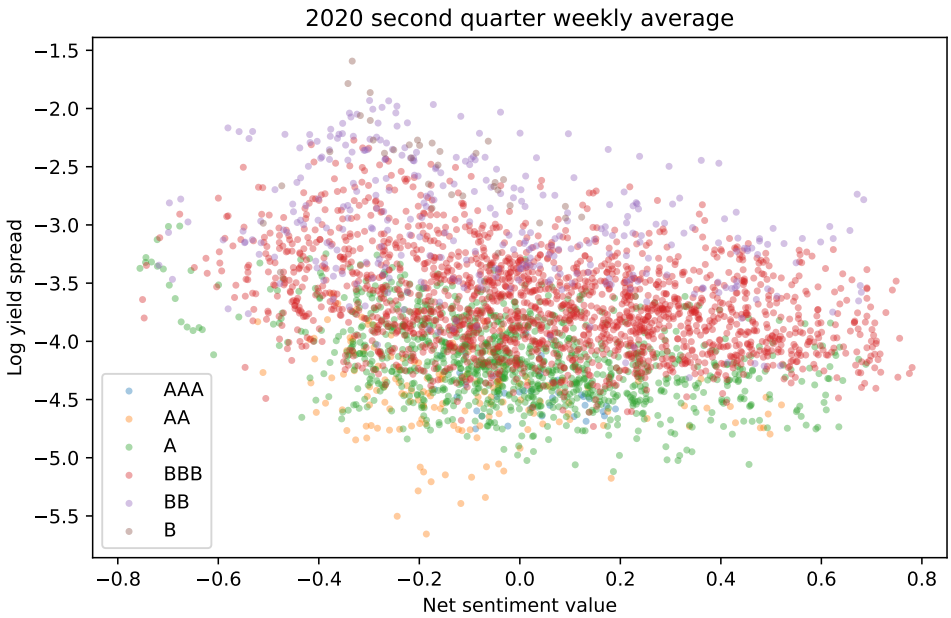

Figure 2: Scatter plot of company-level weekly average log-transformed yield spread against net sentiment value in the second quarter of 2020.

It is clear from the scatter plot that the better the credit rating, the lower the bond yield spread. In the same credit rating group, yield spread is lower for those companies with more positive news sentiment. For lower rated companies, their sentiment scores are more likely to be on the negative side, but for the others, sentiment scores are mostly neutral. A slightly negative relationship is observed already here, and we will further refine this observation in later sections.

Additionally, an Augmented Dickey-Fuller (ADF) test suggests that the time series of yield spread are not stationary, on both company and market level. Therefore, we applied first-order differencing to stationarize them. For later analysis, changes of yield spreads and news sentiment will be the objects of our study rather than the levels:

$$\begin{aligned} \Delta YS_d &= YS_d - YS_{d-1} \\ \Delta MS_d &= MS_d - MS_{d-1}. \end{aligned} \tag{3}$$

3 Sentiment-yield relationship

First, we present the results on the relationship between the news sentiment and yield spread on the market level. We show that there is a significant negative relationship between the yield spread and news sentiment. The effect varies with the specifications of bonds, e.g., the issuer's credit rating. Also, we show, in agreement with previous sentiment-related studies, that the relationship is asymmetric, so that a decrease in sentiment has a bigger impact on yield spread than increase in sentiment. A causal relationship is supported by Granger causality test, with sentiment being a leading indicator.

3.1 Market-wide assessment

The historic series of net market-level news sentiment (blue) and the average corporate bond yield spread (orange) are plotted in Figure 3. It is clear that the news sentiment and yield spread move in opposite directions: when sentiment increases, yield spread declines, and as sentiment falls, yield spread goes up.

