Macroeconomic news: Enhanced forecasting of sovereign bond spreads

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March 23, 2018

Abstract

Sovereign bond spreads are modelled and forecasted taking into account information gained through macro-economic news sentiment. We investigate sovereign bonds spreads of European countries and enhance the prediction of spread changes by taking into account news sentiment. We conduct a correlation and rolling correlation analysis between sovereign bond spreads and accumulated sentiment series and analyse changing correlation patterns over time. These findings are then utilised to monitor sovereign bonds and highlight changing risks through time.

Keywords Sentiment analysis, Rolling correlation, Sovereign bonds, ARIMAX, Credit risk

Contents

1 Introduction

In the wake of the sovereign debt crisis in Europe, managing and monitoring credit risk arising from sovereign bonds is increasingly important. European countries have undergone changes in terms of their financial stability, and credit spreads have widened due to increased financial risk. Modelling of sovereign bond spreads is often linked to various macroeconomic factors such as the countries' GDP growth rate or inflation. These macroeconomic factors are monitored via scheduled announcements from official bodies e.g. treasuries and national banks but are also covered in news articles and unscheduled announcements. Changes in country dynamics and risks are reported and captured in news, which are classified as "macroeconomic news", and can be closely monitored and quantified through news sentiment analysis.

News sentiment for equities and in particular its use in equity trading has been widely covered in various studies over the last years. An overview of equity modelling and predictability enhancements through news sentiment is given in Mitra and Mitra [16]. The dynamics of asset prices, in particular their volatility is clearly affected by news events. These events are classified and quantified, news sentiment can be utilised to enhance volatility prediction (see e.g. Mitra et al [17]). Sentiment Analysis is further used to improve trading decisions in equity markets. Firm-specific news sentiment affects the predicted asset return distribution; taking into consideration sentiment values increases the accuracy of a forecast and contributes to improved portfolio decisions as discussed in [14] and [22], amongst others. In the Fixed Income market however, news sentiment and its potential influence to bond spreads has just recently become more relevant in the light of electronification of bond trading (Lech et al [9]) and sentiment lacks thorough investigation in this market. Especially macroeconomic news sentiment for sovereign bond spreads but also firm-specific news sentiment for corporate bond spreads can add value to both monitoring and forecasting of bonds. In this paper, we aim to fill this current gap and provide an extensive study on effects of news sentiment to bond spread predictions. In particular, we investigate the influence of macroeconomic news sentiment on bond spreads and develop a method to improve prediction and monitoring of sovereign spreads.

When analyzing bond spreads of European countries, various studies (e.g. [4], [6] and [15]) found influencing international and country-specific risk factors such as government debt and characterised market dynamics such as liquidity issues and fiscal policies to effect bond spreads. Economic fundamentals are seen as drivers for sovereign spreads (see Dewachter et al.[7]); they have been utilised to explain yield spread movements and a significant effect has been found. Following a study by Afonso et al. [1], factors that influence sovereign spreads in Europe are time varying. The authors highlight the fact that financial determinants have changing effects on spreads, but that their influence is increasing in times of crisis. A further investigation of time-varying factors can be done by considering macroeconomic news, which reports on changing dynamics and influences from issuing and neighbouring countries. News and sentiments for sovereign bond spreads were investigated by [18] and [5], amongst other. They investigated the influence of news announcements on spreads during the European debt crisis and found evidence, that information from government statements as well as news from a European newsflash platform influenced yield spreads both nationally but also across countries, pointing to spill-over effects in the debt crisis.

Our paper contributes to the current literature an in-depth analysis of the impact of processed macroeconomic news and its sentiment towards European sovereign yield spreads. In particular, we investigate the dynamics of daily sovereign spread changes and find a relation between their daily forecasts and news sentiment time series. Our findings show that the forecast of yield spreads can be enhanced when daily news sentiment is taken into account. News is split into positive and negative news items, their influences are investigated separately as well as jointly in a multivariate ARIMAX set-up. We study various combinations of external variables and give details and results of five model settings, which produce the best forecast outcome. The ARIMAX model gives daily one-step ahead predictions of spread changes and volatility proxies. The in-depth analysis of ARIMAX performance and its improvements through external news variables leads us to propose the enhancement of sovereign bond analysis through including significant news time-series for five European markets.

2 Data

2.1 Bond data

In order to establish rules to monitor a bond portfolio over time, we analyse sovereign bond spreads of various European countries. We distinguish between short-term bonds with a maturity between 3 months and 5 years and long-term bonds with maturities between 5 and 30 years. We analyse sovereign bond data from Thomson Reuters' Datascope and calculate spreads between the bond yields and the AAA-rated bond yield quoted from the European Central Bank (ECB).

Our analysis covers data from five European countries, namely Germany, Great Britain, Italy, Spain and France. For each country, we consider both short-term and long-term bonds issued from the countries between 2007 and 2017. The analysed bond data includes more than 300 bonds, daily closing prices from Thomson Reuters Pricing are utilised.

2.2 Macroeconomic news sentiment

We wish to analyse the effect news articles and announcements have on bond yields. In our study, macroeconomic sentiment comprised by RavenPack is employed. RavenPack marks every news item that arises from various sources with a sentiment value called "ess" - event sentiment score. This sentiment value lies between -1 and 1 and quantifies the sentiment of a particular news item for the chosen entity. In our case, we choose the bond issuer as the entity we would like to follow. We create daily news time series out of all sentiment values that stream in over a given day. Our work clearly distinguishes itself from other literature on sovereign bond spreads and their main determinants, since we do not take into account fiscal time series and fundamentals but rather try to establish a connection between macro-economic news sentiment and bond spreads. One main advantage of this is that we are not limited to scheduled announcements, which are still covered in our news database, and quarterly or semi-annually releases of fundamental figures. On the contrary, news items are observed throughout the day and news sentiment signals are calculated before market closing time. By following these macro-economic news on a daily basis we get daily macro-economic signals which can be included into daily trading decisions. Analysis on fundamentals can be an addition to our signals, however, in this work we concentrate on daily news sentiment and its effect on sovereign bond spreads.

