Enhanced Corporate Bond Yield Modelling Incorporating Macroeconomic News Sentiment

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Abstract

In this study, we introduce a new method of assessing the credit risk of corporate bonds; where in addition to the historical market data news sentiment data is used. Typically, a higher yield spread is usually associated with higher credit risk. By predicting the upward/downward movement of yield and yield spread accurately, the credit risk associated to the bonds can be detected precisely. The corporate bonds studied are issued after 1 January 2007 by seven chosen companies listed in Euro Stoxx 50 index. The time series of bond yields and news sentiment cover the period from 1 January 2007 to 15 May 2017. The modelling of the dynamics of corporate bond yields and credit spreads are based on ARIMA and ARIMAX models. In the ARIMAX model, macroeconomic and firm-specific news sentiment are used as the external explanatory variable. We examine the effect of several categories of macroeconomics news sentiment and firm-specific news sentiment on corporate bond yield spreads. Furthermore, we separate the positive and negative sentiment and investigate their impact on the forecast of corporate bond yields It is found that negative country news sentiment and central bank news sentiment are effective during recession period and positive country news sentiment are effective in the recovery period. Negative government and firm-specific news sentiment, in general, affect corporate bond yield spreads more than positive government and company news sentiment.

Keywords: Macroeconomic News Sentiment, Firm-specific News Sentiment, Autoregressive–moving-average model with exogenous inputs model (ARIMAX)

1. Introduction

1.1 Background: evolving trading venues of fixed income products

Since the electronic trading has been increasingly adopted in all sectors of financial markets, it is essential to highlight the trend of changing fixed income trading situation and trade venues in the market. Electronic trading is the trading of financial instruments through an electronic system where two counterparties are matched and engage in negotiation and execute their orders.

Electronic trading platforms have several forms of trading protocols:

① Request for quote (RFQ). RFQ is a common trading protocol where users request prices on an order of a specific size by contacting with the platform market makers. RFQ systems varies massively in terms of several aspects: disclosure of the participant identities; reveal of the sign of the orders (buy or sell) and execution details of the orders (executable quote or indicative quote). What usually happens in the fixed-income RFQ trading protocols is that the requests from clients are delivered only to dealers and only in restricted numbers. These systems are generally used in the markets with securities which have a wide range of numbers and varieties and which are traded without sufficient large dealers. Tradeweb is an example of using RFQ systems.

② Central limit order book (CLOB): CLOB is a trading protocol where the outstanding bids and offers are stored in a queue and these orders must be executed according to a priority rule. Different from RFQ, the quotes of CLOBs are often transparent to the users before the trades and CLOB systems are mostly used for strategies that require a high-speed trade environment. Examples for CLOB protocols are the BrokeTec and eSpeed.

③ All-to-all: All-to-all trading protocol is an emerging channel of electronic bond trading and allows multiple parties to directly access to one another, creating a highly transparent trading background. Examples for the All-to-all protocols are Tradeweb and MarketAxess.

The following graph (Sources: Bank for International Settlements, 2016; Greenwich Association, 2014; Mckinsey & Company and Greenwich Association, 2013) illustrates a big picture of the current state of electronic trading in fixed income markets:

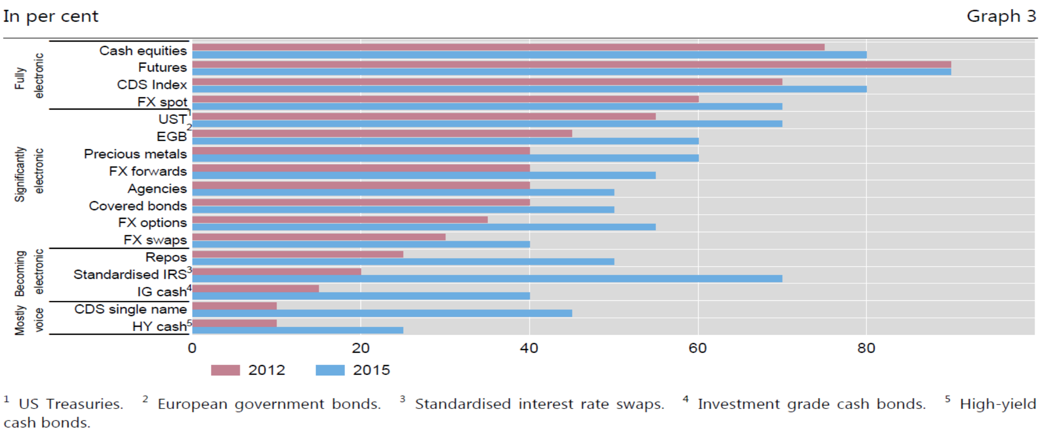

Figure 1.1-1 The electronification of various assets

Electronification has evolved to a more advanced level in the largest, highly liquid, and more standardized markets such as the highly liquid sovereign bond market and fixed income futures. Around 90 percent of the transaction of fixed income futures are traded electronically in 2015, even higher than cash equities, credit default swap (CDS) index and spot foreign exchange (FX) **(Figure 1.1-1)**. A little less electronic asset classes are US treasuries, European government bonds and standardised interest rate swap (IRS), whose electronificaion rate is nearly at 70 percent. As for the corporate bond market, electronic trading is less prevalent because corporate bonds are traded less frequently due to the diversity of the needs of market participants. However, corporate bond trading via electronic protocols has risen in recent years. According to Greenwich Association (2015), roughly four out of five investment-grade bond market participants used an electronic platform in 2015 and this figure in 2010 was only 58%. MarketAxess (2016) stated that around 13% of all the US invesment-grade and high-yield corporate bonds were transacted on their electronic trading platforms.

