Forecasting sovereign bond spreads with macroeconomic news sentiment

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Abstract

We analyse sovereign bond spreads from Germany and enhance their modelling and prediction through macroeconomic news sentiment. Sentiment time series are created which mirror the mood in news regarding political and economical issues in European countries. Positive and negative sentiment is analysed separately taking into account market restrictions and trading venues. We are able to enhance the forecast errors in ARIMAX models through incorporating news sentiment series. Credit risk of sovereign bonds is therefore monitored more efficiently when news sentiment are taken into account.

Keywords Time series model, Bond spreads, News sentiment, 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 [14]. 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 [15]). Sentiment Analysis is 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 the forecast and contributes to improved portfolio decisions as discussed in [12] and [19], 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 [8]) and lacks thorough investigation. 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. [3], [5] and [13]) 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.[6]); 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 by done by considering macroeconomic news, which report on changing dynamics and influences from issuing and neighbouring countries. News and sentiments for sovereign bond spreads were investigated by [16] and [4], 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 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

Table 1: Bond description of analysed Bunds

Bond	First observed date	Days to Maturity	Maturity date	Coupon
Spread 1	2007-05-02	3716	07/04/17	4.25
Spread 2	2008-05-30	3687	07/04/18	4.25
Spread 3	2009-10-27	3537	07/04/19	3.5
Spread 4	2010-05-05	3713	07/04/20	3
Spread 5	2011-05-10	3708	07/04/21	3.25
Spread 6	2012-04-12	3735	07/04/22	1.75
Spread 7	2013-09-13	3623	08/15/23	2
Spread 8	2014-09-11	3626	08/15/24	1
Spread 9	2015-07-16	3683	08/15/25	1
Spread 10	2016-07-13	3685	08/15/26	0
Spread 11	2007-01-05	11868	07/04/39	4.25
Spread 12	2008-08-11	11650	07/04/40	4.75
Spread 13	2010-08-02	11659	07/04/42	3.25
Spread 14	2012-04-26	11757	07/04/44	2.5
Spread 15	2007-01-05	11857	08/15/46	2.5

of processed macroeconomic news and its sentiment towards European sovereign yield spreads. In particular, we investigate the dynamics of German Bubills and Bund spreads and find a relation between their 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 find that negative sentiment as well as the volume of incoming news lead to better one-step ahead predictions of spreads. We find significant correlations between sentiment time series and yield spreads and analyse these correlation overtime. 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.

2 Data

2.1 Bond data

We analyze long- and short-term bonds issued by Germany in this study. During the Eurozone debt crisis, German bonds were considered as the "safe haven", often referred to as the "riskless" asset. We analyse in our study 36 Bubills (short-term bonds) and 15 Bunds (long-term bonds) issued from Germany between 2007 and 2017. We analyse time series 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).

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. 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. Out of all sentiment values that stream in over the day, we create daily news time series. The news time series are all based on RavenPack's Macroeconomic News Sentiment.

For our particular experiment in this paper, we follow macroeconomic news, which are bundled under the key words for Germany, namely "Germany" and "Government Germany", representing the issuer of the bonds. A typical macroeconomic news example from our database includes the time stamp, a relevance of the news with respect to the key word as well as the sentiment value ("ess").

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 close time until market close time on the following day for the daily news sentiment. We create

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

for the three categories

a. all news
b. positive news
c. negative news

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 ARIMA model. Furthermore their correlation with the yield spread is calculated for the whole time period as well as in a rolling window.

3 Model

In order to establish whether a relation between the different news time series and the yield spread series exists, we test for correlation between the daily yield spread 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 observed 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 spreads. All nine news time series are taken as regressors in a variety of combinations. We report here results for regression with three news series regressors.

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 spreads. 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. We model the first difference of our time series, therefore $i = 1$. An ARIMAX model was also successfully applied by Apergis [2] to analyse CDS spreads and newswire sentiments. His study results in improved forecast errors when external news time series were allowed. We model the yield spreads firstly with an ARIMA(p,1,q) model and compare the resulting in-sample and out-of-sample one-step ahead forecast errors to those which arise from ARIMAX(p,1,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 throughout all 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 results for long-term bonds

Yields and spreads of “Bundesanleihen”, national bonds emitted by the Federal Republic of Germany, are affected by various internal and external factors. Bundesanleihen express expectations about inflation and economic growth but likewise depend on numerous determinants that cannot be isolated explicitly. These other factors might well be captured through news sentiment time series. In the following we would like to determine whether these sentiment series can add value to regression analysis and bond spread forecasts through an ARIMAX model.

We firstly analyze long-term loans emitted by Germany, the so-called Bunds. In total, we analyze 15 instruments with a maturity between 5 and 30 years. The AAA-rated European bond is chosen as a benchmark, therefore the spread series which we model is created as a spread with ECB AAA Svenson yields. For all 15 loans, we perform experiments with news-sentiment time series and model the spread time series by including this information from our news sources. Firstly, the correlation between the spread series and nine different news-related time series are estimated and its significance checked.

In addition, we find an appropriate ARIMA order for the spread series’. Our conducted tests calculate the Akaike information criterion and reveal that ARIMA (2,1,2) is an appropriate model order for a typical spread series from the Bunds.

Furthermore, we conduct a unit root test (Augmentend Dickey Fuller) to see whether the time series is non-stationary and differencing is necessary. The null-hypothesis is that of non-stationarity, therefore a small p-value (less than 5%) points to a stationary time series, the null-hypothesis of non-stationarity can be rejected. A second unit root test is the KPSS test (Kwiatkowski-Phillips-Schmidt-Shin), where the null-hypothesis is that of stationarity. For our bond data sets, a small p-value is reported, so stationarity can be rejected.

In the following, we will analyse 15 Bunds and report the results of a correlation test, a linear regression and the ARIMAX model. We firstly state the significance of correlation between the spread series and the nine news-related time series. The second result for each Bund shows the summary statistics for a linear regression, whereby the number of all news, the positive impact and the negative impact time series were chosen regressors. The choice of these regressors is the results of a variety of regression analysis with changing regressors. This combination is most suitable for a majority of Bunds.

Lastly we perform ARIMA modelling of the instruments. The ARIMAX(2,1,2) models were fitted in an in-sample period and the one-step ahead forecast was further evaluated in an out-of-sample window. For all Bunds, we analysed different news time series as external variables and show here the results for the most promising model set-ups. We show error measures for a one-step ahead forecast in the in-sample as well as out-of-sample window and distinguish between eight model set-ups. Our ARIMAX models have the following external regressors:

1. no external regressor
2. Number of all news; All News Impact; Number of positive news; Positive news impact
3. Number of all news; All News Impact; Number of negative news; Negative news impact
4. Number of all news; All News Impact
5. Positive Impact; Negative Impact
6. Mean Positive Sentiment
7. All News Impact
8. Number of all news

The estimated models cover both multi- as well as univariate external variables. The models in this final analysis were chosen from a larger set of univariate and multivariate model set-ups and represent the most promising forecast models for these bonds.

4.1 Correlation with news time series

The correlation analysis shows that we find a significant correlation between the spread time series and the news sentiment time series for most cases . Table 4.1 shows the percentages of bonds with significant correlations for each sentiment time series with spread and squared spread time series. In 87% of analysed spread time series, at least one news sentiment series showed significant correlation with the spread series.

4.2 Linear regression

A linear regression was performed on all 15 bunds, where the number of all news, the positive impact series and the negative impact series were the chosen regressors. We report here the summary statistics as well as the diagnostic plots and find significant

Table 2: Percentage of significant correlations between spread and sentiment time series'

News time series	Spread	Squared spread
All Sentiment	40%	40%
Nr all news	73%	73%
All impact	33%	33%
Positive Sentiment	20%	13%
Nr positive news	80%	73%
Positive impact	20%	13%
Negative Sentiment	60%	67%
Nr negative news	67%	73%
Negative impact	60%	67%

regressors for most of the spreads, supporting the fact that sentiment information plays a role in explaining bond spreads. Significant regressors for the first bond are the number of all news as well as the negative impact series. The diagnostics plots show a more or less vertical plot for the residuals, therefore the residuals so not exhibit any trend that could be captured further.

The second bond with a duration of 10 years chooses all three regressors as significant. Again, diagnostic plots do not show any trends or outliers in the residuals that would have to be removed.

Spread Nr.3 also chooses all three regressors as significant. Positive impact has a negative coefficient here, opposite to the coefficient for the second analysed spread.

All three regressors are again significant for the fourth analysed spread, which has a duration of 10 years with a start date of May 2010.

The regression analysis plots for Spread 5 show no trends in the residuals.

Spread 6 does not identify the positive news impact series as a significant regressors, but number of all news and negative impact are chosen.

The number of all news is the only significant regressor for Spread 7. Again, for Spread 8, just the number of news is identified as significant, the diagnostic plot show some deviation from the normal distribution.

For Spread 9 and 10, neither of the regressors is flagged as being significant.

Spread 11 exhibits once again significant regressors from the "number of all news".

The linear regression analysis for spread 12 chooses the Number of All News as well as the Negative Impact time series as regressors.

The same analysis is valid for Spread 13, the number of all news as well as Negative Impact is chosen.

Bund Spread time series: 1

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.1062	0.0150	-7.10	0.0000
NrOfAllNews	-0.0003	0.0001	-3.48	0.0005
PosImpact	0.0329	0.0261	1.26	0.2070
NegImpact	0.1904	0.0206	9.24	0.0000

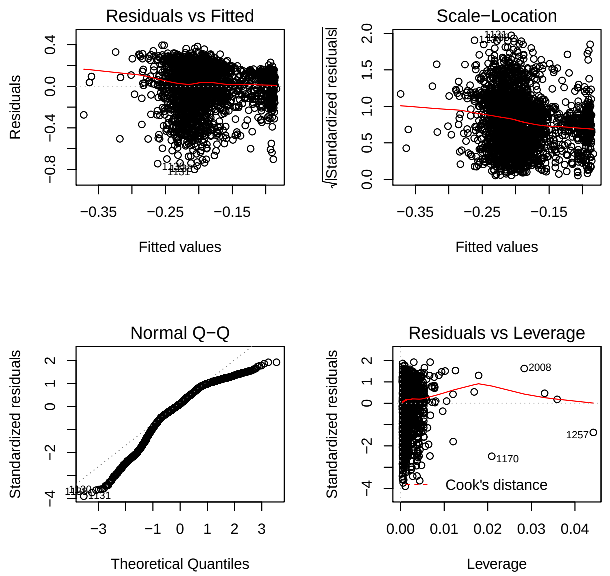


Table 3: Summary and diagnostic plots for regression analysis

Again, the same regressors are chosen for Spread 14. The last spread exhibits significant correlations with the negative sentiment time series.

Bund Spread time series: 2				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.1647	0.0185	-8.91	0.0000
NrOfAllNews	-0.0002	0.0001	-2.07	0.0390
PosImpact	0.0674	0.0320	2.11	0.0352
NegImpact	0.2242	0.0248	9.02	0.0000

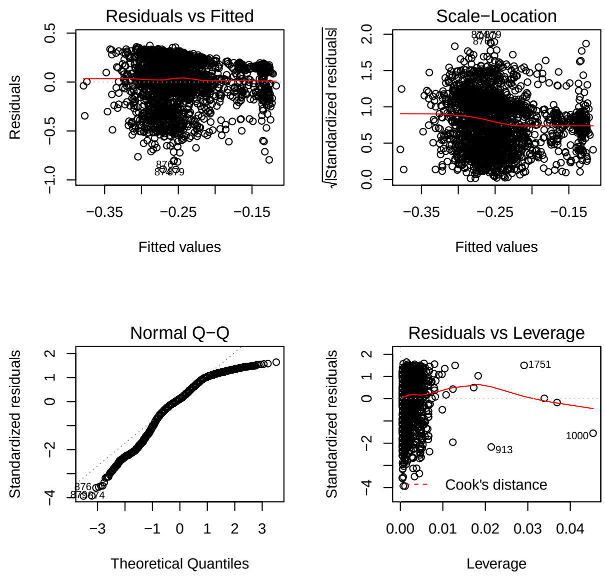


Table 4: Summary and Diagnostic plots for regression analysis

4.3 ARIMAX model

We model the 15 bunds which we analyse through an ARIMAX (2,1,2) model. The forecast errors of the pure ARIMA(2,1,2) model are compared to those of the extended ARIMAX model. For in- and out-of-sample one-step ahead forecasts, we consider the error measures Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Scaled Error (MASE). We analyse for each bond an in-sample period, which covers 85% of the length of the time series, and an out-of-sample period, which is the remaining 15% of length of the time series.