We follow macroeconomic news, which are bundled under the entities Germany, Great Britain, Italy, Spain and France, respectively, representing the issuer of the bonds. A typical macroeconomic news example from our database includes the time stamp, the relevance of the news with respect to the key word as well as the sentiment value.

Depending on weekday and time, the news item is mapped to its relevant trading day. Weekend news are shifted to Monday and any news coming in after market closing time is shifted to the next working day. For each news item N_i we have given a time stamp timest which consists of the date and time of the release of the news item, $\text{timest}(N_i) = (date(N_i), time(N_i))$, where $i = 1, ..., n$ and n denotes the number of news items in the data set. We map the time stamp of each news item to a trading day for that news item $\text{TrD}(N_i)$ where $\text{TrD}(N_i) \in \{TD_t\}, t = 1, ...m$. We have that $\text{TD}_1 \geq \min_i(date(N_i))$ and $\text{TD}_m \leq \max_i(date(N_i))$ and m is the number of trading days in the given time interval $[\min_i(date(N_i)), \max_i(date(N_i))]$. With c denoting the market closing time we set

$$\text{TrD}(N_i) = \begin{cases} date(N_i), & \text{if } date(N_i) \in \{TD_t\} \wedge time(N_i) < c \text{ ;} \\ date(N_i) + 1, & \text{if } (date(N_i) + 1) \in \{TD_t\} \wedge time(N_i) > c \text{ ;} \\ date(N_i) + k, & \text{if } date(N_i) \notin \{TD_t\} \wedge k = min_l(date(N_i) + l \in \{TD_t\}), l \in \mathbb{N}. \end{cases}$$

We create nine different time series based on the relevance and sentiment value we receive from RavenPack's database to build daily news sentiment values which can be utilized as an input variable for our time series models. Firstly, we split the sentiment values into two sub-categories handling positive and negative news-sentiment separately. We conduct a pre-analysis of our news sentiment data which allows us to consider all news after market closing time until market closing time on the following day for the daily news sentiment. We create

1. a mean news-sentiment value time series
2. a volume of news time series
3. a news-impact time series

for the three categories

a. all news

b. positive news

c. negative news

We build the volume of news time series $V(t)$ with n denoting the number of news items and t with $t = TrD_1, ...TrD_m$ denoting the current trading day, as

$$V(t) = \sum_{i=1}^{n} 1_{\{TrD(N_i)=t\}}.$$

The mean news-sentiment time series takes into account the event sentiment score "ESS", which is delivered with each news item, $-1 \leq ESS \leq 1$. The mean over all sentiment is calculated for each trading day leading to a trading-day mean-sentiment time series. The mean news-sentiment value time series $MS(t)$ is calculated as

$$MS\left(t\right)=\frac{1}{V\left(t\right)}\sum_{j=1}^{V(t)}ESS(N_j)1_{\{TrD(N_i)=t\}}.$$

The news-impact time series takes into account the potential influence decay of a news story. The news items for each working day are weighted keeping in mind that the most recent news item before closing has the highest effect on the closing yield. The other news items, which come in before that, have a decaying importance. The news-impact time series $IS(t)$ with c denoting the closing time of the market is given as

$$IS\left(t\right)=\frac{1}{V\left(t\right)}\sum_{j=1}^{V(t)}ESS(N_j)e^{\lambda(c-time(N_j))}1_{\{TrD(N_i)=t\}}.$$

The calculation of the news-impact time series was introduced by Yu and Mitra [23]. The sentiment value ess is multiplied by a decreasing exponential weight leading to the news impact score I, $I = \text{ess} * e^{(-\lambda(c-time))}$. The closing time of the market c is the reference time, $c - time$ measures the difference between news time $time$ and market closing time and the decaying factor λ is determined through $e^{(-\lambda(240))} = 1/2$. We choose a time span of 240 minutes, after which news stories only have half of their impact left.

Time series of volume of the news items are examined as well. We count the number of relevant news items for the entity considered for a given trading day. Again, weekend news and news after market closing are shifted to the next trading day. We count all incoming news items (neutral, positive and negative) to create the volume of all news time series and distinguish between positive and negative news sentiment to create volume of positive and negative news time series.

Therefore, we create nine different time series observed throughout the time interval where the bond is active. All news time series are utilized as regressors in a regression model as well as external variables in an ARIMAX model. Furthermore their correlation with the yield spread is calculated for the whole time period and trough a rolling window approach.

In Figure 1 a typical time series of news volume is depicted. Here we show a volume series for Germany, where we distinguish between positive and negative news items. Since we would like to analyse effects of macro-economic news on bond spreads we are less interested in news collected under the topic "social", instead we concentrate in the following on news from broad topics "politics" and "economics".

3 Model

In order to establish whether a relation between the different news time series and the yield spread changes exists, we test for correlation between the daily spread change series and all nine news time series. We calculate Pearson's correlation between the daily time series and test whether the correlation is significant. Furthermore, the correlation is estimated within a rolling window to see time-varying features of the correlation between time series.

Secondly, a linear regression is performed to analyse the effects of news time series on the yield spread changes. All nine news time series are taken as regressors

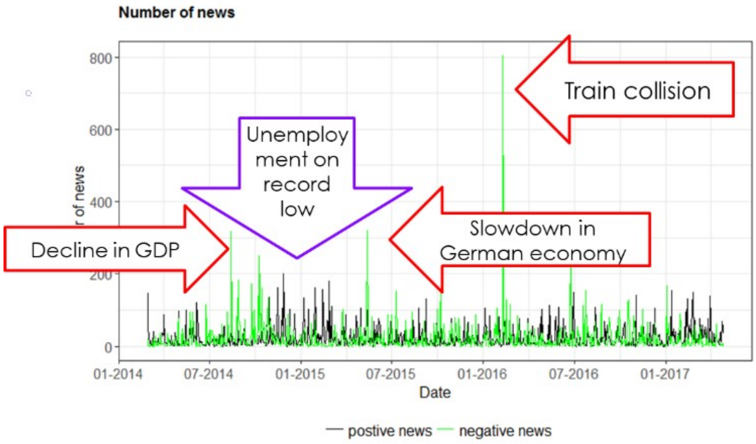

Figure 1: Daily news volume from entity "Germany" between 2014 and 2017

in a variety of combinations. We report here results for regression with three news series regressors, namely the Volume of All News, Positive Impact and Negative Impact.