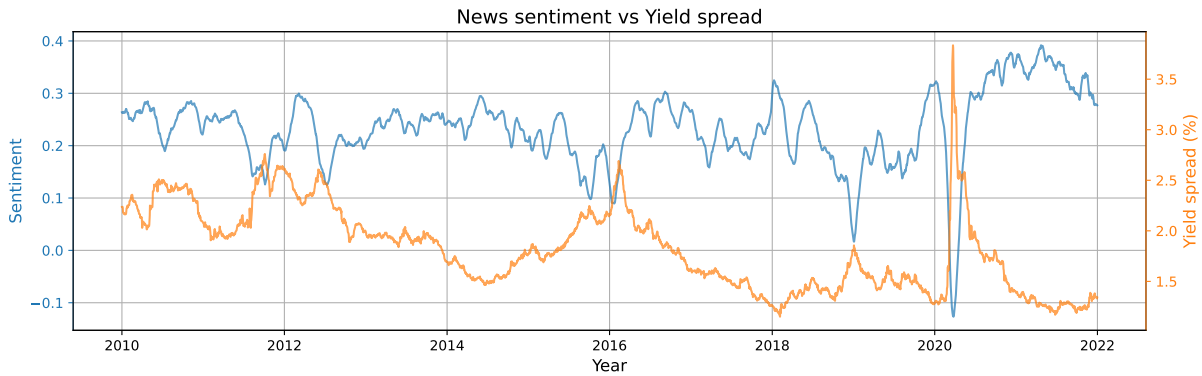

Figure 3: S&P 500 Bond Index news sentiment and average yield spread over the time period of 2010 - 2021.

It can be shown that the two series in Figure 3 are *cointegrated* of order 1: the linear combination of these series (in our case the sum) is a stationary mean-reverting process. This is consistent with our expectations. Yield spread is related to creditworthiness of a firm and this (percieved) creditworthiness declines when a firm is portrayed negatively in the news. For example, Figure 3 shows that in Q1 of 2020, yield spreads peak and sentiment plunged. As the economy slowly recovered later in 2020, sentiment re-bounced to a slightly higher level than before COVID-19 and yield spread dropped back down.

Figure 3 can be also interpreted from a supply-and-demand perspective. During depressed periods, investors have a inclination to sell, pushing down the prices of sufficiently liquid bonds.

Since bond yield increases as its price decreases, the yield spread is then widened by the elevated supply. Following the same reasoning, when there is a higher demand, bond price increases and yield spread narrows.

It turns out that the impact of news sentiment on yield spread varies with the borrower's credit rating. Figure 4 shows the average yield spread for the credit rating groups BBB (orange) and BB (red).

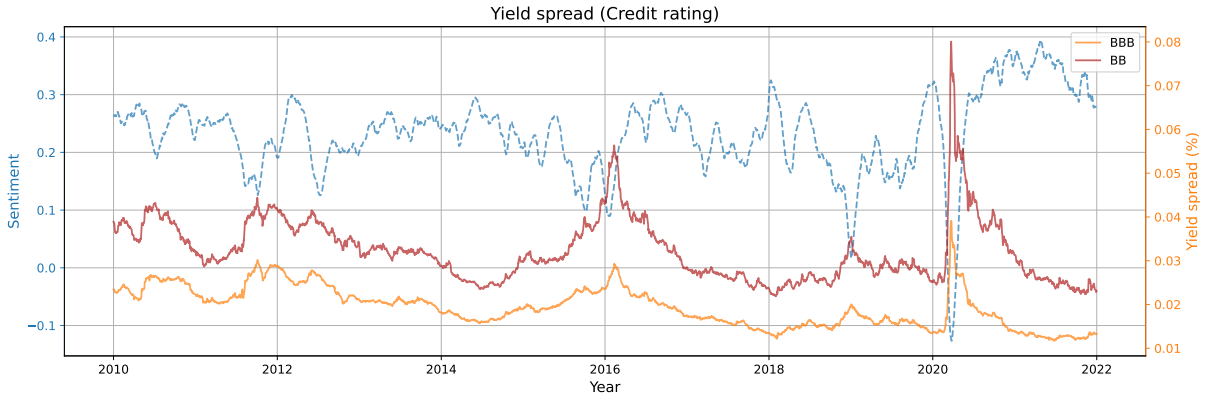

Figure 4: S&P 500 Bond Index news sentiment and average yield spread for different credit rating groups over the time period of 2010 - 2021. *BBB:* Investment-grade bond. *BB:* High-yield bond.