Below, the results for the ARIMAX (2,1,2) models are plotted. Error measure tables for all Bunds are stated in Appendix 7. For Spread 1, in the one-step ahead forecast within the in-sample period, model 3 gives the best results, in the out-of sample period, bet results are achieved for model 6. Spread 2 finds the best ARIMAX model for the in-sample period is model 2 and 4, whereas the best model in the out-of sample period is Model 7 and 8. There is therefore not a single best suited model, since nearly all sentiment series show significant correlation with the spread series, various regressors and external variables can be chosen and add value to the model forecast. Best ARIMAX models for Spread 3 are the third one for the in-sample period and the first one for the out-of-sample period. This means that in this particular case, adding news sentiment data does not add extra value to the ARIMAX model.

The best forecast ARIMAX model for Spread 4 is model 3 and 8, various com-

Bund Spread time series: 3

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0988	0.0212	-4.66	0.0000
NrOfAllNews	-0.0003	0.0001	-3.34	0.0009
PosImpact	-0.1254	0.0389	-3.22	0.0013
NegImpact	0.1583	0.0262	6.05	0.0000

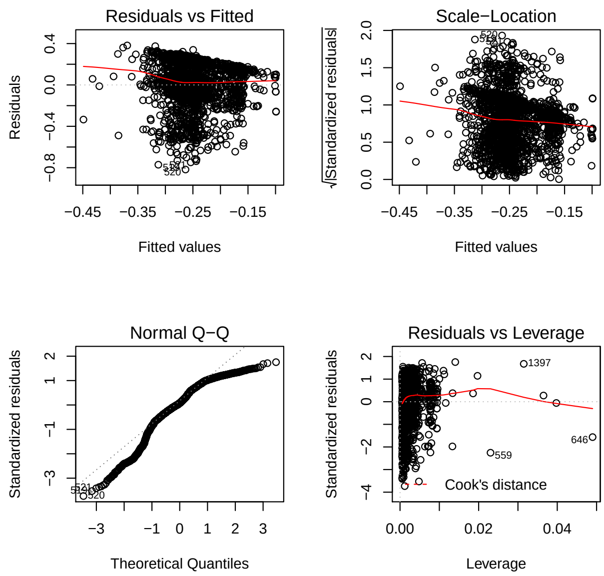


Table 5: Summary and Diagnostic plots for regression analysis

binations of external explanatory variables can be chosen to achieve better error measures. The best ARIMAX model for spread 5 is model 3 for the in-sample period and model 7 for the out-of-sample period. Best ARIMAX models for Spread 6 are models 6 and 8.

Best ARIMAX models are model 6 and 7 for Spread 7. Model 4 and 6 are the best choice for the ARIMAX model for Spread 8. Spread 9 is rather uncommon. Neither of the regressors is flagged as being significant. However, the ARIMAX one-step ahead forecast is improved for Spread 9 when the sentiment data is added.

Best ARIMAX models for Spread 12 are models 7 and 8. However, the best ARIMAX models for Spread 13 are models 2 and 7. Model 2 (in-sample) and model 4 (out-of sample) lead to the smallest one-step ahead forecast errors for Spread 14. In line with the regression analysis, the regressor "Negative Impact" is significant for Spread 15. Forecast errors are smallest for models and 1, making it the second spread to prioritise a simple ARIMA(2,1,2) model over a ARIMAX model with external explanatory variables.

Overall, the best performing ARIMAX model over these bunds spread time series are Model 2 and 3 for in-sample and Model 7 for out-of sample one-step ahead predictions. Therefore, multivariate models with Number of all news, All News Impact, Number of positive news, Positive news impact or Number of all news, All News Impact Number of negative news Negative news impact add the most value to the ARIMAX model for in-sample forecast. Out-of-sample forecast is best in univariate settings. Here, choosing Mean Positive Sentiment or All News

Figure 1: Out-of-sample 1-step ahead forecast for Spread 1

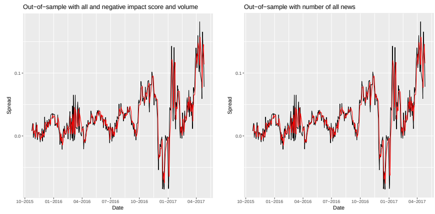


Figure 2: Out-of-sample 1-step ahead forecast for Spread 2

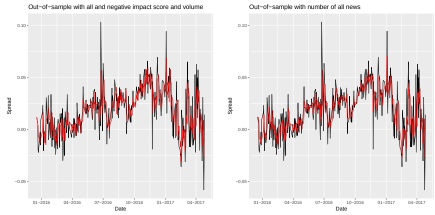


Figure 3: Out-of-sample 1-step ahead forecast for Spread 3

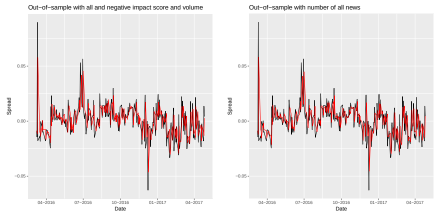


Figure 4: Out-of-sample 1-step ahead forecast for Spread 4

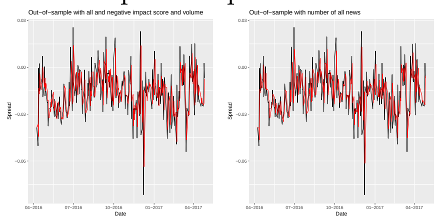


Figure 5: Out-of-sample 1-step ahead forecast for Spread 5

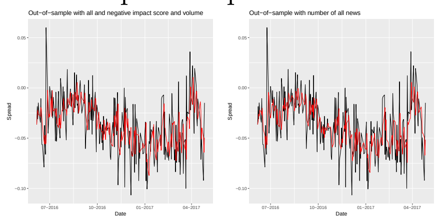


Figure 6: Out-of-sample 1-step ahead forecast for Spread 6

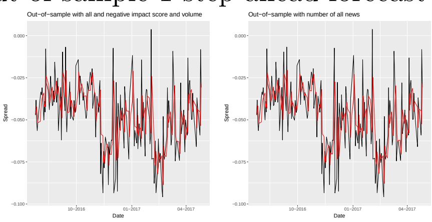


Figure 7: Out-of-sample 1-step ahead forecast for Spread 7

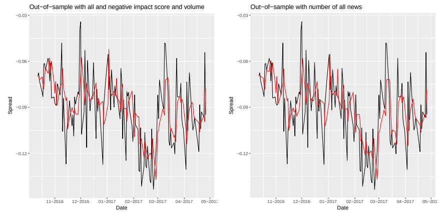


Figure 8: Out-of-sample 1-step ahead forecast for Spread 8

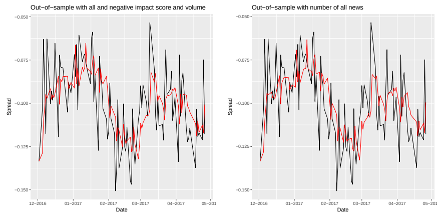


Figure 9: Out-of-sample 1-step ahead forecast for Spread 9

Figure 10: Out-of-sample 1-step ahead forecast for Spread 10

Figure 11: Out-of-sample 1-step ahead forecast for Spread 11

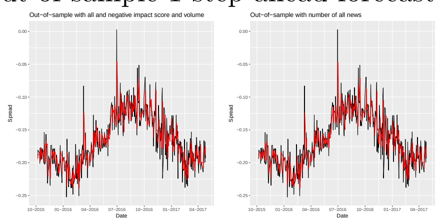
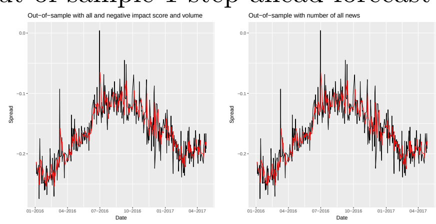


Figure 12: Out-of-sample 1-step ahead forecast for Spread 12



Bund Spread time series: 4				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.1141	0.0233	-4.91	0.0000
NrOfAllNews	-0.0003	0.0001	-3.40	0.0007
PosImpact	-0.1243	0.0428	-2.90	0.0037
NegImpact	0.1784	0.0288	6.20	0.0000

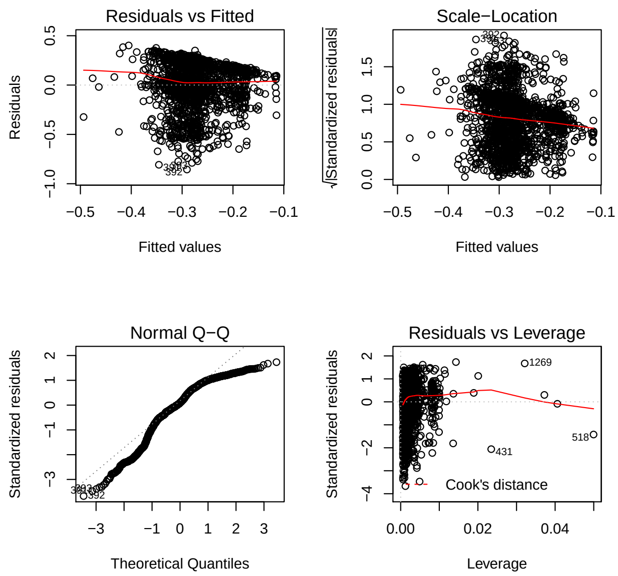


Table 6: Summmary and Diagnostic plots for regression analysis

Impact brings the best results. All these models outperform the simple ARIMA model without external regressor in terms of the chosen error measures.

5 Empirical results for short-term bonds

The following analysis concentrates on short-term bonds, Bubills, issued from the Federal Republic of Germany. We analyse the spreads of these Bubills which were active between 2007 and 2017 and utilize the aforementioned news time series from Section 2 to model the spreads.

5.1 Correlation with news time series

We start by analyzing the correlation between the spreads of Bubills to ECB AAA-rated rates and the news time series. To create news time series', we observe news for "Government of Germany" and include all news sentiment items above a relevance of 60. We tested the percentage of spread series showing a significant correlation with at least one of the news time series. Table 5.1 shows the percentages of spreads with significant correlations with news time series, where the cut-off point for relevance was varied between 30 and 90. A similar picture emerges when we observe news from topic "Germany".

We further distinguish between all news items as well as news items from categories "economics", "politics" and "business". We analyse the correlation between

Bund Spread time series: 5

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.1246	0.0256	-4.87	0.0000
NrOfAllNews	-0.0004	0.0001	-3.44	0.0006
PosImpact	-0.0952	0.0474	-2.01	0.0448
NegImpact	0.2044	0.0321	6.36	0.0000

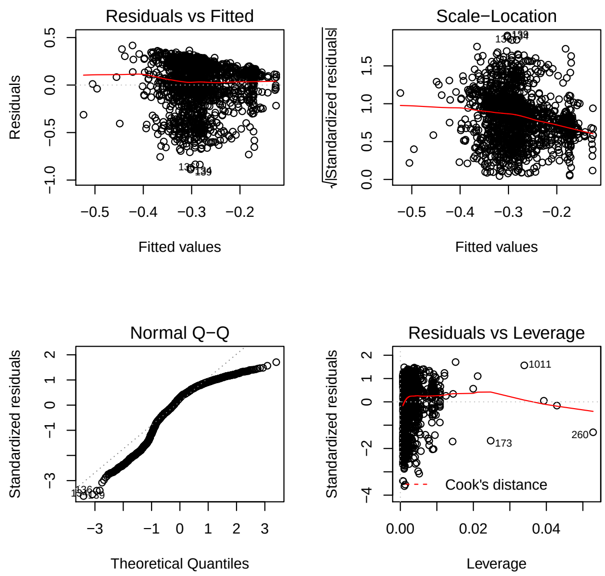


Table 7: Summary and Diagnostic plots for regression analysis

these news time series and several spread time series: for each bond, we create the spread series, the first difference spread time series as well as the squared spread time series, which serves as a proxy for daily volatility.