Lastly, we apply an Integrated Autoregressive Moving Average (ARIMA) model to analyse and forecast bonds yields. We additionally add external explanatory variables to the model, therefore fitting an ARIMAX(p,i,q) model to yield spread changes. The ARIMAX(p,i,q) model is given through

$$d_t = \phi_0 + \sum_{k=1}^{p} \phi_k d_{t-k} + a_t + \sum_{k=1}^{q} \theta_k a_{t-k} + \sum_{l=1}^{m} x_{lt} \tag{1}$$

where d_t is the i-th differenced series of the time series r_t, $\{a_t\}$ is a white noise series and x_{lt} is the $l-$th external explanatory variable, $l = 1, ..., m$. The explanatory variable are uni- or multivariate. An ARIMAX model was also successfully applied by Apergis [3] to analyse CDS spreads and newswire sentiments. His study results in improved forecast errors when external news time series were allowed. We model the spread changes firstly with an ARIMA(p,i,q) model and compare the resulting in-sample and out-of-sample one-step ahead forecast errors to those which arise from ARIMAX(p,i,q) model with various external regressors. We run a considerable amount of models on our daily yield spread series, taking into account uni- as well as multivariate external explanatory variables. We can improve the forecast errors of analysed bonds when sentiment is taken into consideration. This points to the fact that news sentiment has value for bond yield modelling and risk assessment. Monitoring macroeconomic news sentiment series in addition to the actual yield spread can lead to early warning signs for unexpected changes in yields or structural changes visible in the yield spreads.

4 Empirical analysis of sovereign bond spreads

We distinguish between short- and long-term bonds. In our categorization, short-term bonds have a maximum number of days to maturity of 1,500.

First we wish to investigate whether significant correlation can be found between spread time series from long-term bonds and our created sentiment time series. The state of the markets, changes to it and therefore news that affect market behaviour have an effect on prices and spreads in the Fixed Income market. Up until now, less effort has been put into establishing the link between daily news sentiment and the dynamics of bond spreads. We would like to analyse the correlation between the daily news sentiment series and bond spread changes and decide which of the news sentiment series shall be incorporated into the prediction of bond spreads. The daily news sentiment series have information on market movements and activities consolidated in a daily signal. We concentrate here on macroeconomic news to underline the effect that these news have on the sovereign risk of the issuer of the bond and therefore also on the bond spread. In equity markets, the question arises if the news or the market is quicker, meaning if news contains information which is not already reflected in the prices. This question is difficult to answer and there might be cases for both scenarios. However, Fixed Income markets in general are less likely to absorb macroeconomic information as fast as equity markets, since bond portfolios tend to be medium- to long-term investments and algorithmic trading decisions play a significant smaller role then in equity markets. We therefore like to use the daily macroeconomic news sentiment series as a source of information on current market affairs and market changes for the sovereign bonds. A correlation analysis gives us the insight whether a general connection between news signals and bond spread movements exists and if so, how stable the correlation is and how news series can be utilised for daily predictions.

To conduct the correlation analysis we create three spread time series, namely the spread series S_t, $t = 1, ..., K$, the first difference time series of this spread D_t, $t = 2, ..., K$, and the volatility time series V_t of D_t, $t = 2, ..., K$. Our proxy volatility time series is calculated by taking the absolute value of D_t, $t = 1, ..., K$. The duration of the bond in days is denoted by K.

$$\begin{aligned} S_t &= B_t - Y_t \\ D_t &= S_t - S_{t-1} \\ V_t &= |D_t| \end{aligned}$$

We denote the benchmark bond to calculate the spread by B_t, the yield of the investigated bond is Y_t. Time series S_{jt}, D_{jt} and V_{jt} $j = 1, ...J, t = 1, ..., K$ are calculated for all J bonds.

We calculate the rolling correlation between news and spread time series with a window size of 250 days. We analyse the significance of the correlation coefficient for each individual bond in our data set as well as for a mean spread time series $M_t, t = 1, ..., N$ for each considered country. The time window covers the N days including all time intervals from all analysed long-term bonds. The mean spread is given by

$$M_t = \frac{1}{n_t} \sum_{j=1}^{J} \mathbf{I}_{\{S_{jt} \neq 0\}} S_{jt}$$

with n_t denoting the number of available spreads at time t. A mean spread is derived separately for each country, so that we can analyse thoroughly the country specifics.

By calculating rolling correlations between daily news sentiment series and bond spread series we establish the correlation through time. We would like to find out if the correlations are more or less stable over time or if we have large variations of correlation values. In particular we are interested to investigate changing points in the rolling correlation series. We assume that a significant change from positive to negative correlations points to changes in the market environment. These changes

Spain: News time series	S_t	D_t	V_t
All Sentiment	66%	75%	47%
Volume All news	97%	31%	88%
All impact	50%	78%	28%
Positive Sentiment	78%	0%	56%
Volume Positive news	88%	37%	91%
Positive impact	78%	0%	59%
Negative Sentiment	91%	3%	78%
Volume Negative news	97%	59%	84%
Negative impact	91%	3%	78%

Table 1: Percentage of significant correlations between spread and sentiment time series for long-term bonds issued by Spain

can be captured in a regime-switching setting, where market states of the underlying bond spread can be filtered out by estimating the current state of the rolling correlation time series. In the literature, exogenous break points in sovereign bond spread series have been established in our considered time window between 2007 and 2017. The exogenous breaks often mark a division into pre- and post crisis periods (see, amongst others, Caggiano and Greco [6] and Afonso et al [2]). On the other hand, we like to work in a regime-switching setting, where news and their correlation to bond spreads are analysed and regime switches are estimated by filtering out information on the observed rolling correlation.