BB-rated bond yield spread fluctuates more with movements in sentiment: when the news sentiment falls, the yield spread of high yield bonds increases by a bigger amount than the investment-grade bonds. This is especially pronounced in periods of declining sentiment (and hence, rising yield spreads). The difference in BB and BBB yield spreads is most pronounced when the sentiment declines, from which we can deduce that high-yield bonds are less resilient to the sentiment-driven crowd selling than investment-grade bonds. In fact, people tend to switch from high-risk investments to lower-risk alternatives during market crash.

Already from these simple graphs it is clear that a negative relationship exists between news sentiment and corporate bond yield spread. This relationship is asymmetric and the impact of sentiment on yield spread varies with the characteristics of individual bonds, such as credit rating. To strengthen these observations, we use company-specific sentiment and yield spread, in Sections 4 and 5, and assess the magnitude of this relationship by means of regression models. But first, we will provide some further evidence on the asymmetry of the relationship, and see whether news sentiment is a leading indicator, i.e., that provides information ahead of yield spread movement.

3.2 Asymmetric relationship

To show the asymmetry of negative relationship between yield spread and sentiment, we performed an event study as outlined in Tetlock (Tetlock, Saar-Tsechansky, & Macskassy, 2008). An *event* day is defined as a day d on which the average change of market sentiment ΔMS_d passed the threshold of first (or last) decile. In other words, ΔMS_d falls in the top or bottom 10% of the ΔMS historical distribution, which is an empirical distribution constructed by records from the past year. The *event window* is 40 days (20 days before and after the event day). From the beginning of event window $d-20$, we start to accumulate ΔYS towards the other end of the window $d+20$, then see how positive events (ΔMS in top 10%) and negative events (ΔMS in bottom 10%) impact the development of cumulative ΔYS differently. The cumulative changes

of yield spread for all such event windows were averaged for both positive and negative events, and a graphic representation is shown in Figure 5. Over our 12 years of time period, there are more than 400 positive and negative events respectively.

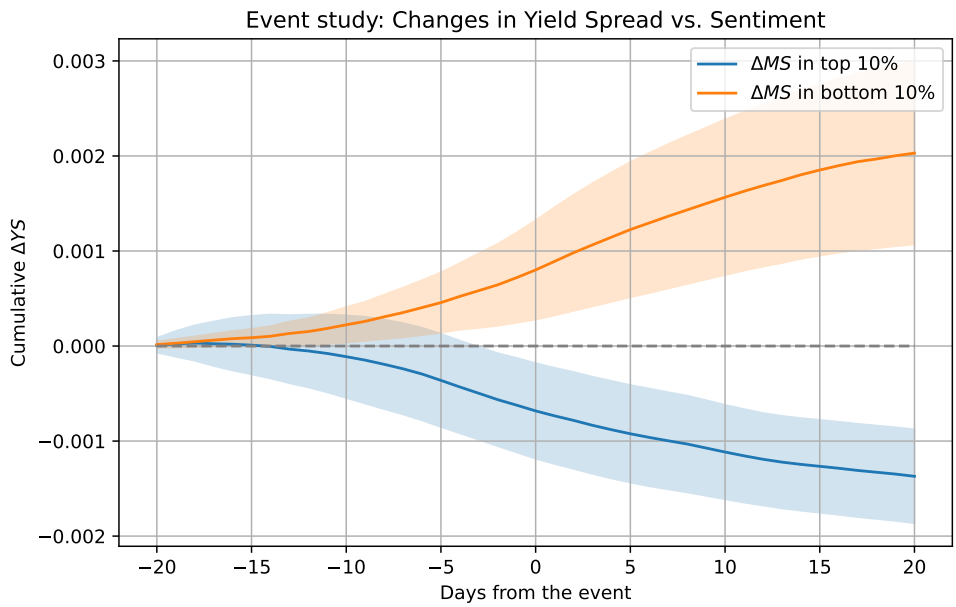

Figure 5: Cumulative changes of bond yield spread ΔYS for positive and negative events. *Positive event:* Change of market sentiment ΔMS in top 10%. *Negative event:* Change of market sentiment ΔMS in bottom 10%. Shaded area indicates ± 0.2 standard deviation.