The results show significant correlations mainly between the squared spreads and the news time series, followed by significant correlations between spreads and news time series'. Analysing squared spreads, we find the highest number of significant correlations with the news time series "All Sentiment" and "Negative Sentiment". Here, significant correlations can be found in around 25 % of cases. Similar correlations can be found for the spread time series itself. The highest number of significant correlations can be seen with the number of negative news time series, whereas "All Sentiment", "Positive Sentiment" and "Negative Sentiment" time series show a similar proportion of significant correlations. It has to be noted that the percentage of Bubill bond spreads series showing significant correlation with news time series is lower than that of long-term bond spreads over the same time period. Bubill spreads often show a sharp increase in volatility over the last weeks or month before maturity. Especially these time intervals are less likely to exhibit significant correlation with news time series.

In the following, we utilize the news category covering the entity "Government of Germany" and test its influence on the German Bubills. We would like to analyze whether news classified as "governmental" have a stronger impact on Bubill spreads. Again, we analyze pure spreads as well as squared spreads and conduct correlation tests, regression analysis as well as one-step-ahead forecasts through an

Bund Spread time series: 6				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.1289	0.0192	-6.73	0.0000
NrOfAllNews	-0.0003	0.0001	-3.37	0.0008
PosImpact	-0.0320	0.0355	-0.90	0.3673
NegImpact	0.1277	0.0246	5.20	0.0000

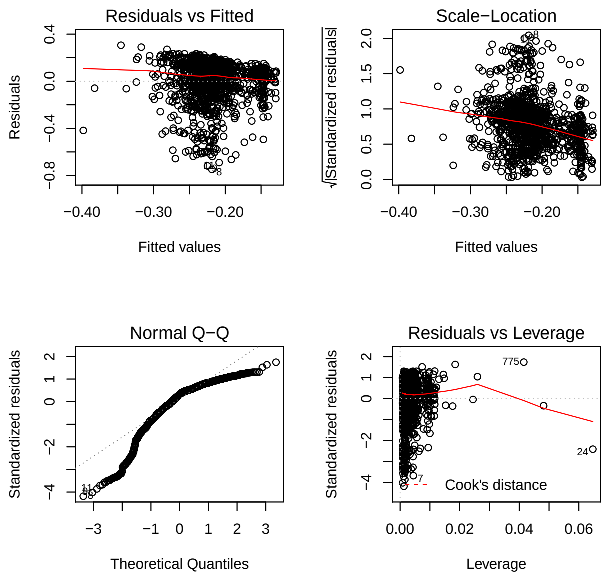


Table 8: Summary and Diagnostic plots for regression analysis

ARIMA(1,1,1) model with external regressors. We analyze the effect of news sentiment with a relevance > 60. Our results show significant influences from news time series associated to “Government Germany” to both pure and squared spreads. In addition, both positive and negative sentiment time series seem to have an effect on the spreads. However, rarely all news time series show significant correlations, typically either time series regarding all and positive or time series regarding all and negative sentiment have significant correlation. Whether positive or negative news series are significant is thought to be due to the business cycle state the analysed Bubill falls under, meaning that in times of recession negative news have a higher impact than positive news and vice versa.

5.2 Bubill examples - correlation and ARIMAX models

The following example shows the spread of a zero-coupon Bubill issued on 25th September 2009 with a duration of 110 days until January 2010 where significant correlation with negative news time series can be observed. We firstly depict the spread time series as well as the all, positive and negative sentiment time series over the duration of the bond.

Forecasts through the ARIMAX-model with various uni- and multivariate external variables lead to results stated in Figure 5.2. The chosen ARIMA order is here $(1, 1, 1)$, which was again determined through the Akaike Information criterion. The graphs of the forecasts show a close forecast, the error analysis points to

Figure 13: Out-of-sample 1-step ahead forecast for Spread 13

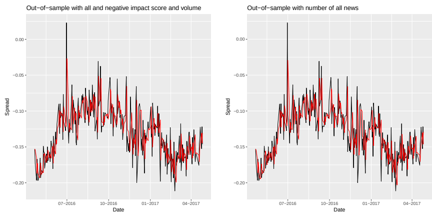


Figure 14: Out-of-sample 1-step ahead forecast for Spread 14

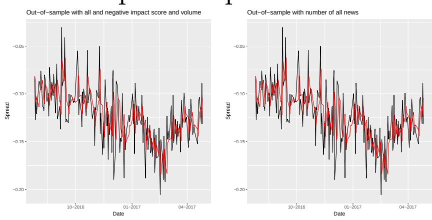
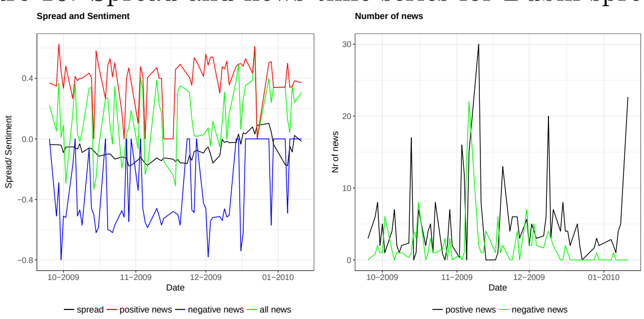


Figure 15: Out-of-sample 1-step ahead forecast for Spread 15

Figure 16: Spread and news time series for Bubill spread 1




```
P-value All Sentiment: 0.008656504  Correlation significant
P-value Nr all news 0.3328246
P-value All impact 0.001045843  Correlation significant
P-value Positive Sentiment 0.1791648
P-value Nr positive news 0.6119549
P-value Positive impact 0.1003025
P-value Negative Sentiment 0.0144835  Correlation significant
P-value Nr negative news 0.01172509  Correlation significant
P-value Negative impact 0.01388118  Correlation significant
```

Bund Spread time series: 7

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.1309	0.0066	-19.79	0.0000
NrOfAllNews	0.0001	0.0000	2.45	0.0144
PosImpact	0.0012	0.0124	0.10	0.9207
NegImpact	0.0050	0.0087	0.57	0.5677

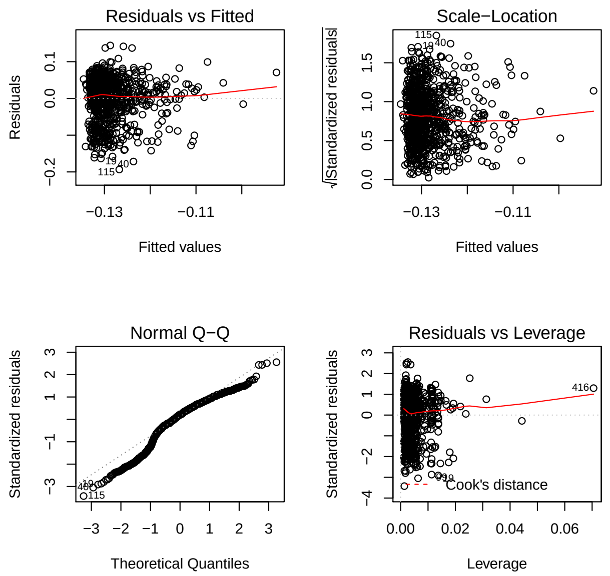


Table 9: Summary and Diagnostic plots for regression analysis

ARIMAX-models 3 and 5 being the best models for this Bubill.

The next example shows a spread time series which exhibits significant correlation with the positive news sentiment time series. Furthermore, the regression analysis shows a significance for this explanatory variable. The ARIMA(1,1,1) analysis and forecast highlights the fact that the external regressor improves the one-step ahead forecast which is computed in both settings, an in-sample and out-of-sample framework. The ARIMA with the lowest forecast errors are Model 2 and 8, which include the time series “Nr of all news”, “Impact of all news”, “Nr of positive news” and “Impact of positive news” as external regressors. The analysed zero-coupon Bubill is issued on 13/07/16 with a duration of 182 days until 01/11/17.

THese two examples highlight the fact, that correlations between spread and news time series vary over time, leading to different “best” external variables for the ARIMAX model. However, in all our examined cases, including the external variables in the ARIMAX models improved the one-step ahead forecast. We therefore conclude that including news sentiment in modelling spreads improves the forecast accuracy and gives valuable input to the forecast.

We analysed 36 Bubill spreads with issuing dates between 2007 and 2017. For all thee instruments, we analysed and tested the correlation, performed regression analysis and conducted one-step ahead ARIMAX prediction within eight different model set-ups. For our experiments, the best performing ARIMAX model is Model 3, followed closely by Model 4. The chosen regressors in the analysed eight model set-ups are a combination of 1.)All Sentiment, 2.) Number Of All News 3.) All

Figure 17: 1-step ahead forecast: In-Sample ARIMA(1,1,1) modelling for Bubill spread 1

Figure 18: 1-step ahead forecast: Out-of-Sample ARIMA(1,1,1) modelling for Bubill spread 1


```
Order ARIMA-Model: 1 1 1
Forecast errors for in-sample period
   RMSE         MAE         MPE      MAPE       MASE
0.03074824 0.02198856 -51.91019 86.05754 0.9093398
0.02934609 0.02147398 -50.72114 85.42070 0.8880590
0.02925527 0.02048970 -52.73251 84.60440 0.8473543
0.03010934 0.02156802 -52.98171 85.14980 0.8919482
0.03015991 0.02169355 -52.80185 84.78836 0.8971396
0.03074753 0.02199991 -51.83295 85.99636 0.9098092
0.03001816 0.02172572 -50.50191 85.13274 0.8984698
0.03045630 0.02221311 -51.41322 86.16472 0.9186261
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   3    3    7    3    3
Forecast errors for out-of-sample period
    RMSE         MAE        MPE      MAPE       MASE
0.07940348 0.06167461 65.86530 115.1556 0.9251956
0.08013167 0.06194097 65.66878 116.1546 0.9291914
0.07811581 0.06039459 72.72946 116.4577 0.9059937
0.07908702 0.06105272 71.98895 115.5768 0.9158666
0.07819238 0.05994889 71.90847 113.6667 0.8993077
0.07942550 0.06171400 65.82163 115.1924 0.9257866
0.08054846 0.06285854 64.11149 117.3379 0.9429561
0.07905087 0.06174226 68.06148 117.1462 0.9262104
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   3    5    7    5    5
```

Bund Spread time series: 8

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0908	0.0049	-18.45	0.0000
NrOfAllNews	0.0001	0.0000	2.35	0.0190
PosImpact	0.0065	0.0094	0.69	0.4898
NegImpact	0.0046	0.0064	0.72	0.4712

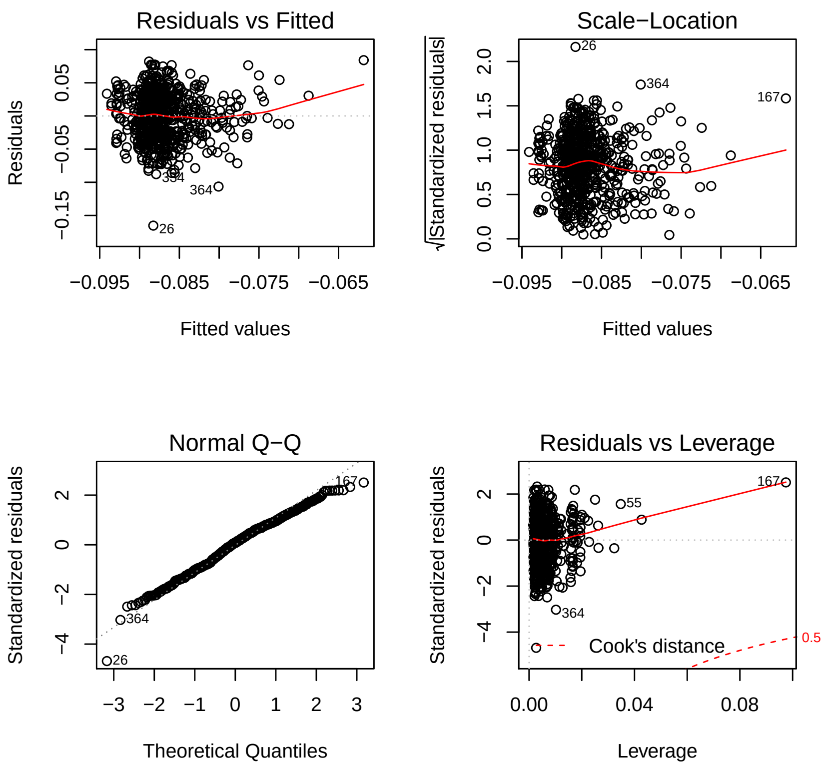


Table 10: Diagnostic plots for regression analysis

Impact, 4.) Positive Sentiment, 5.) Number Of Positive News, 6.) Positive Impact, 7.) Negative Sentiment, 8.) Number Of Negative News, 9.) Negative Impact. ARIMAX Models 1 to 8 are:

1. without regressor
2. Regressors 2,3,5,6
3. Regressors 1,2,7,8
4. Regressors 1,4,7
5. Regressors 6,9
6. Regressors 4
7. Regressors 3
8. Regressors 2

Bund Spread time series: 9

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0719	0.0062	-11.55	0.0000
NrOfAllNews	-0.0000	0.0000	-0.31	0.7548
PosImpact	-0.0041	0.0121	-0.34	0.7354
NegImpact	-0.0062	0.0086	-0.72	0.4701

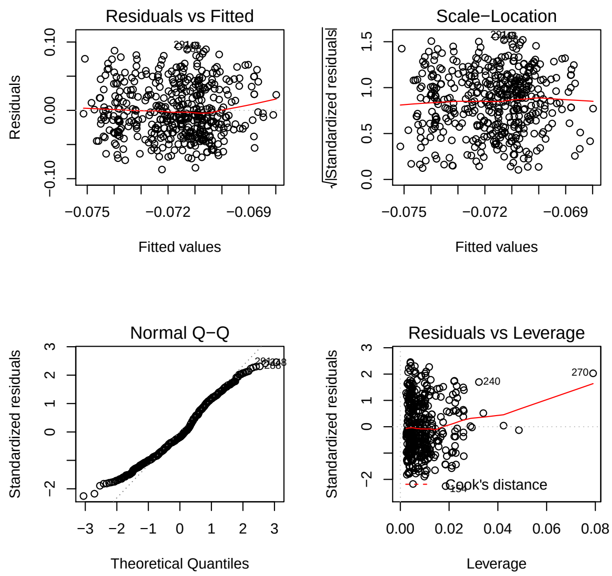


Table 11: Summary and Diagnostic plots for regression analysis

Our analysis resulted in the following percentages of best-performing ARIMAX-Models with respect to analyse external regressors:

Model	Fit	Forecast
1	2%	8%
2	21%	11%
3	26%	21%
4	15%	18%
5	10%	16%
6	2%	5%
7	13%	16%
8	11%	5%

6 Correlation over time

In order to address changing dynamics of both spreads and news time series, we investigate, how the correlation between the spread series and the nine news time series is evolving over time. In particular, we plot rolling correlation for Bubills and Bunds, investigating two spread series in depth.

First, we would like to consider Bunds and their correlation with news time series aggregated from Raven Pack news for the entity “Germany” with a relevance of above 60. The rolling correlation is calculated with a window size of 250 days. In Figures 6 and 6, we depict the evolution of the correlation between spread and

Bund Spread time series: 10

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0024	0.0111	-0.21	0.8312
NrOfAllNews	-0.0000	0.0001	-0.33	0.7416
PosImpact	-0.0173	0.0203	-0.85	0.3943
NegImpact	-0.0111	0.0157	-0.71	0.4777

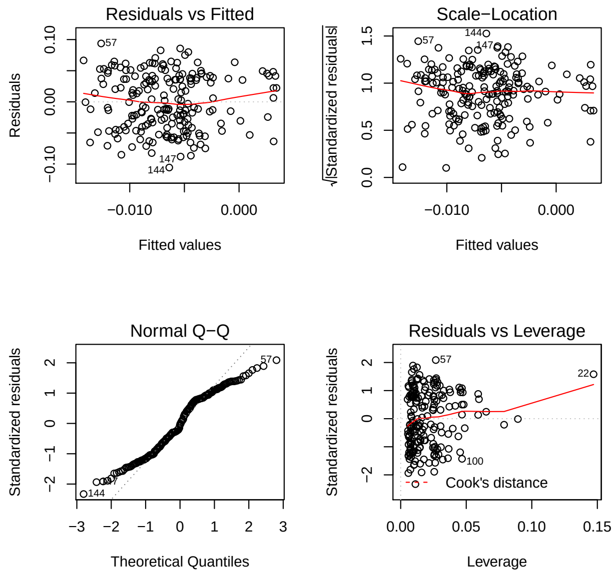


Table 12: Diagnostic plots for regression analysis

i) average sentiment series, ii) news volume series and iii) impact series. We can clearly see, that the observed correlation changes over time for all three settings, running through periods with positive and negative correlations as well as periods with very low correlation between the spreads and the news time series.

The first example shows the evolution of a bond spread between 2011 and 2017. Most notable is the shift from positive to negative and back to positive correlation of the spread and the news time series “All Sentiment”.

Secondly, we investigate the rolling correlations for Bubill spreads. The considered news entity is “Government Germany” and all news items with a relevance of above 60 are taken into account. Here, the rolling window size is 120 days, since the time series are typically shorter. The example in Figure 6 shows correlation for sentiment, volume and impact series. All plots exhibit changing correlation over time, but they remain relatively stable in the considered time frame. Positive sentiment and impact series have the highest positive correlation with the Bubill spread, whereas the negative volume series has the highest correlation from the considered volume series. This correlation undergoes a change, it increases over the second half of the time period.

Bund Spread time series: 11

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.1850	0.0106	-17.50	0.0000
NrOfAllNews	-0.0004	0.0001	-7.27	0.0000
PosImpact	0.0136	0.0184	0.74	0.4609
NegImpact	0.1130	0.0145	7.78	0.0000

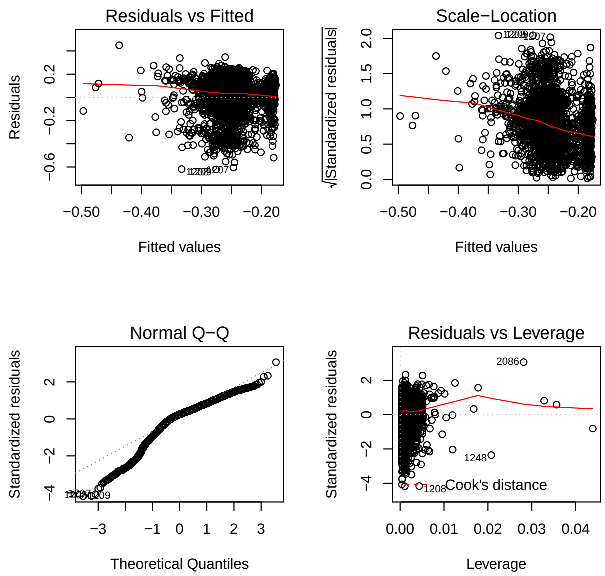


Table 13: Summary and Diagnostic plots for regression analysis

7 Conclusion

Our analysis finds clear links between aggregated 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 spread time series as well as news time series, which take into account either the news sentiment or the volume of the news. We distinguish between all, 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 might depend on the business cycle. We therefore recommend to take several sentiment series into account to cover various characteristics in changing markets.

Our analysis further showed 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. A multivariate model set-up utilizing All Sentiment, Number Of All News, Negative Sentiment and Number Of Negative News as regressors outperformed the other set-ups in terms of smallest forecasts errors.

Future work will cover an in-depth analysis of regressors and their influence on bond spreads. The instrument universe shall be broadened, in particular other countries shall be taken into account and further spreads shall be investigated. A

Bund Spread time series: 12				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.1926	0.0126	-15.26	0.0000
NrOfAllNews	-0.0003	0.0001	-5.57	0.0000
PosImpact	-0.0244	0.0220	-1.11	0.2678
NegImpact	0.0808	0.0167	4.83	0.0000

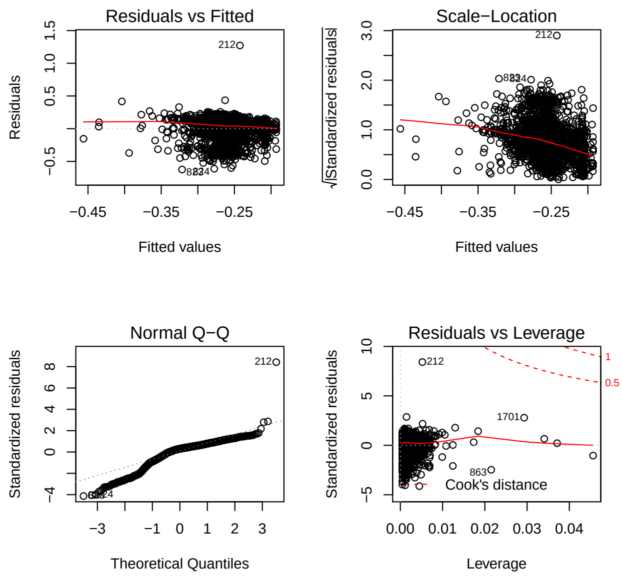


Table 14: Summary and Diagnostic plots for regression analysis

first outlook confirmed the findings in this paper for other countries, an in-depth analysis will be considered in the near future.

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.

Bund Spread time series: 13

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.1678	0.0162	-10.37	0.0000
NrOfAllNews	-0.0003	0.0001	-4.23	0.0000
PosImpact	-0.0368	0.0297	-1.24	0.2154
NegImpact	0.1079	0.0202	5.35	0.0000

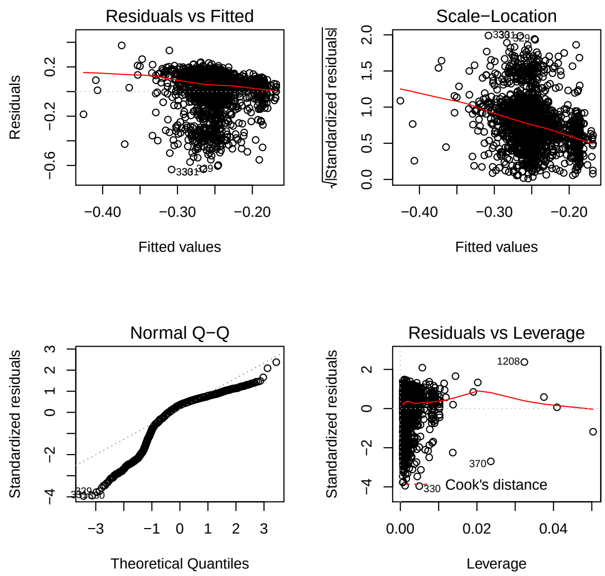


Table 15: Summary and Diagnostic plots for regression analysis

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Bund Spread time series: 14

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.1510	0.0116	-13.02	0.0000
NrOfAllNews	-0.0002	0.0001	-3.80	0.0001
PosImpact	0.0036	0.0215	0.17	0.8671
NegImpact	0.0303	0.0149	2.03	0.0422