4.1 Sovereign bonds spreads in Spain

Firstly, we analyse sovereign bonds issued by Spain. Over the last years, markets in Spain were in turmoil due to the European sovereign debt crisis. We expect to find changing correlations between the news sentiment series and Spanish bond spreads over the last years, especially between the years 2008 and 2015. These changing dynamics might have been influenced by European adjustment programs, e.g. the European Financial Stability Fund (EFSF), see e.g. Afonson et al ([1]). The increased financial risk arisen from the sovereign debt crisis lead to a widening of sovereign bond spreads, the response from the European Union e.g. introducing EFSF had softening effect on correlation between fundamental risk factors and sovereign risk. Turbulent market times are also mirrored in more turbulent times in the news, therefore we expect to find changing correlations over time.

We analyse the correlation between the Mean Spread series and the News Sentiment series and find significant correlation with "All Sentiment","All Impact" and "Nr of Neg News" and D_t. Table 1 shows the percentages of bonds with significant correlations for each sentiment time series with S_t, D_t and V_t for long-term bonds in Spain. The highest percentage of significant correlations arise with Volume of All and Volume of Negative News as well as with the time series on Negative Impact.

Furthermore, we depict the rolling correlation analysis on long-term bonds in Figure2. The rolling correlation between a mean long-term spread and the news impact series is stated as well as the number of news items for the entity Spain between 2007 and 2017. It can clearly be seen that the news volume steadily increased between 2011 and 2014, a time where the sovereign debt crisis hit Spain, its companies and people. It is not surprising that the number of news increased in that period, furthermore an increase in correlation between news volume and long-term bond spreads can be detected. Noticeable is furthermore that positive and negative news volume increased their correlation, both showing a positive correlation in times of crisis and large news volumes. This points to the fact that overall the volume can be chosen as an indicator, highlighting the positive correlation between widening of sovereign spread and news volume. Analysing the news volume correlation time series in more detail, one can see that switching market regimes might lead to a switch in the direction of correlation. Between 2007 and 2009, the correlation between positive news volume and spread has been negative indicating smaller spreads when more positive news were detected. However, this sign changed when the state of the market changed, leading to overall positive correlations between news volume and spread, regardless of the tone of the news. Therefore in bear markets the importance of the overall news volume is highlighted.

To underpin the occurrence of changing regimes in the rolling correlation between sovereign bond spreads and the volume of news, we analyse the switching behaviour of the correlation time series. We assume an underlying Hidden Markov Model to find the best suitable state sequence. To analyse this, we fit a 3-state Hidden Markov Model to the time series and adapt the Viterbi algorithm for finding the best suitable state sequence. Figure 3 depicts the estimated market state when analyzing the correlation between bond spreads and the volume of positive news. We can see here, that the estimated market states are in line with the actual observed fact of widening credit spreads from 2011 to 2014. Before and after this period, the market in Spain is estimated to be neutral and in a bull state, which mirrors the real market situations in these larger time windows.

Additional information on Hidden Markov models and its estimation can be found in [19] or [10] amongst others. A in-depth analysis of changing market states and their effects on news sentiment influences is the topic of future work.

German bonds, which have been in a stable market within this time period, also exhibit changing rolling correlations over time. We depict the rolling correlation between the mean long-term spread issued by Germany and the volume of news items in Figure 4. It can be seen that when the credit spread gets narrower and even becomes negative in 2011, the correlation between positive news volume and mean spread changes to negative, an increase in positive news is linked to a decrease in the bond spread. This is true since the Fixed Income market in Germany within this period is stable and not in a bear market.

Furthermore, short-term bonds with a duration of less then 1500 days are analysed. In the following, all of the analysed bonds were issued by the Government of Spain between 2007 and 2017. We analyse 20 bonds, the spread, spread change and volatility of the spread series are calculated and their correlations with the sentiment series estimated. Table 2 shows the percentages of bonds with significant correlations for each sentiment time series with S_t, D_t and V_t for 20 short-term bonds in Spain. We find that the volatility series are typically stronger correlated to the daily news-sentiment series than the spread difference. Sentiment series in this country for short-term bonds can be utilised to improve prediction of daily volatility. The sentiment series, especially the volume series of all news and the “all sentiment” series give an additional insight for one-step ahead predictions of bond spread volatilities.