Figure 5 clearly shows that, when the change of sentiment is positive, the change of yield spread is negative, and vice versa. For changes in yield spread corresponding to both positive and negative events, their cumulative values tracked from 20 days before the event to the event day are approximately the same, at a magnitude of 0.08%. An additional increase of 0.12% in yield spread can be observed 20 days after the event day in the case of negative events, while only a 0.06% decrease can be found when positive event happens. In real world terms, when a news is released with a negative sentiment, the credit market reacts more forcefully to it than to a positive news: a phenomenon frequently observed for equities and commodities.

3.3 Granger causality

Granger causality indicates *causal* relationship between two series, i.e., it assesses whether one series is useful in predicting another. Here we investigate whether the news sentiment is useful for predicting the yield spread. By determining the time lag that gives the best prediction results, we are also able to determine the speed of information propagation.

Using the daily market net sentiment change and yield spread change ΔMS_d and ΔYS_d, we perform the Granger causality test, by looking at the so-called *F-statistic*:

$$F_{df1,df2} = \frac{\text{Estimate of Explained Variance}}{\text{Estimate of Unexplained Variance}} = \frac{(SSE_{RM} - SSE_{UM})/df1}{SSE_{UM}/df2} \tag{4}$$

where $df1$ and $df2$ are the degrees of freedom of the restricted model RM (prediction model that uses only a series' own past history) and unrestricted model UM (model that also uses the history of another series) and SSE is the Sum of Squared Errors. The larger the F-statistic is,

the more variance is explained by the incorporation of the other lagged time series. The results of Granger causality test are demonstrated in Figure 6.

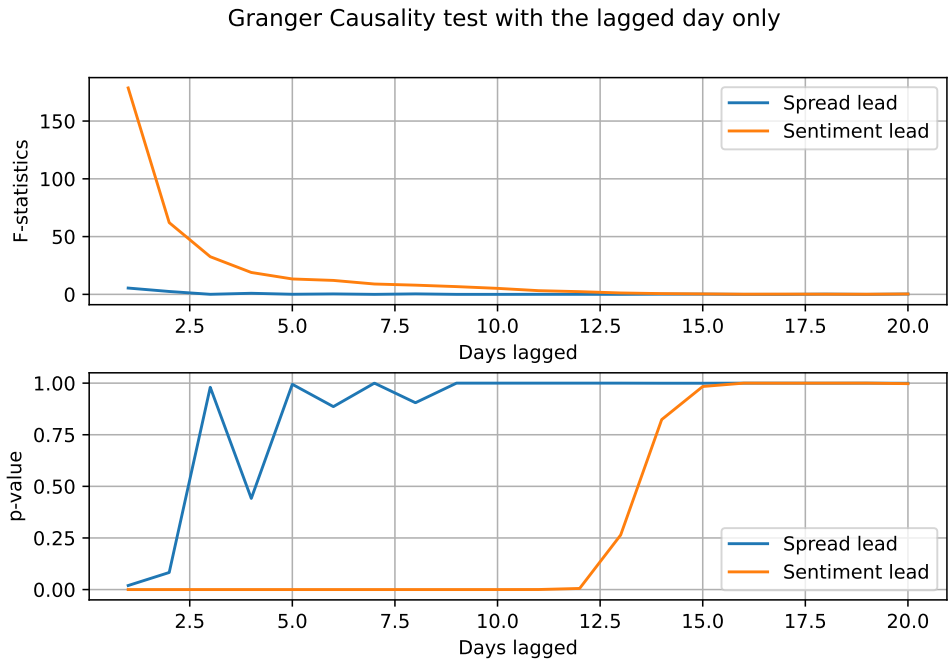

Figure 6: Results of Granger causality test on daily changes of market net sentiment and yield spread, for time period 2010-2021. Maximum lag is 20 days. *(Top)* F-statistics. *(Bottom)* P-values.