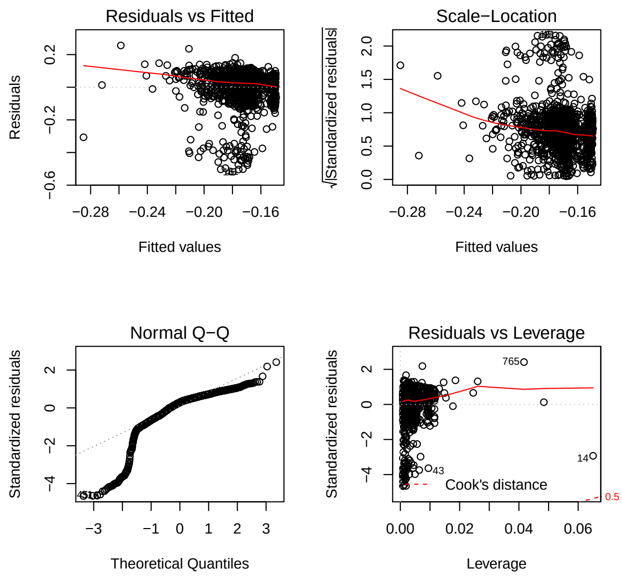

Table 16: Diagnostic plots for regression analysis

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Bund Spread time series: 15

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.1287	0.0094	-13.63	0.0000
NrOfAllNews	0.0001	0.0001	1.13	0.2605
PosImpact	-0.0081	0.0177	-0.46	0.6465
NegImpact	-0.0314	0.0125	-2.51	0.0122

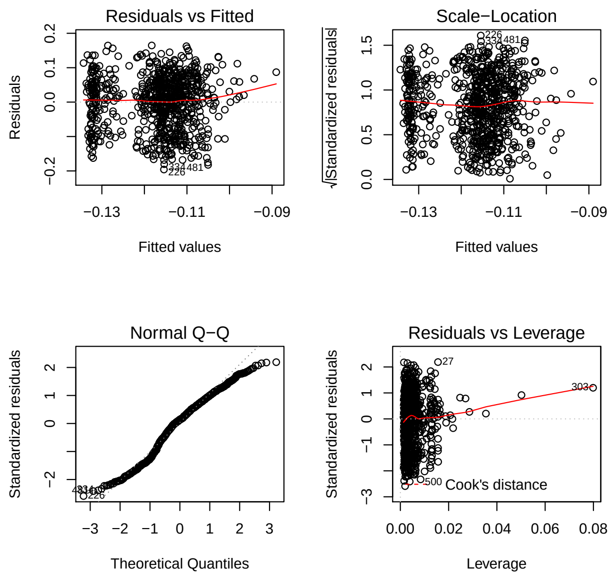

Table 17: Summary and Diagnostic plots for regression analysis

Relevance	> 30	> 40	> 50	> 60	> 70	> 80	> 90
Bond spreads with sign. correlation	61%	50%	56%	61%	61%	42%	33%

Table 18: Percentage of significant correlation between short-term bond spreads and news time series

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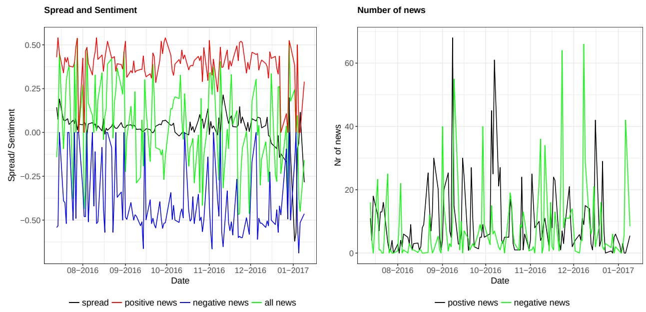
Figure 19: Spread and news time series for Bubill spread 2




```
P-value All Sentiment: 0.7374913
P-value Nr all news 0.03652966  Correlation significant
P-value All impact 0.1707299
P-value Positive Sentiment 3.095744e-05  Correlation significant
P-value Nr positive news 0.2534435
P-value Positive impact 5.862235e-05  Correlation significant
P-value Negative Sentiment 0.2486
P-value Nr negative news 0.0541304
P-value Negative impact 0.2821196
```

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Appendix

Error analysis of ARIMAX models for long-term bonds issued by Germany:

Figure 20: 1-step ahead forecast: In-Sample ARIMA(1,1,1) modelling for Bubill spread 2

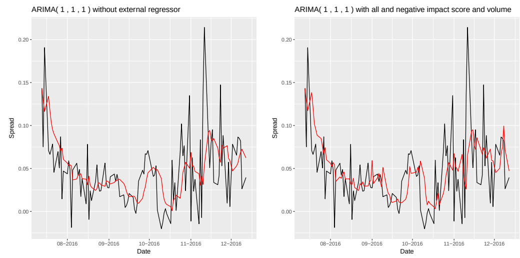

Figure 21: 1-step ahead forecast: Out-of-Sample ARIMA(1,1,1) modelling for Bubill spread 2


```
Order ARIMA-Model: 1 1 1
Forecast errors for in-sample period
RMSE        MAE        MPE       MAPE      MASE
0.03815193 0.02767686 -33.92700 163.9234 0.8159254
0.03748349 0.02727129 -33.11175 152.7413 0.8039693
0.03694460 0.02721440 -40.78214 155.4171 0.8022919
0.03718025 0.02737835 -48.56116 161.0616 0.8071252
0.03783861 0.02722910 -40.14470 161.6709 0.8027254
0.03808133 0.02753248 -38.33215 159.7144 0.8116691
0.03807868 0.02770850 -36.01472 167.5584 0.8168582
0.03774094 0.02713811 -38.71573 157.5582 0.8000431
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   3    8    2    2    8

Forecast errors for out-of-sample period
RMSE       MAE       MPE      MAPE      MASE
0.2251164 0.1670523 60.62028 137.6925 0.8805567
0.2241789 0.1665841 59.79154 139.7525 0.8780888
0.2240375 0.1658857 58.97553 138.5852 0.8744073
0.2274210 0.1687363 56.24815 140.5185 0.8894337
0.2248952 0.1658480 60.25344 135.5232 0.8742089
0.2273081 0.1686339 60.11690 138.3420 0.8888939
0.2237602 0.1662307 62.26870 135.1865 0.8762261
0.2229657 0.1656692 63.17779 136.1997 0.8732662
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   8    8    4    7    8
```

Figure 22: Rolling correlation between Bunds and news

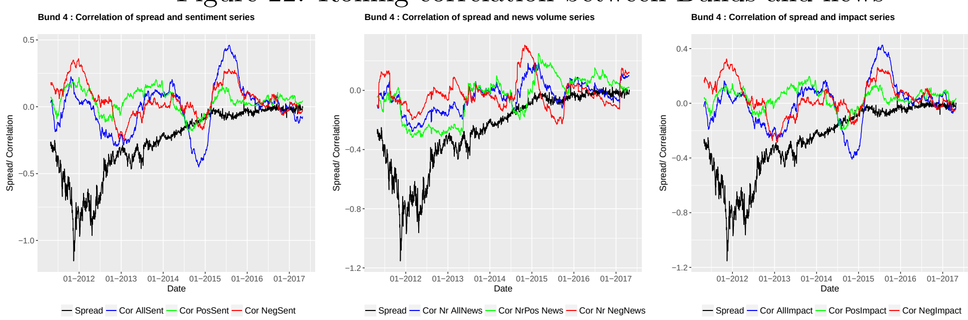

Figure 23: Rolling correlation between Bunds and news

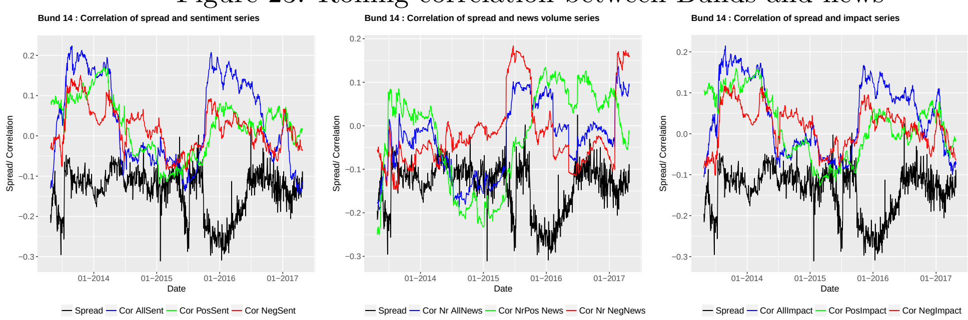

Figure 24: Rolling correlation between Bubills and news

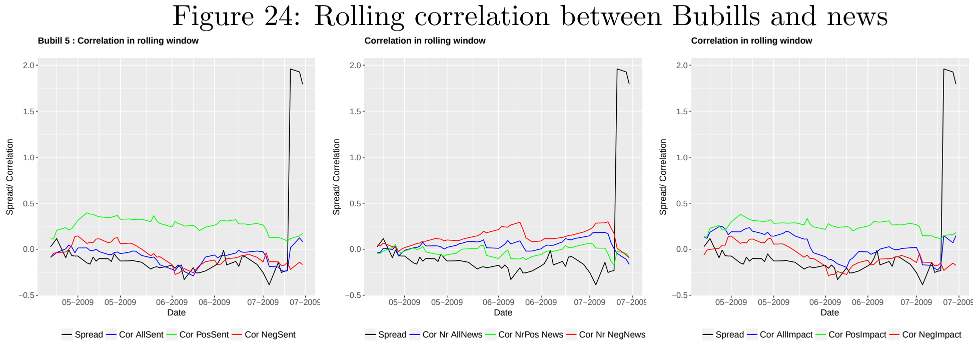

Figure 25: In-sample 1-step ahead forecast for Bund Spread 1

Figure 26: ARIMAX models: Forecast errors for Spread 1

Order ARIMA-Model: 2 1 2

Forecast errors for in-sample period

	RMSE	MAE	MPE	MAPE	MASE
Model 1	0.03213247	0.02222351	2.840216	39.55883	0.9242948
Model 2	0.03211425	0.02221234	3.243932	39.66175	0.9238304
Model 3	0.03210756	0.02219977	3.315172	39.48296	0.9233074
Model 4	0.03213210	0.02222458	2.850158	39.62802	0.9243394
Model 5	0.03211138	0.02220733	3.143650	39.57101	0.9236217
Model 6	0.03212388	0.02222132	2.828735	39.65265	0.9242036
Model 7	0.03213232	0.02222269	2.852097	39.57826	0.9242608
Model 8	0.03213228	0.02222495	2.836466	39.59568	0.9243548

In-sample: Model with lowest forecast error

RMSE	MAE	MPE	MAPE	MASE
3	3	6	3	3

Forecast errors for out-of-sample period

	RMSE	MAE	MPE	MAPE	MASE
Model 1	0.01980518	0.01347483	345.8247	505.8271	0.9880384
Model 2	0.01984469	0.01351324	341.3912	496.9488	0.9908544
Model 3	0.01995010	0.01365937	370.0649	529.6197	1.0015697
Model 4	0.01981239	0.01348789	347.7079	507.0985	0.9889957
Model 5	0.01985638	0.01356497	352.9571	514.1669	0.9946473
Model 6	0.01977306	0.01344331	337.4393	493.9219	0.9857266
Model 7	0.01980449	0.01347321	347.2408	506.3292	0.9879192
Model 8	0.01981064	0.01348587	346.2196	506.5039	0.9888479

Out-of-sample: Model with lowest forecast error

RMSE	MAE	MPE	MAPE	MASE
6	6	6	6	6

Figure 27: In-sample 1-step ahead forecast for Bund Spread 2

Figure 28: ARIMAX models: Forecast errors for Spread 2

```
Order ARIMA-Model: 2 1 2

Forecast errors for in-sample period
              RMSE        MAE      MPE     MAPE      MASE
Model 1 0.04264081 0.02981789 24.51972 64.93835 0.8906101
Model 2 0.04256071 0.02974920 24.79284 64.98835 0.8885585
Model 3 0.04250348 0.02978933 30.40421 69.85325 0.8897573
Model 4 0.04262312 0.02979358 25.50014 64.54829 0.8898842
Model 5 0.04258927 0.02980309 27.05524 66.49195 0.8901680
Model 6 0.04260874 0.02978793 25.29414 65.03840 0.8897154
Model 7 0.04262509 0.02979279 25.11718 64.85747 0.8898605
Model 8 0.04263999 0.02981950 24.52941 64.69433 0.8906584

In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   3    2    1    4    2

Forecast errors for out-of-sample period
              RMSE        MAE      MPE     MAPE      MASE
Model 1 0.01867765 0.01366076 292.2786 397.7499 0.8170953
Model 2 0.01857593 0.01362219 309.9956 405.7377 0.8147882
Model 3 0.01870016 0.01371103 318.2917 417.2910 0.8201018
Model 4 0.01855466 0.01346121 303.3802 400.3746 0.8051595
Model 5 0.01882477 0.01373133 302.5221 406.7313 0.8213159
Model 6 0.01862606 0.01351864 299.5526 399.7037 0.8085942
Model 7 0.01858050 0.01346084 303.6030 402.3374 0.8051373
Model 8 0.01867022 0.01366839 291.9199 396.7518 0.8175514

Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   4    7    8    8    7
```