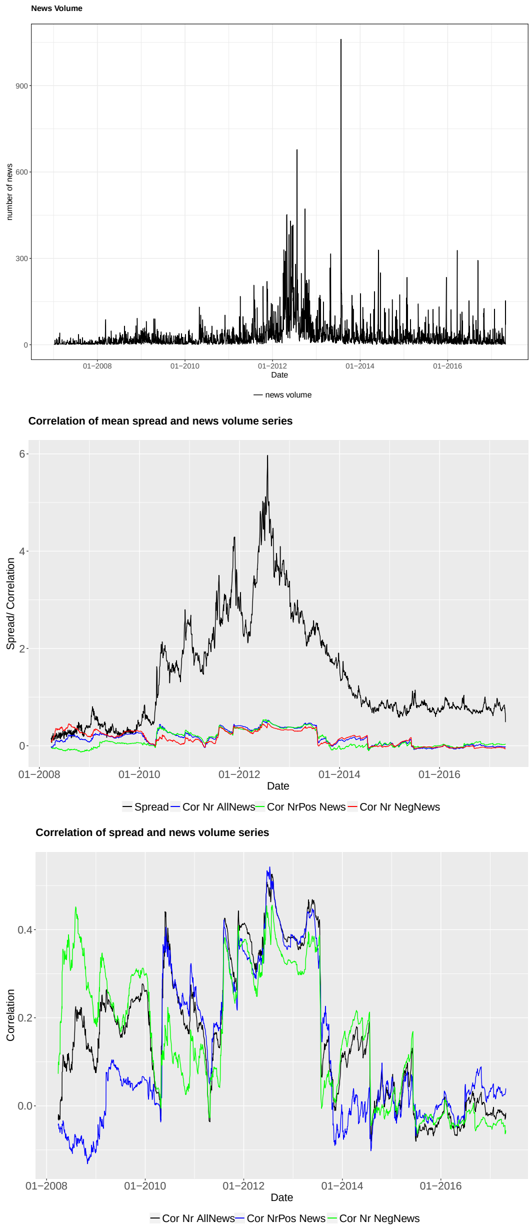

Figure 2: News volume and its rolling correlation with a mean spread of Spanish sovereign bonds

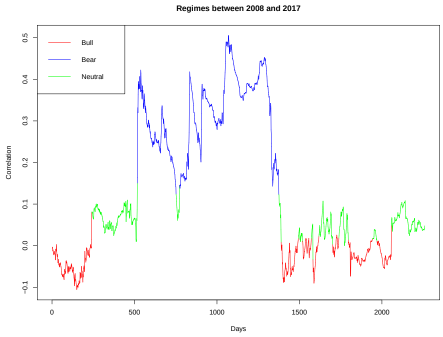

Figure 3: Estimation of market states through changing correlations between volume of news and bond spreads

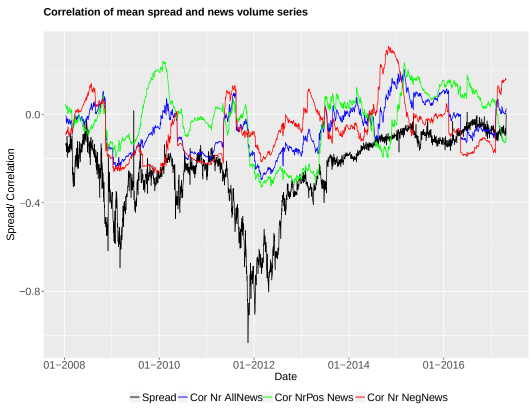

Figure 4: News volume and its rolling correlation with a mean spread of German sovereign bonds

Spain: News time series	S_t	D_t	V_t
All Sentiment	55%	30%	30%
Volume All news	70%	15%	50%
All impact	55%	25%	25%
Positive Sentiment	35%	0%	30%
Volume Positive news	60%	30%	60%
Positive impact	40%	5%	25%
Negative Sentiment	60%	0%	30%
Volume Negative news	75%	30%	35%
Negative impact	60%	5%	35%

Table 2: Percentage of significant correlations between spread and sentiment time series for short-term bonds issued by Spain

4.2 Analysis of mean bond spreads

In this section we would like to focus our analysis on mean bond spreads from Spain and the additional European countries Germany, Italy, France and the UK. We consider here the mean spread at any given point in time over all available bond spreads in our database for each of the countries. When analysing the mean spread we investigate in general the impact of impact values and news volume for each entity. In particular, the correlation between bonds spread series and news time series shall be analysed, a linear regression is performed and a one-step ahead prediction through an ARIMAX model is analysed. This gives an understanding about the enhancement of predictions by involving external variables. The external news variables carry information on macro-economic changes and topics in the considered countries. Analysing the mean spread leads to a general view on influence and correlations between Fixed Income markets and news items for a specific country.

First, we analyse the mean bond yield of 53 long- and short term government bonds in Spain, which were active between 2007 and 2017. The mean bond yield and its first difference are calculated and the rolling correlation between this differenced series and the sentiment time series are estimated. The rolling correlation with a rolling window of 250 days is determined. The volatility proxy, which shows significant correlation with the volume of news time series leads to changing correlation patterns over time. We consider here the changing correlation between the volatility of the mean spread of all sovereign bonds from Spain in our dataset, which covers the time period between 2008 and 2017. Figure 5 depicts the rolling correlation between the volatility and the three volume of news time series. The correlation with the volume of all news changes from a negative to a positive correlation in times when the volatility increases. Again, when the markets start to be calmer, the rolling correlation value decreases. This pattern can be observed for the other analysed countries as well, leading to the fact that the volume of all news is utilised as an informative time series for further predictions. In turbulent market times, the correlation between the volume of all news time series and the volatility proxy fluctuates around 0.2, it decreases sharply when the markets enter a quieter period.

Figure 6 depicts the spread change of the mean of the Spain bond yield and the rolling correlations. The window size is set to 250 days, correlation is calculated for 6 different time series. Rolling correlation changes in particular when market circumstances change, against pointing to the fact that news have a different impact in different regimes and that shifts can be examined through the correlation with news volume.

We test for significant correlation and find that, considering only one time window,the correlation between the mean spread and the three time series for all news sentiment is significant at $\alpha = 0.01$. Correlations between the mean yield and the sentiment and impact series are negative, correlation with the time series of volume of all news is positive. Furthermore, considering a linear regression, we find that the number of all news is a significant regressor.