The top panel of Figure 6 clearly shows that the highest F-statistic value is achieved with sentiment leading by one day. As the number of lags increases, the variance in ΔYS_d explained by adding ΔMS_{d-p} decreases. On the other hand, there is no evidence that ΔYS_{d-p} can add information for forecasting of ΔMS_d, i.e., the lagged change of yield spread does not help predict change of sentiment.

Thus, we can conclude that news sentiment is indeed a leading indicator, which is priced in corporate bond yield spread after about one day. If properly integrated in to trading strategies, news sentiment can potentially enhance portfolio performance, as we will demonstrate in the last section.

4 Regression models

So far we explored the relationship between news sentiment and corporate bond yield spread on a market level. Now we proceed to explore this relationship on a company level. We do it by means of a regression model with the daily change of yield spread $\Delta YS_{i,d}$ as the dependent variable, and the daily change of market sentiment $\Delta MS_{d'}$ and company-specific sentiment $\Delta CS_{i,d'}$ as the independent variables, where i stands for an individual company. We aggregate the sentiment variables over last seven days:

$$\Delta CS_{i,d'} = \frac{1}{7}\sum_{k=d-7}^{d-1} \Delta CS_{i,k}$$
$$\Delta MS_{d'} = \frac{1}{7}\sum_{k=d-7}^{d-1} \Delta MS_{k}. \tag{5}$$

Note that, for simplicity, we use only sentiment-related variables to explain bond yield spread and no control variables such as maturity, risk-free rate (which we subtracted from the yield anyway), or credit rating. Maturity- and coupon-related information was averaged out in the calculated yield spread. Credit rating of a company issuing bonds will be accounted for in a later discussion.

As mentioned in Section 2, not all companies in S&P 500 Bond Index have sufficient news coverage to generate a reliable daily sentiment score. So for our regression analysis, we use the 200 companies with highest news item counts. First, we fit **Model 1**, which put more emphasis on the change of company-level sentiment $\Delta CS_{i,d'}$:

$$\Delta YS_{i,d} = c_i + \beta_{i,1}\Delta CS_{i,d'} + \beta_{i,2}\Delta MS_{d'}\Delta CS_{i,d'} + \varepsilon_{i,d}, \tag{6}$$

where c_i is the company-specific baseline level of yield spread and $\varepsilon_{i,d}$ are the residuals. The coefficients $\beta_{i,1}$ and $\beta_{i,2}$, along with c_i and $\varepsilon_{i,d}$ were estimated by the OLS regression. The $\beta_{i,1}\Delta CS_{i,d'}$ term represents the contribution of sentiment change on a company level, while $\beta_{i,2}\Delta MS_{d'}\Delta CS_{i,d'}$ is the interaction term which implies how much influence the market sentiment has, additional to the company sentiment. Regressions are fitted on the total of 682250 observations of daily yield spread and sentiment data over the years 2010-2021.