Figure 29: In-sample 1-step ahead forecast for Bund Spread 3

Figure 30: ARIMAX models: Forecast errors for Spread 3

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
              RMSE        MAE      MPE     MAPE      MASE
Model 1  0.02813136 0.01914454 5.241755 23.95501 0.9343494
Model 2  0.02810672 0.01915336 5.494474 24.32999 0.9347798
Model 3  0.02809193 0.01911347 5.389821 24.33334 0.9328333
Model 4  0.02811931 0.01915748 5.155780 23.94903 0.9349812
Model 5  0.02810554 0.01912666 5.536499 24.49337 0.9334771
Model 6  0.02812201 0.01915382 5.444171 24.23415 0.9348023
Model 7  0.02812280 0.01915227 5.179378 23.90610 0.9347266
Model 8  0.02812815 0.01914785 5.216714 24.00473 0.9345111
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   3    3    4    7    3
Forecast errors for out-of-sample period
              RMSE         MAE        MPE     MAPE      MASE
Model 1  0.01476147 0.009923028 -15.448704 359.9734 0.8845386
Model 2  0.01499660 0.010083953 -13.724165 383.9425 0.8988835
Model 3  0.01498532 0.010188350   3.515632 396.0516 0.9081894
Model 4  0.01486167 0.009994870 -18.934800 369.3973 0.8909426
Model 5  0.01498796 0.010156042   5.913461 393.7733 0.9053095
Model 6  0.01491421 0.010056793 -12.036378 384.4304 0.8964625
Model 7  0.01480723 0.009963518 -20.068364 367.4962 0.8881479
Model 8  0.01480896 0.009940353 -14.514772 360.5034 0.8860830
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   1    1    3    1    1
```

Figure 31: In-sample 1-step ahead forecast for Bund Spread 4

Figure 32: ARIMAX models: Forecast errors for Spread 4

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
               RMSE        MAE       MPE     MAPE      MASE
Model 1  0.02872113 0.01941466 -1.812478 10.57563 0.9300209
Model 2  0.02868627 0.01941906 -1.824229 10.63202 0.9302316
Model 3  0.02866480 0.01938077 -1.823905 10.58648 0.9283972
Model 4  0.02869409 0.01942227 -1.824011 10.63000 0.9303852
Model 5  0.02870604 0.01939291 -1.803036 10.56443 0.9289787
Model 6  0.02871431 0.01941222 -1.811114 10.58448 0.9299040
Model 7  0.02869425 0.01942483 -1.823689 10.62948 0.9305079
Model 8  0.02872152 0.01941371 -1.808846 10.57375 0.9299754
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   3    3    5    5    3
Forecast errors for out-of-sample period
               RMSE        MAE      MPE     MAPE      MASE
Model 1  0.01488595 0.01108451 5.349864 171.5357 0.8870765
Model 2  0.01510830 0.01117779 6.409129 170.6746 0.8945419
Model 3  0.01516780 0.01130752 6.291465 170.6354 0.9049237
Model 4  0.01499011 0.01111866 5.639947 171.5102 0.8898097
Model 5  0.01508285 0.01127011 3.822869 172.1903 0.9019302
Model 6  0.01500493 0.01120129 4.882325 172.7696 0.8964228
Model 7  0.01497761 0.01110639 5.752612 171.3306 0.8888276
Model 8  0.01488006 0.01107965 5.430413 171.5091 0.8866879
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   8    8    5    3    8
```

Figure 33: In-sample 1-step ahead forecast for Bund Spread 5

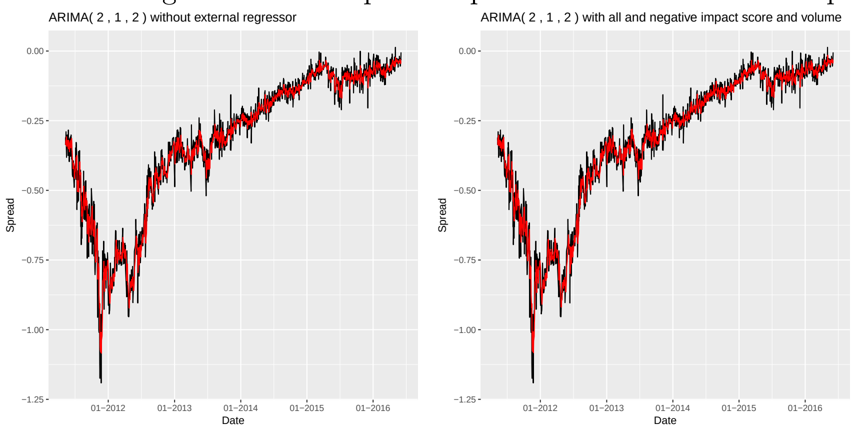

Figure 34: ARIMAX models: Forecast errors for Spread 5

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
              RMSE        MAE       MPE     MAPE      MASE
Model 1  0.04551712 0.03251135 -19.03939 31.55486 0.8640701
Model 2  0.04529856 0.03214814 -17.81320 30.15882 0.8544169
Model 3  0.04521759 0.03211923 -17.47098 29.85524 0.8536484
Model 4  0.04539763 0.03228208 -18.31797 30.70052 0.8579765
Model 5  0.04547197 0.03245610 -18.48261 30.96273 0.8626016
Model 6  0.04547809 0.03244220 -18.51032 30.97946 0.8622322
Model 7  0.04541098 0.03230322 -18.33019 30.73813 0.8585386
Model 8  0.04550774 0.03249451 -19.02922 31.52357 0.8636225
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   3    3    3    3    3
Forecast errors for out-of-sample period
              RMSE        MAE       MPE     MAPE      MASE
Model 1  0.02641224 0.02042963 -73.67076 213.7756 0.7824412
Model 2  0.02630925 0.02023777 -70.71468 213.4371 0.7750927
Model 3  0.02640154 0.02020716 -71.70896 213.6937 0.7739205
Model 4  0.02604267 0.02000847 -71.40281 215.4397 0.7663109
Model 5  0.02641073 0.02059951 -64.33285 207.6477 0.7889473
Model 6  0.02643483 0.02061408 -64.12746 208.0875 0.7895053
Model 7  0.02598977 0.01996735 -72.51309 214.5401 0.7647362
Model 8  0.02645490 0.02046102 -72.82301 214.6189 0.7836432
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   7    7    6    5    7
```

Figure 35: In-sample 1-step ahead forecast for Bund Spread 6

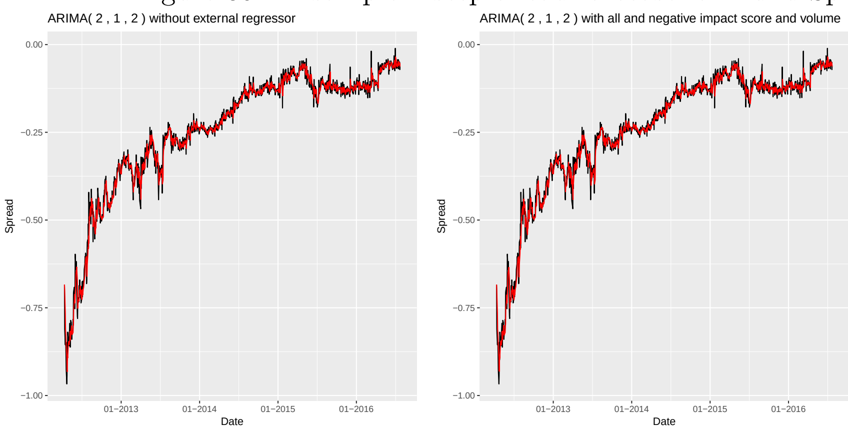

Figure 36: ARIMAX models: Forecast errors for Spread 6

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
              RMSE        MAE       MPE     MAPE      MASE
Model 1  0.02316101 0.01592237 -2.649828 9.956263 0.8865528
Model 2  0.02313925 0.01591927 -2.645949 9.933144 0.8863801
Model 3  0.02314337 0.01592416 -2.629698 9.931910 0.8866522
Model 4  0.02314644 0.01592203 -2.644538 9.933228 0.8865335
Model 5  0.02315739 0.01592526 -2.647972 9.951464 0.8867135
Model 6  0.02316821 0.01590048 -2.578637 9.943471 0.8853335
Model 7  0.02315067 0.01592176 -2.657624 9.950766 0.8865186
Model 8  0.02315619 0.01592284 -2.642216 9.936564 0.8865787
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   2    6    6    3    6
Forecast errors for out-of-sample period
              RMSE        MAE       MPE     MAPE      MASE
Model 1  0.01851920 0.01381328 -14.19691 53.85950 0.8389190
Model 2  0.01850355 0.01382844 -13.99788 54.11753 0.8398393
Model 3  0.01854416 0.01387216 -14.02496 54.26987 0.8424947
Model 4  0.01851905 0.01383761 -14.13982 54.13301 0.8403966
Model 5  0.01853411 0.01383506 -14.08736 54.08014 0.8402418
Model 6  0.01853527 0.01384673 -14.21932 53.86090 0.8409502
Model 7  0.01854769 0.01386346 -14.27437 54.06032 0.8419666
Model 8  0.01848320 0.01378223 -14.06749 53.93354 0.8370328
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   8    8    2    1    8
```