Let us furthermore consider bond spreads from Germany, a rather stable economy within the European union in the considered time interval. The number of news covered for this entity between 2007 and 2017 is 360,864. When filtering for news with a relevance > 60 and leaving out news from the topic "society" the database has 167,359 news items within this time period which are considered for creating daily news time series. We find significant correlation ρ between the volatility of the

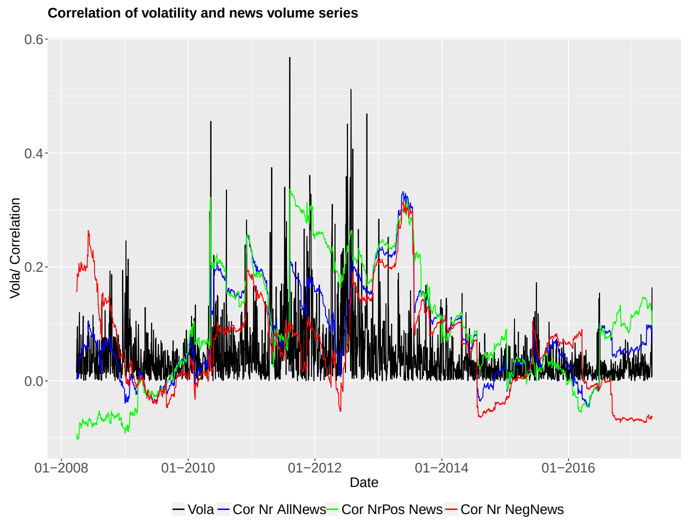

Figure 5: Rolling correlation between Spain bond volatility proxy and news volume time series

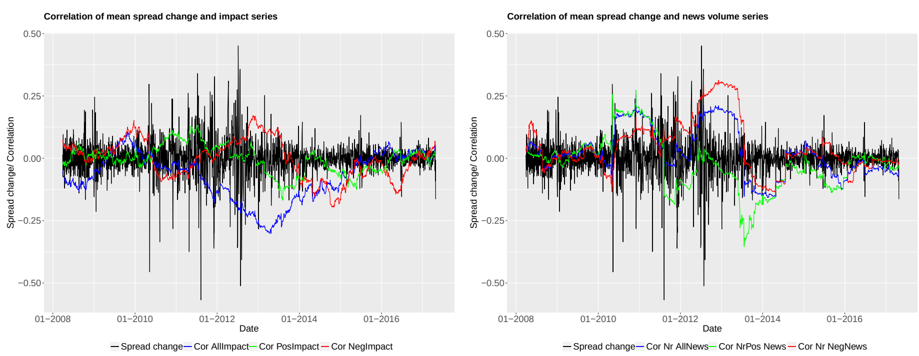

Figure 6: Rolling correlations between mean spread change in Spain and news time series

Coefficients:					
	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	2.520e-02	2.938e-03	8.576	< 2e-16	***
NrOfAllNews	-8.215e-06	9.455e-06	-0.869	0.385006	
PosImpact	-2.430e-02	5.073e-03	-4.790	1.76e-06	***
NegImpact	-1.354e-02	3.754e-03	-3.606	0.000317	***
	(Intercept)	NrOfAllNews	PosImpact	NegImpact	
	2.519741e-02	-8.215097e-06	-2.430199e-02	-1.353792e-02	

Table 3: Regression analysis for volatility of German mean bond spread difference
Residual standard error: 0.0283 on 2582 degrees of freedom Multiple R-squared: 0.0133, Adjusted R-squared: 0.01215 F-statistic: 11.6 on 3 and 2582 DF, p-value: 1.496e-07

spread difference and the news time series All Sentiment ($\rho = -0.14$), All Impact ($\rho = -0.14$), Positive Sentiment ($\rho = -0.1$), Volume of positive news ($\rho = -0.04$), Positive Impact ($\rho = -0.11$), Negative Sentiment ($\rho = -0.06$) and Negative Impact ($\rho = -0.06$). All news time series are negatively correlated to the volatility of the bond spread difference, leading to the conclusion that lower sentiment and impact can be observed when higher volatility is present. Moving on from these correlation findings, we conduct a linear regression where the three time series “Volume of all news”, “Positive impact” and “Negative impact” are chosen as regressors. The results, depicted in Table 4.2 show that the impact time series are significant regressors at a 0.1% level.

The regression results show that the positive and negative impact series are informative input variables for the volatility proxy. We receive similar regression results for the experiments on other countries’ volatility time series, leading to the conclusion that news sentiment adds value to modelling and forecasting of these sovereign bond spreads and spread volatilities.

5 Prediction of sovereign bond spreads through news sentiment

We now turn our focus on the enhancement of predicting bond spreads through macroeconomic news sentiment. Our previous results on correlation in both static and rolling windows as well as on linear regression with daily news sentiment time series lead us to utilise news sentiment time series as an external variable in an Integrated Autoregressive Moving Average Model with explanatory variables (ARIMAX) setting.

After testing for best suited parameters we perform fitting and forecasting an ARIMAX(2,0,2) model on 51 sovereign bonds issued by Germany. We choose different external variables and compare five model set-ups

ARMAX 1 No external variable

ARMAX 2 Positive Impact and Negative Impact time series

ARMAX 3 Volume of All News and All Impact time series

ARMAX 4 Volume of Positive News

ARMAX 5 Volume of All News

	ARIMAX 1	ARIMAX 2	ARIMAX 3	ARIMAX 4	ARIMAX 5
In-Sample					
Min.	0.01424	0.01400	0.01418	0.01421	0.01424
1st Qu.	0.02337	0.02328	0.02326	0.02334	0.02327
Median	0.02930	0.02895	0.02924	0.02926	0.02925
Mean	0.04532	0.04492	0.04478	0.04513	0.04496
3rd Qu.	0.04043	0.04015	0.04036	0.04042	0.04037
Max.	0.41261	0.41258	0.41236	0.41233	0.41244
Out-of-Sample					
Min.	0.01430	0.01431	0.01430	0.01432	0.01430
1st Qu.	0.02147	0.02251	0.02233	0.02256	0.02152
Median	0.03570	0.03537	0.03513	0.03547	0.03513
Mean	0.05260	0.05307	0.05300	0.05291	0.05280
3rd Qu.	0.06758	0.06843	0.06808	0.06795	0.06776
Max.	0.33667	0.32860	0.33296	0.33527	0.33662

Table 4: Error distribution of ARIMAX models for in-sample and out-of-sample window.

An error analysis shows that adding external variables decreases the forecast error in both the in-sample and out-of-sample period. Table 4 shows the empirical error distribution of each model. The lowest median RMSE is reached by ARIMAX 2 (in-sample) and ARIMAX 3 (out-of-sample).