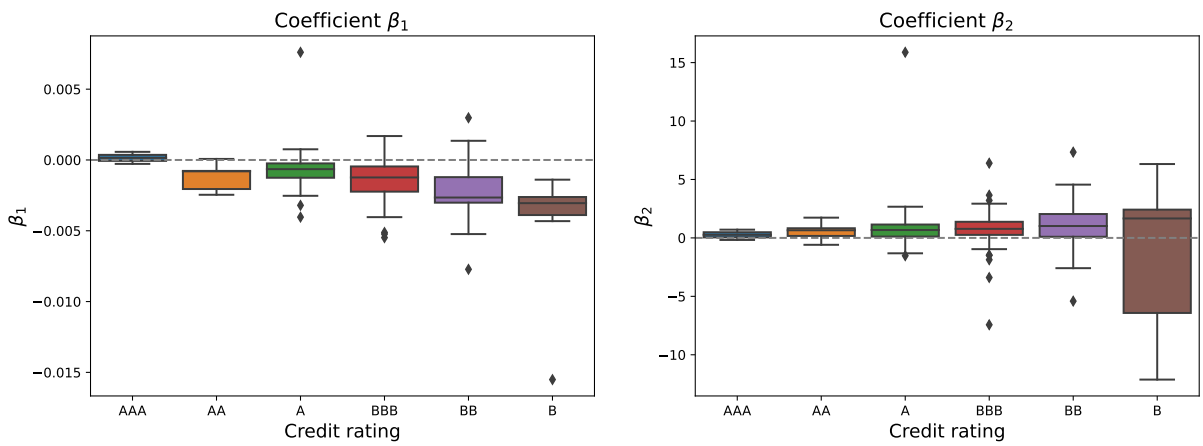

Figure 7: Estimated coefficients of **Model 1** per credit rating. *(Left)* Coefficient β_1 for company-specific sentiment change term $\beta_{i,1}\Delta CS_{i,d'}$. *(Right)* Coefficient β_2 for interaction term $\beta_{i,2}\Delta MS_{d'}\Delta CS_{i,d'}$

The estimated coefficients β_1 and β_2 are displayed in Figure 7. Almost all the β_1s in the left panel are below zero. This is consistent with our market-level observation that the movement of corporate bond yield spread is negatively impacted by change of news sentiment. This impact depends on the credit rating. The lower a company's creditworthiness, the more negative the coefficient of company-specific sentiment change. The AAA-rated companies seem to be unaffected by news sentiment, while the BB- and B-rated corporate bonds have β_1s well below

zero. This result again strengthens our belief that companies with higher credit risk are more susceptible to sentiment change: when sentiment goes down, investors sell relatively riskier assets first.

In the right panel of Figure 7 coefficient β_2 for interaction term $\beta_{i,2}\Delta MS_{d'}\Delta CS_{i,d'}$ are shown. In contrast to β_1, majority of β_2 are positive. Since **Model 1** can be rewritten as

$$\Delta YS_{i,d} = c_i + (\beta_{i,1} + \beta_{i,2}\Delta MS_{d'})\Delta CS_{i,d'} + \varepsilon_{i,d}, \tag{7}$$

$\beta_{i,2}\Delta MS_{d'}$ acts as a reinforcement of the $\Delta CS_{i,d'}$ if it is negative. Our result shows that corporate bond yield spreads do not significantly depend on the market sentiment, as values of β_2, although slightly positive, do not significantly differ from zero.

We performed similar analysis for bonds from various sectors (financial, tech etc). However, there is no significant difference in β coefficients between sector groups, and hence, the results are omitted.

For robustness check, we include more terms into the regression model, such as the change of market sentiment as a separate term $\alpha_1\Delta MS_{d'}$ and the yield spread change lagged by one day $\alpha_2\Delta YS_{i,d-1}$ (**Model 2** and **Model 3**):

$$\Delta YS_{i,d} = c_i + \beta_{i,1}\Delta CS_{i,d'} + \beta_{i,2}\Delta MS_{d'}\Delta CS_{i,d'} + \alpha_1\Delta MS_{d'} + \varepsilon_{i,d} \tag{8}$$

$$\Delta YS_{i,d} = c_i + \beta_{i,1}\Delta CS_{i,d'} + \beta_{i,2}\Delta MS_{d'}\Delta CS_{i,d'} + \alpha_1\Delta MS_{d'} + \alpha_2\Delta YS_{i,d-1} + \varepsilon_{i,d} \tag{9}$$

As a benchmark, we use an auto-regression model, which predict the change of yield spread on day d using only the yield spread change on the previous day (**Model 4**):

$$\Delta YS_{i,d} = c + \alpha_2\Delta YS_{i,d-1} + \varepsilon_{i,d} \tag{10}$$

The summary statistics of the four regression models as well as the values of α_1 and α_2 in respective models are reported in Table 2. As we can see, the coefficient α_1 of market sentiment change $\Delta MS_{i,d'}$ is always negative, meaning that market-level sentiment change in general negatively contributes to the change of yield spread, as does company-specific sentiment. On the other hand, the auto-regressive coefficient α_2 has positive values in both **Model 3** and **Model 4**, which signifies that some kinds momentum exist in the time series of yield spread: if the yield spread widens yesterday, then there is a higher chance that it continue to widen today. All the models that consider news sentiment perform better than a merely auto-regressive prediction, indicated by higher adjusted R-squared values and low p-values .