Figure 37: In-sample 1-step ahead forecast for Bund Spread 7

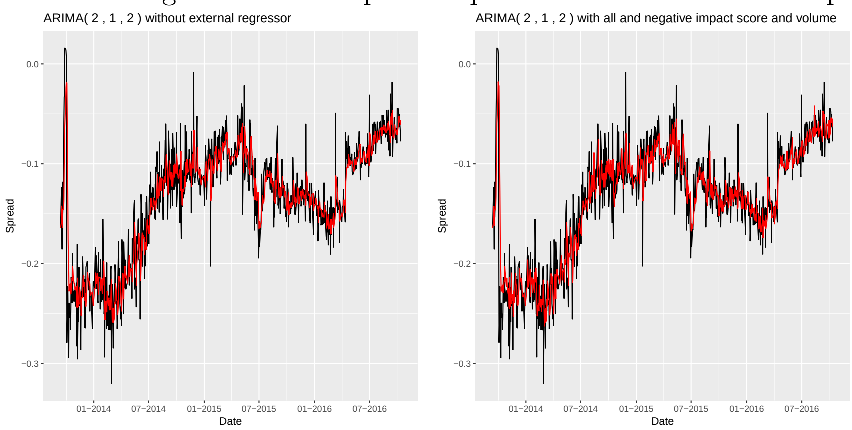

Figure 38: ARIMAX models: Forecast errors for Spread 7

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
             RMSE        MAE       MPE     MAPE      MASE
Model 1  0.02685910 0.01867746 -4.617483 20.05460 0.8378633
Model 2  0.02651821 0.01863829 -4.225770 19.58218 0.8361063
Model 3  0.02647487 0.01866500 -4.250764 19.61952 0.8373046
Model 4  0.02652315 0.01863054 -4.199860 19.56643 0.8357586
Model 5  0.02675585 0.01868481 -4.616058 19.96583 0.8381931
Model 6  0.02684013 0.01865309 -4.595754 20.03462 0.8367701
Model 7  0.02685007 0.01866583 -4.647683 20.02428 0.8373419
Model 8  0.02652998 0.01863080 -4.169520 19.58641 0.8357703
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   3    4    8    4    4
Forecast errors for out-of-sample period
             RMSE        MAE       MPE     MAPE      MASE
Model 1  0.01930489 0.01482760 -3.883363 18.21212 0.8297289
Model 2  0.01925600 0.01502088 -3.744408 18.43922 0.8405449
Model 3  0.01937048 0.01501833 -3.741561 18.44304 0.8404020
Model 4  0.01927052 0.01502890 -3.741976 18.42845 0.8409935
Model 5  0.01949709 0.01492010 -3.932098 18.35387 0.8349055
Model 6  0.01910797 0.01466240 -3.808466 17.99459 0.8204850
Model 7  0.01933599 0.01481477 -3.944982 18.20022 0.8290114
Model 8  0.01925163 0.01504934 -3.689844 18.45038 0.8421374
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   6    6    8    6    6
```

Figure 39: In-sample 1-step ahead forecast for Bund Spread 8

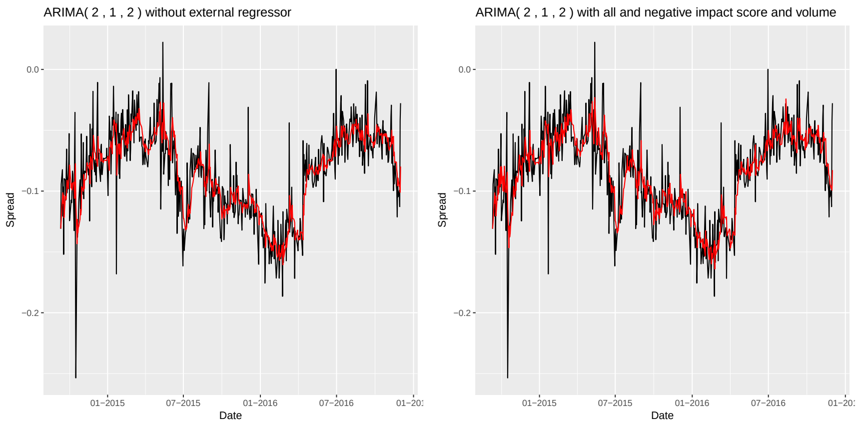

Figure 40: ARIMAX models: Forecast errors for Spread 8

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
              RMSE        MAE      MPE     MAPE      MASE
Model 1  0.02326189 0.01650100 85.63757 130.3877 0.8217934
Model 2  0.02294110 0.01649100 74.81666 119.5710 0.8212954
Model 3  0.02296146 0.01646255 72.61697 117.3472 0.8198786
Model 4  0.02296594 0.01645951 71.65120 116.3346 0.8197273
Model 5  0.02324587 0.01649324 87.00405 131.6522 0.8214073
Model 6  0.02325782 0.01648824 85.30132 130.0267 0.8211579
Model 7  0.02325786 0.01648575 86.32872 131.0196 0.8210342
Model 8  0.02297825 0.01646118 74.12761 118.8240 0.8198104
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   2    4    4    4    4
Forecast errors for out-of-sample period
              RMSE        MAE       MPE     MAPE      MASE
Model 1  0.02017049 0.01623334 -4.247339 17.79214 0.8122666
Model 2  0.02007269 0.01643304 -4.162451 18.09198 0.8222589
Model 3  0.01993295 0.01637552 -4.100153 17.99783 0.8193806
Model 4  0.01995711 0.01639607 -4.106647 18.02203 0.8204093
Model 5  0.02017775 0.01630004 -4.283316 17.84091 0.8156040
Model 6  0.02006665 0.01617921 -4.177839 17.71455 0.8095579
Model 7  0.02020683 0.01622563 -4.294387 17.79639 0.8118809
Model 8  0.01985600 0.01641822 -4.075808 18.00218 0.8215176
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   8    6    8    6    6
```

Figure 41: In-sample 1-step ahead forecast for Bund Spread 9

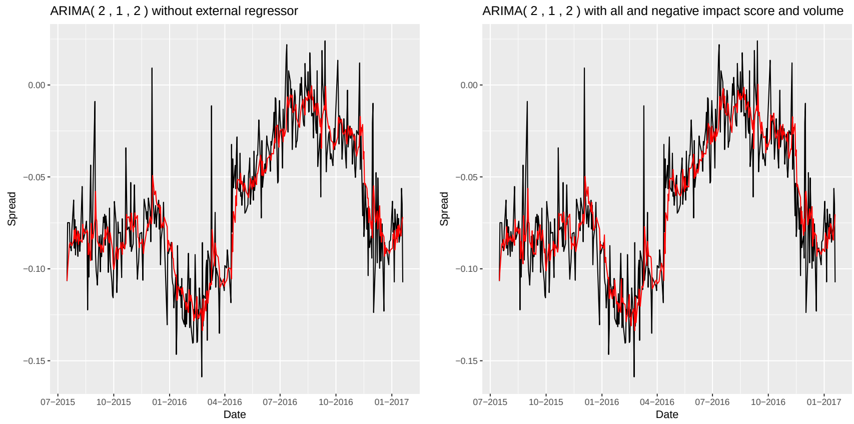

Figure 42: ARIMAX models: Forecast errors for Spread 9

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
                RMSE         MAE       MPE      MAPE      MASE
Model 1    0.02004899 0.01477402 10.189049 64.57100 0.8116739
Model 2    0.01994812 0.01478464  7.142526 61.21201 0.8122574
Model 3    0.01996783 0.01476147  5.214035 61.07296 0.8109844
Model 4  0.02002026 0.01480431  5.538086 60.33921 0.8133383
Model 5  0.01997570 0.01481612  7.845787 62.63841 0.8139872
Model 6  0.01997527 0.01477422  6.518670 62.17121 0.8116851
Model 7  0.02004896 0.01477227 10.115431 64.54697 0.8115778
Model 8  0.02002047 0.01480649  5.691398 60.39930 0.8134582
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   2    3    3    4    3
Forecast errors for out-of-sample period
                RMSE         MAE       MPE      MAPE      MASE
Model 1    0.01966967 0.01617032 -2.266881 16.54723 0.8390916
Model 2    0.01966926 0.01617263 -2.178187 16.51385 0.8392117
Model 3    0.01986543 0.01625674 -2.251959 16.64129 0.8435763
Model 4    0.01963329 0.01614817 -2.231554 16.52376 0.8379425
Model 5    0.01968372 0.01616485 -2.236582 16.50980 0.8388078
Model 6    0.01950617 0.01608269 -2.196386 16.42663 0.8345446
Model 7    0.01967804 0.01618122 -2.266073 16.55787 0.8396573
Model 8  0.01962149 0.01613401 -2.232673 16.50852 0.8372076
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   6    6    2    6    6
```

Figure 43: In-sample 1-step ahead forecast for Bund Spread 10

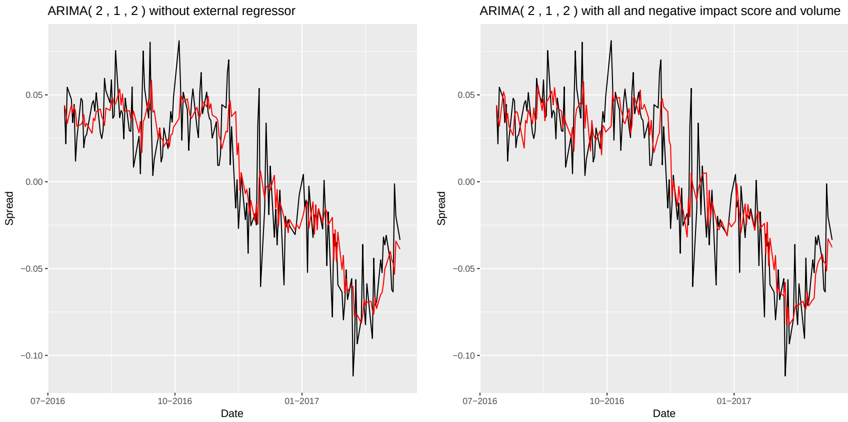

Figure 44: ARIMAX models: Forecast errors for Spread 10

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
             RMSE        MAE         MPE      MAPE      MASE
Model 1    0.02112342 0.01621805 -39.68612 119.5092 0.7981631
Model 2    0.02066336 0.01603717 -39.04804 122.7273 0.7892613
Model 3    0.02091928 0.01613474 -41.21531 124.7112 0.7940632
Model 4    0.02092904 0.01616055 -41.74694 125.2783 0.7953331
Model 5    0.02083498 0.01618949 -38.64048 118.8837 0.7967572
Model 6    0.02071150 0.01613586 -38.69777 118.1040 0.7941180
Model 7    0.02112022 0.01620052 -39.34063 119.5490 0.7973005
Model 8    0.02093137 0.01618113 -42.04010 125.2994 0.7963459
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   2    2    5    6    2
Forecast errors for out-of-sample period
             RMSE        MAE         MPE      MAPE      MASE
Model 1   0.01732641 0.01352390 -11.38375 31.52525 0.7464720
Model 2   0.01771949 0.01425832 -10.90680 32.49426 0.7870096
Model 3   0.01762689 0.01375413 -11.13977 31.84881 0.7591799
Model 4   0.01746988 0.01362539 -11.17237 31.59843 0.7520743
Model 5   0.01742743 0.01418379 -11.24243 32.60837 0.7828956
Model 6   0.01735043 0.01385035 -11.22327 32.03756 0.7644909
Model 7   0.01735373 0.01345079 -11.34597 31.32475 0.7424365
Model 8   0.01744503 0.01368609 -11.20376 31.76645 0.7554245
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   1    7    2    7    7
```