We see that when modelling daily spread changes the lowest RMSE in the in-sample period is gained through Model 2.) (in 55%), followed by Model 3.) (in 33 %). For the out-of-sample period we find that the lowest RMSE is obtained through Model 2.) (in 31 %) followed by Model 1.) (in 23 %). A similar pattern arises when the volatility proxy is predicted.

For the UK we analyse 100 sovereign bonds, 28 long term and 72 short term bonds. We predict the spread changes as well as the volatility with the same model set-up as explained above and find that the lowest RMSE in the in- and out-of-sample set-up is reached by Model 2.) (60% and 32% of bonds) and Model 3.) (30% and 26% of bonds).

5.1 Countries' mean bond spreads

We now perform our analysis on the mean bond spread for each European country we consider. We calculate for each point in time the mean spread value of the bonds available in each country. This is taken as a reference bond spread for the country, which reflects the typical movements of the issued sovereign bonds.

We conduct one-step ahead prediction through the ARIMAX model with varying external variables. We first perform the ARIMAX analysis on four non-overlapping windows of the mean spread change time series from Spain, for each window we set an in-sample and out-of sample interval of 85% and 15% of the length, respectively. By dividing the spread change time series into four intervals, we can see whether the prediction results are stable over time. We measure the one-step ahead prediction within each model set-up through the root mean squared error (RMSE), the error measure is depicted in Table 5. The external variables for the model set-ups are as before, ARIMAX 6 and ARIMAX 7 are estimated additionally, which include four external variables each:

ARIMAX 6 Volume of all news; All News Impact; Volume of positive news; Positive news impact

ARIMAX 7 Volume of all news; All News Impact; Volume of negative news; Negative news impact

	Jan07-Oct09	Oct09 - Apr12	Apr12 - Oct14	Oct14 - Apr17
ARIMAX 1	0.061888	0.11838	0.09797	0.044519
ARIMAX 2	0.061864	0.11830	0.09784	0.044514
ARIMAX 3	0.061856	0.11824	0.09776	0.044359
ARIMAX 5	0.061886	0.11831	0.09793	0.044510
ARIMAX 6	0.061884	0.11818	0.09786	0.044329
ARIMAX 7	0.061782	0.11815	0.09781	0.044353

Table 5: RMSE for ARIMAX analysis on four windows for Spain

	Jan07-Oct09	Oct09 - Apr12	Apr12 - Oct14	Oct14 - Apr17
ARIMAX 1	0.049553	0.128433	0.043149	0.037381
ARIMAX 2	0.049334	0.128494	0.043398	0.037380
ARIMAX 3	0.049319	0.127939	0.043517	0.037744
ARIMAX 5	0.049596	0.127327	0.043190	0.037434
ARIMAX 6	0.049639	0.123493	0.042784	0.037658
ARIMAX 7	0.049491	0.124309	0.043434	0.037797

Table 6: RMSE for out-of sample ARIMAX analysis on four windows for Spain

The estimated models cover both multi- as well as univariate external variables. The models in this analysis were chosen from a larger set of univariate and multivariate model set-ups and represent the most promising forecast models for these bonds. We see that the models of order (1,1,1) with external variables outperform the pure ARIMA(1,1,1) model in terms of the smallest RMSE. The best model set-up is our fourth ARIMAX model, where positive and negative news sentiment as well as the volume of all news are the external regressors.

The results for the out-of sample setting are similar, however, the forecast errors for the simple ARIMA model without external regressor is the best for two out of four windows. The out-of sample error measures are stated in Table 5.1.

We see that there is a difference between best performing models in the in-sample and out-of sample prediction. ARMAX 6, which includes All News volume and impact as well as Positive News volume and impact is the best performing model in the out-of-sample interval in 2 windows, the in-sample period shows it best performing in one window. Here, ARMAX 7 is best in two our of four time windows. ARIMAX 3 performs best in time window 1 (in-sample) and 3 (out-of-sample). Overall, the external variables All News Impact and Volume of All News add information value to the prediction.

In addition, we compare the performance of the ARIMAX models in different countries. The analysis of the mean bond spread results in RMSE values can be seen in Table 8 for the analysed mean spread change for five countries. We consider roughly 50 bonds in each country between 2007 and 2017, for the UK we analyse 100 sovereign bonds. The results show that including sentiment series as an external variable improves the forecast both in the in-sample and out-of-sample period. Models ARIMAX 2 and ARIMAX 3 are the best performing model set-ups. Choosing the news sentiment impact time series as well as the volume of all news as external variables improves the one-step ahead prediction of the spread change. For each country, the prediction of the mean spread change can be improved when news time series are utilised.

Our analysis is done furthermore on the volatility proxy, the absolute value of the mean bond spread change. Here, we can find a similar result. Again, using

Country	ARIMAX 1	ARIMAX 2	ARIMAX 3	ARIMAX 4	ARIMAX 5
Spain	0.072433	0.072432	0.072271	0.07234	0.072424
Germany	0.035505	0.035497	0.035504	0.035504	0.035504
UK	0.064901	0.064787	0.064854	0.064901	0.064894
Italy	0.13653	0.13651	0.13546	0.13651	0.13586
France	0.038858	0.038844	0.038857	0.038858	0.038857

Table 7: RMSE for In-sample period

Country	ARIMAX 1	ARIMAX 2	ARIMAX 3	ARIMAX 4	ARIMAX 5
Spain	0.033000	0.033034	0.033607	0.033134	0.033023
Germany	0.015871	0.015865	0.015890	0.0158887	0.015890
UK	0.024018	0.024417	0.024654	0.023867	0.024867
Italy	0.035887	0.035851	0.042381	0.036024	0.040118
France	0.049948	0.049947	0.049954	0.049948	0.049951