In summary, regression models have shown that, the lower is a company's credit rating, the more its bonds' yield spread is affected by the change in the company-specific sentiment. No obvious distinction among sector groups was observed. Furthermore, incorporating news sentiment as a dependent variable enhances the prediction power of a regression model. Market-level news sentiment contributes negatively to change in yield spread and some momentum can be found in the dynamics of corporate bond yield spread.

Table 2: Summary of regression results

	Model 1	**Model 2**	**Model 3**	**Model 4**
Adj. R-squared	0.004	0.013	0.014	0.002
F-statistic	6.087	16.01	16.73	1026
p-value	0.00	0.00	0.00	5.36e-225
Log-Likelihood	4.057e+06	4.060e+06	4.060e+06	4.055e+06
α_1		-0.0283	-0.0276	
α_2			0.0254	0.0387

5 Trading strategies

So far, we demonstrated different aspects of the relationship between corporate bond yields and news sentiment. This relationship is clearly visible even by a naked eye, and its statistical significance is confirmed by various models. Now we would like to see how this knowledge can be used in real-world trading scenarios and whether news sentiment can help bond investors improve portfolio performance.

Sentiment-based signals can be applied in investment and trading in a myriad of ways: as an in- and/or out-signal, as a risk overlay (risk-off signal), in addition to other trading signals. It can be used on an individual company's level, sector level or even index level. Obviously, it is not possible to explore all these options in a single paper. So we will test the sentiment signal on the basis of a simple strategy with sentiment being the sole consideration for constructing a bond portfolio. The sentiment signal is considered on the individual company's level and the signal is defined via the change of sentiment (rather than its level). According to our earlier analysis, positive news is negatively related to the bond's yield and positively to the bond's price, so we would like to see whether the portfolio containing bonds with a good sentiment history outperforms the benchmark.

For simplicity, we rebalance the portfolio monthly. However, for better results, weekly or even daily rebalancing could be employed, as sentiment is incorporated into prices rather quickly (but for bonds certainly not intraday). More frequent rebalancing would, however, increase the turnover and incur more trading costs.

At the beginning of each month, we look at the change of net sentiment with respect to the previous month, for all the companies in the index, and rank them in the descending order. These companies are then divided into four portfolios, each containing the same number of companies. These portfolios are Quartile 1 to Quartile 4 in our summary Table 3, where Quartile 1 is made of companies that have the best net sentiment change (improvement) in the last month and Quartile 4 - the worst. Since we have data from 2010 to 2021 and the first month needs to be used for sentiment initiation, the portfolio returns were calculated for a total of $12*12-1=143$ periods. The benchmark portfolio consists of bonds of all available companies and the 1-month Treasury yield at the beginning of each month is taken as the risk-free interest rate.

Note that a bond's return does not comes solely from price movement, but the coupon payments should also accounted for. Since different bonds pay coupons on different days and at various frequencies, it is quite complicated to track when and how much these coupons are paid in monthly rebalanced portfolios. Therefore, for the simplicity, the annual coupon rate for each bond was divided by twelve and added to the monthly return.

The resulted portfolio performance measures are reported as annualized quantities in Table

3.