Figure 45: In-sample 1-step ahead forecast for Bund Spread 11

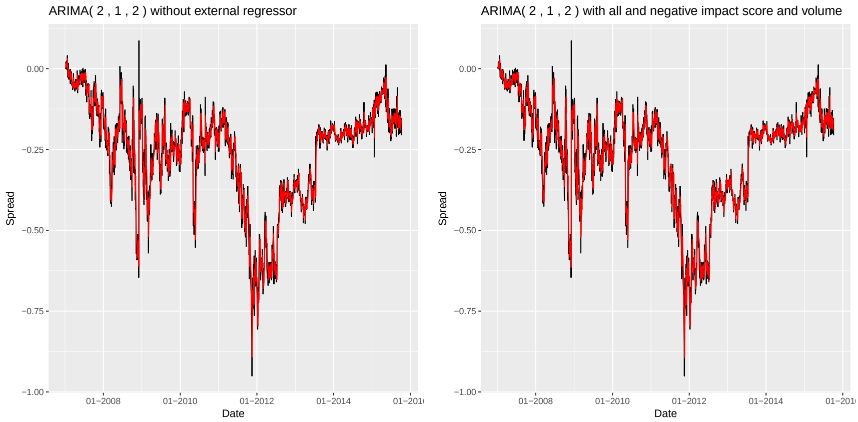

Figure 46: ARIMAX models: Forecast errors for Spread 11

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
             RMSE        MAE        MPE     MAPE      MASE
Model 1  0.03747466 0.02448748 -1.480277 22.12226 0.9243553
Model 2  0.03741805 0.02447120 -2.242754 22.55836 0.9237408
Model 3   0.03741107 0.02448796 -2.571573 22.91928 0.9243734
Model 4   0.03744579 0.02448891 -1.581116 22.04622 0.9244091
Model 5   0.03742757 0.02445623 -3.222451 23.81139 0.9231756
Model 6   0.03745902 0.02447105 -2.180870 22.74762 0.9237352
Model 7   0.03744661 0.02448614 -1.522318 22.00476 0.9243048
Model 8   0.03747410 0.02448958 -1.531223 22.15802 0.9244346
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   3    5    1    7    5
Forecast errors for out-of-sample period
             RMSE        MAE        MPE     MAPE      MASE
Model 1   0.02714511 0.02034043 10.094451 25.63006 0.8476207
Model 2   0.02731405 0.02060869 10.276072 25.98630 0.8587993
Model 3   0.02751094 0.02079751 10.121097 25.97427 0.8666679
Model 4   0.02724419 0.02052319  9.843970 25.52440 0.8552367
Model 5   0.02722465 0.02047979 10.232602 25.83226 0.8534282
Model 6   0.02700324 0.02028020 10.061990 25.53410 0.8451107
Model 7   0.02727498 0.02053080  9.887745 25.57196 0.8555539
Model 8   0.02712170 0.02033900 10.055033 25.59050 0.8475610
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   6    6    4    4    6
```

Figure 47: In-sample 1-step ahead forecast for Bund Spread 12

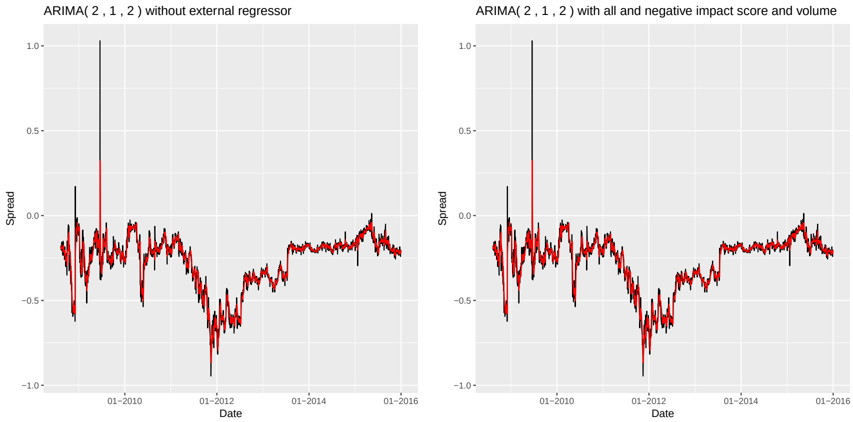

Figure 48: ARIMAX models: Forecast errors for Spread 12

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
              RMSE        MAE       MPE     MAPE      MASE
Model 1   0.05374189 0.02698553 -2.407877 13.91084 0.9498730
Model 2   0.05371123 0.02705320 -2.448080 13.93462 0.9522548
Model 3   0.05372039 0.02699165 -2.438108 13.91205 0.9500884
Model 4   0.05374024 0.02699927 -2.410853 13.92590 0.9503564
Model 5   0.05370596 0.02704891 -2.418765 13.96522 0.9521036
Model 6   0.05370689 0.02707558 -2.424731 13.96853 0.9530425
Model 7   0.05374025 0.02699991 -2.413554 13.92443 0.9503791
Model 8   0.05374188 0.02698388 -2.406356 13.91002 0.9498149
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   5    8    8    8    8
Forecast errors for out-of-sample period
              RMSE        MAE      MPE     MAPE      MASE
Model 1   0.02706263 0.02040311 6.641519 23.26584 0.8116201
Model 2   0.02738795 0.02050755 6.774238 23.50535 0.8157746
Model 3   0.02727994 0.02052825 6.880260 23.59557 0.8165981
Model 4   0.02705236 0.02036854 6.699868 23.28979 0.8102448
Model 5   0.02749129 0.02057256 6.775870 23.57333 0.8183603
Model 6   0.02747718 0.02057527 6.701891 23.49443 0.8184684
Model 7   0.02704330 0.02036446 6.690048 23.27609 0.8100825
Model 8   0.02706516 0.02040459 6.643084 23.26815 0.8116789
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   7    7    1    1    7
```

Figure 49: In-sample 1-step ahead forecast for Bund Spread 13

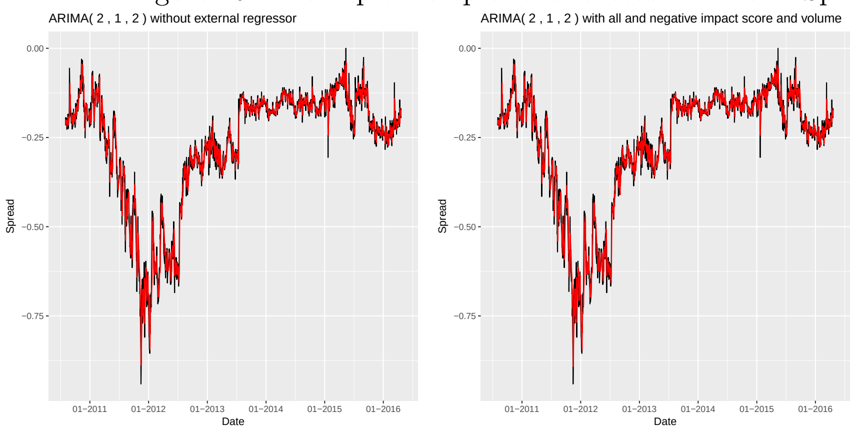

Figure 50: ARIMAX models: Forecast errors for Spread 13

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
             RMSE        MAE        MPE     MAPE      MASE
Model 1   0.03320634 0.02301497 -267.1275 276.1111 0.9229970
Model 2   0.03310889 0.02310848 -219.6502 228.6838 0.9267473
Model 3   0.03313208 0.02310811 -223.6803 232.7105 0.9267323
Model 4  0.03317094 0.02305017 -246.7065 255.7055 0.9244089
Model 5   0.03318772 0.02303533 -266.1085 275.1066 0.9238138
Model 6   0.03318526 0.02304322 -265.7505 274.7545 0.9241299
Model 7   0.03320284 0.02301311 -267.2059 276.1870 0.9229225
Model 8   0.03317353 0.02304976 -246.6596 255.6582 0.9243923
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   2    7    2    2    7
Forecast errors for out-of-sample period
             RMSE        MAE        MPE     MAPE      MASE
Model 1   0.02873870 0.02149838 -1.564736 21.05080 0.8571706
Model 2   0.02910143 0.02185049 -1.558878 21.41467 0.8712095
Model 3   0.02886032 0.02166511 -1.563774 21.23376 0.8638183
Model 4   0.02864411 0.02153057 -1.581835 21.05510 0.8584537
Model 5   0.02895465 0.02160563 -1.584694 21.17131 0.8614465
Model 6   0.02903370 0.02166041 -1.597657 21.20894 0.8636308
Model 7   0.02872098 0.02145591 -1.545458 21.02228 0.8554772
Model 8  0.02864837 0.02156104 -1.598899 21.07375 0.8596685
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   4    7    7    7    7
```

Figure 51: In-sample 1-step ahead forecast for Bund Spread 14

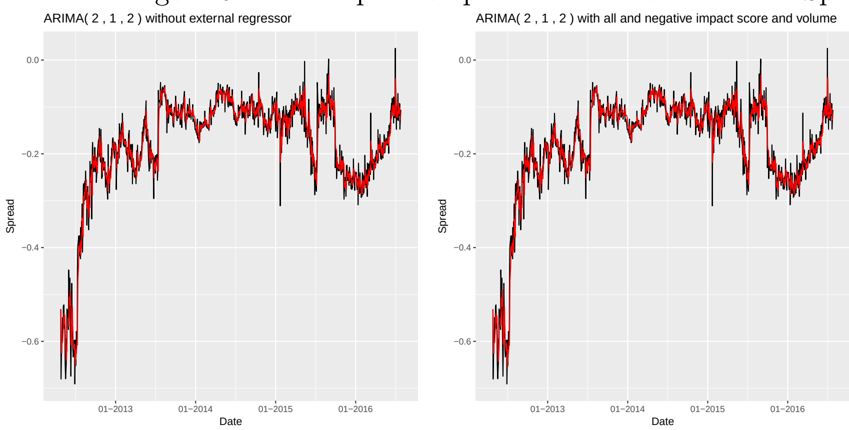

Figure 52: ARIMAX models: Forecast errors for Spread 14

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
               RMSE        MAE        MPE      MAPE      MASE
Model 1   0.02964232 0.02055978 -4.233090 21.44071 0.9041822
Model 2   0.02958520 0.02058376 -3.853492 21.05085 0.9052372
Model 3   0.02961122 0.02057088 -3.854051 21.09345 0.9046707
Model 4   0.02961478 0.02057869 -3.959893 21.21368 0.9050141
Model 5   0.02961570 0.02055517 -4.243403 21.37174 0.9039795
Model 6   0.02961158 0.02054991 -4.232424 21.38661 0.9037482
Model 7   0.02963926 0.02055249 -4.212294 21.45185 0.9038619
Model 8   0.02961714 0.02058863 -3.974425 21.20367 0.9054512
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   2    6    2    2    6
Forecast errors for out-of-sample period
               RMSE        MAE        MPE      MAPE      MASE
Model 1   0.02669899 0.02106374 -4.640221 19.55454 0.8099840
Model 2   0.02690444 0.02104527 -4.681395 19.59241 0.8092738
Model 3   0.02665095 0.02100066 -4.626419 19.52093 0.8075583
Model 4   0.02659865 0.02092262 -4.617035 19.44797 0.8045575
Model 5   0.02696739 0.02115561 -4.701097 19.64705 0.8135167
Model 6   0.02707371 0.02126188 -4.722724 19.75159 0.8176031
Model 7   0.02669323 0.02103895 -4.645851 19.52878 0.8090306
Model 8   0.02660329 0.02093859 -4.611764 19.46593 0.8051714
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   4    4    8    4    4
```

Figure 53: In-sample 1-step ahead forecast for Bund Spread 15

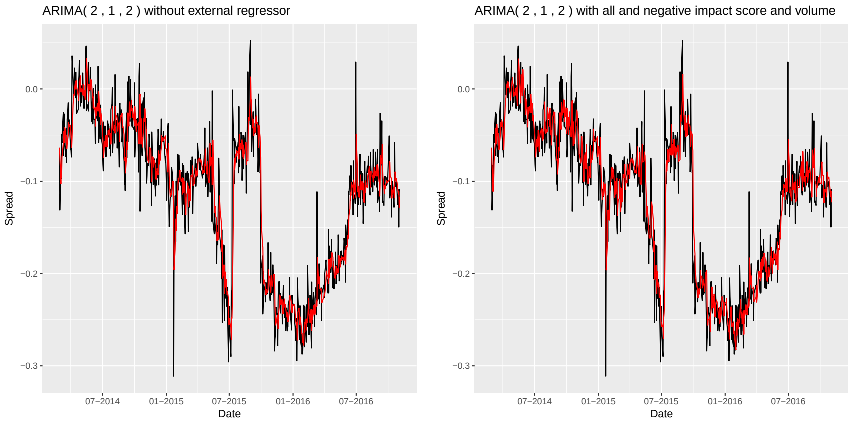

Figure 54: ARIMAX models: Forecast errors for Spread 15

```
Order ARIMA-Model: 2 1 2
Forecast errors for in-sample period
             RMSE        MAE        MPE     MAPE      MASE
Model 1    0.03154018 0.02274253 -25.34777 104.1556 0.8562207
Model 2    0.03119428 0.02275400 -19.33379 105.2406 0.8566526
Model 3    0.03124365 0.02277991 -20.63031 104.7732 0.8576280
Model 4    0.03124372 0.02277955 -20.60280 104.7793 0.8576145
Model 5    0.03152682 0.02274257 -25.30791 104.4192 0.8562222
Model 6    0.03153969 0.02274136 -25.31865 104.1995 0.8561765
Model 7    0.03152722 0.02272087 -25.34321 104.1600 0.8554054
Model 8    0.03125695 0.02280143 -20.62199 104.7924 0.8584380
In-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   2    7    2    1    7
Forecast errors for out-of-sample period
             RMSE        MAE        MPE     MAPE      MASE
Model 1    0.02701631 0.02179020 -3.100809 17.13627 0.7707261
Model 2    0.02720671 0.02198940 -3.089679 17.42327 0.7777719
Model 3    0.02697601 0.02192729 -3.024298 17.35672 0.7755753
Model 4    0.02696894 0.02191935 -3.023888 17.35054 0.7752942
Model 5    0.02715217 0.02186740 -3.110590 17.20261 0.7734567
Model 6    0.02704389 0.02180405 -3.107265 17.14763 0.7712162
Model 7    0.02701805 0.02185624 -3.106565 17.18865 0.7730620
Model 8   0.02696313 0.02183063 -3.018065 17.27598 0.7721563
Out-of-sample: Model with lowest forecast error
RMSE  MAE  MPE MAPE MASE
   8    1    8    1    1
```