Table 8: RMSE for out-of-sample period

Country	ARIMAX 1	ARIMAX 2	ARIMAX 3	ARIMAX 4	ARIMAX 5
Spain	0.049003	0.048996	0.048972	0.048867	0.048972
Germany	0.028480	0.028455	0.028443	0.028478	0.028480
UK	0.054074	0.053979	0.053868	0.054074	0.054054
Italy	0.084966	0.084950	0.080648	0.083615	0.080722
France	0.035559	0.035486	0.035510	0.035481	0.035514

Table 9: Volatility forecast: RMSE for In-sample period

Country	ARMAX 1	ARMAX 2	ARMAX 3	ARMAX 4	ARMAX 5
Spain	0.021855	0.021876	0.021889	0.022415	0.021893
Germany	0.012011	0.012087	0.012076	0.012003	0.012009
UK	0.018621	0.019222	0.020254	0.018591	0.019527
Italy	0.027662	0.027744	0.047507	0.028939	0.047335
France	0.047645	0.048033	0.047683	0.047741	0.047616

Table 10: Voaltility forecast: RMSE for Out-of-sample period

sentiment news time series as an input variable decreases the RMSE of the one-step ahead forecast. Table 10 depicts the RMSE for the five countries. We can therefore conclude that news time series with our derived daily news signals are a valuable input variable and contain information to forecast spread changes and its volatility.

Furthermore, we depict in Figure 7 the mean bond spread change as well as the rolling correlation between those and the volume of news.

The Figure shows how the correlation changes over time. As was pointed out in the previous section, changing correlation patterns are an important hint to detect changing market states. Furthermore, by comparing the rolling correlation dynamics in the five European countries, we can see that

6 Conclusion

Our analysis finds significant correlations between aggregated macroeconomic news time series and sovereign bond spreads. We investigate the behaviour of both long- and short-term bonds and find in most cases significant correlations between the three time series of spreads (yield spreads, spread changes and the volatility of spreads) and daily news time series. Those take into account either the news sentiment of an news item or the volume of the news. We distinguish between all,

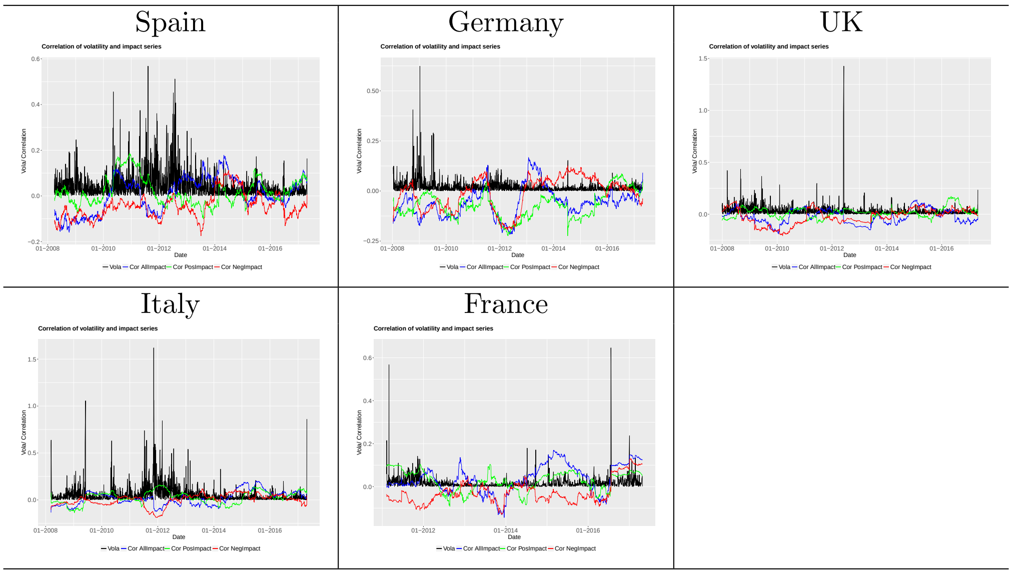

Figure 7: Mean volatility of daily spread change and its correlation with daily news impact series for five European countries.

positive and negative news items and found significant correlations between these series and the bond spread. Whether positive or negative news series showed a higher correlation depends on the state of the business cycle. The changing dynamics of correlations is analysed through rolling correlations. We found that changing signs of the correlation between spread and the volume of positive news can be taken as an indicator to detect changing market conditions. In good economic times, volume of positive news is negatively correlated with bond spreads whereas bear markets seem to generally exhibit positive correlation with news volume time series. We therefore recommend to take volume and impact news series into account to capture characteristics in changing markets.

We find that the best-suited external variables are Positive Impact and Negative Impact daily time series (Model 2) as well as Volume of All News and All Impact daily time series (Model 3) which outperfom the ARIMAX model without news information for the European countries considered. The RMSE of the one-step ahead forecast is smaller, the prediction of the one-step ahead spread change and the volatility proxy is improved when external news variables are taken into account. Our findings support earlier results on time-varying factors, since also for news sentiment, correlations vary over time and have changing dynamics depending on the state of the market. We conclude that news sentiment adds value to modelling sovereign yield spreads and should be taken into account when analyzing and monitoring spreads.

Our analysis further shows that correlation and forecast errors clearly vary through time. We propose to monitor correlation changes over time to recognise changing market conditions as well as to identify relevant external regressors for a one-step ahead forecast. The ARIMAX models show enhanced error measures in both in-sample and out-of sample performance when news time series were taken into account.

Future work will cover an in-depth analysis of regressors and their influence on bond spreads. The instrument universe shall be broadened, and corporate spreads shall be investigated. A first outlook confirmed the findings in this paper for other instruments, an in-depth analysis will be considered in the near future. Furthermore, regime-switching characteristics between news variables and spreads shall be studied in more detail.

Acknowledgement:

This work is part of the project SENRISK E!10488 supported by funding from Eurostars-2 joint programme with co-funding from the European Union Horizon 2020 research and innovation programme, which we gratefully acknowledge.

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