Table 3: Summary of portfolio performance with the benchmark portfolio and Treasury yield (annualized over the period 2010 to 2021)

	Return (%)	Std. Dev. (%)	Tracking Error (%)	Information ratio	Sharpe ratio
Reference					
All available bonds	3.031	7.011	NaN	NaN	0.104
Treasury	0.493	0.216	NaN	NaN	NaN
Portfolios					
Quartile 1	4.078	6.953	1.184	0.884	0.149
Quartile 2	3.186	7.142	0.966	0.161	0.109
Quartile 3	2.584	7.051	0.883	-0.506	0.086
Quartile 4	2.407	7.104	0.918	-0.680	0.078

As expected, holding corporate bonds is more profitable than sovereign bonds, with an excess return of about 2.5% per year. The results of our four sentiment-based portfolios show that an improvement in sentiment leads to higher returns, without incurring extra risk. The first two quartile portfolios outperform the benchmark and the last two under-performed it, as expected. The volatilities of the four portfolios and the benchmark are comparable at 7%. By always holding the portfolio of companies whose sentiment, i.e., perception in the media is improving, one can get approximately 1% more return annually. And those companies that have the worst drop in last-month sentiment diminish the portfolio return by about 0.6%. These results refer to almost simplest possible strategy, and more superiour results are undoubtedly possible with e.g., more sophisticated strategies and/or more frequent rebalancing.

The takeaway message is that it is worthwhile for bond investors to monitor sentiment and incorporate it into their portfolio construction. Preferentially investing into improving-sentiment bonds (or avoiding those with declining sentiment) generates extra return, even if acting on a monthly basis.

So to complement our statistical evidence, we hereby demonstrated also economic significance of news sentiment in corporate bond trading, albeit in a simple investment setting.

Concluding Remarks

Modern investors and asset managers are increasingly incorporating alternative data sources in their investment strategies. Sentiment of news and social media is one such data source. It has been shown again and again that adding sentiment signals to equity investment and trading strategies enhances returns and limits risk.

Less attention has been given to the use of sentiment for bond trading and investment. The objective of this paper is to address exactly this topic. Using a large database encompassing 6000 bonds of over 600 US companies over the period 2010-2021, we have shown that there is a significant relationship between company-specific news sentiment and corporate bonds yield spread. This relationship is asymmetric: the reaction of bond yield to negative sentiment is twice as large as to positive sentiment. The news sentiment leads the development in bond yields by approximately one day.

We have also demonstrated that corporate bonds are impacted differently by news sentiment

depending on their credit ratings: lower-rated companies are more susceptible to news sentiment. Last but not least, our sentiment-based corporate bond portfolio is able to outperform the benchmark by over 1% pa without bearing higher volatility. Using month-on-month sentiment change, we can exclude those companies whose bonds suffer due to negative sentiment, by this limiting portfolio downside. Overall, our evidence suggests that news sentiment is a valuable investment and trading signal, also for bond investors.

References

Borovkova, S., Garmaev, E., Lammers, P., & Rustige, J. (2016). Sensr: A sentiment-based systemic risk indicator. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2759289

Borovkova, S., & Lammers, P. (2018). Sector news sentiment indices. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3080318

Borovkova, S., & Mahakena, D. (2015). News, volatility and jumps: the case of natural gas futures. *Quantitative Finance*, *15*(7), 1217–1242. doi: 10.1080/14697688.2014.986513

Borovkova, S., & Reiniers, C. (2021). *Adding sentiment to multifactor equity strategies* (Tech. Rep.). Amsterdam, The Netherlands: Probability & Partners and Vrije Universteit Amsterdam.

Dangl, T., & Salbrechter, S. (2021). News sentiment and equity returns. Retrieved from https://ssrn.com/abstract=3971880

Nelson, C., & Siegel, A. F. (1987). Parsimonious modeling of yield curves. *The Journal of Business*, *60*(4), 473-89.

Smales, L. A. (2016). News sentiment and bank credit risk. *Journal of Empirical Finance*, *38*, 37-61. Retrieved from https://www.sciencedirect.com/science/article/pii/S0927539816300421

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *Journal of Finance*, *63*, 1437–1467. doi: http://dx.doi.org/10.2139/ssrn.923911

Contact

Dr. Svetlana Borovkova
svetlana.borovkova@probability.nl