Varieties of innovations in electronic platforms have emerged in the corporate bond markets. One of the innovations that should be highlighted is the all-to-all trading platform. It is estimated that around 5% of investment grade and high-yield bonds which are electronically traded are transacted via all-to-all protocols (Bank for International Settlements, 2016). Since all-to-all platforms allow end clients to participate equally and directly with each other, the transaction costs are lower and liquidity is more accessible.

1.2 News Sentiment in fixed income market

Before reviewing the literature on news sentiment, we will briefly review literature regarding investor sentiment and outline some research on the effect of investor sentiment and macroeconomic fundamentals on fixed income markets. The investor sentiment referred in this section is a broad concept including all the sentiment generated from market, media, economic fundamentals and so on. Researchers have used several indicators or indexes to represent investor sentiment in their research. Baker and Wurgler (2006) proposed to use six separate proxies (the average first-day return and number of initial public offerings, the average of the closed-end fund discount, NYSE stock turnover, the newly issued equity share and the dividend premium) to construct a sentiment index. Based on these proxy variables as sentiment measures, Baker and Wurgler (2006) have found that investor sentiment has the explanatory power on the cross-section future stock returns. Laborda and Olmo (2014) adopted these sentiment proxies as well. However, they applied sentiment analysis in the fixed income market instead and found that market sentiment possesses the predictive power on U.S. treasury bond excess return and this effect is even extraordinary in the recession period.

Fernandes, Gama and Vieira (2016) investigated the predictability of sovereign bonds by exploiting the irrational sentiment in Portugal and the Euro area. In their study, they regressed the Economic Sentiment Indicator from the European Commission on macroeconomic fundamentals and obtained the residuals as the irrational sentiment. Their research indicated that the investor sentiment in Portugal and the Euro area negatively impacted future sovereign bond yield spreads and this effect is more obvious in the bailout period.

Although scare, several researchers have conducted research about the effect of sentiment on the corporate bond market. Nayak (2010) is inspired by the sentiment measure index created by Baker and Wurlger (2006) and applies this sentiment measure into the study of the sentiment effect in the US corporate bond yield spreads. Nayak (2010) found that US corporate bonds appear to be undervalued when the sentiment is pessimistic and overvalued when the sentiment is optimistic. This result indicates that corporate bond yield spreads are likely to be positively correlated with the sentiment in the market. In addition, Nayak (2010) suggests that high-yield bonds are more vulnerable to the effect of sentiment than the investment grade bonds.

As plenty of empirical evidence demonstrates the valuable role of sentiment on the valuation of assets, the extent to which news sentiment affects the credit quality of corporate bond merits investigation. In our research, we investigate the impact of news sentiment on European corporate bond yield spreads. The news sentiment we discuss in the report is sentiment arising from machine learning textual analysis of news articles. RavenPack is the provider of the news sentiment data, its news analytic tool, RavenPack News Analytics (RPNA), provides structured sentiment data processed and transformed from reputable sources including Dow Jones Newswires, the Wall Street Journal, and over 19,000 other news media sites. A big advantage of RPNA is that all the events in news article and social media are assigned with entity-specific relevance and sentiment score. With such a data analytics tool, we can measure the news sentiment, identify the relevant entity and evaluate the extent to which the news is relevant to the entity.

News sentiment applied in credit risk assessment is a new research area which merits further investigation. diBartolomeo (2016) illustrated the role of news and sentiment for credit risk assessment of corporate debt and proposed that news flows help to improve the calibration of a contingent claims model. More efficient and transparent estimate of key parameters and probability of default can be obtained. Apergis (2015) explored the predictive power of the newswire messages to forecast credit default swaps (CDSs) spreads in the European market during the financial distress period. CDS spread is widely known as an important indicator of the quality of the associated bonds Apergis (2015) argued that CDS spreads can also be influenced by the sentiment conveyed through news articles and social media. By comparing the out-of-sample forecasting results of ARIMA (without news) and ARIMAX (with news), it was found that news sentiment provides the superiority in the forecasting of CDS spreads especially in the financial distress period. Inspired by the methodology of Apergis (2015), our research will examine the individual effect of positive and negative sentiment in forecasting corporate bond yield spreads.

1.3 Outline of the paper

The structure of this report in the following chapters is as follows. Section 2 outlines the data preparation approach, including both the bond and sentiment data. In Section 3, several model set-ups are explained and techniques used to test the accuracy of models are provided. Section 4 illustrates the results of fitting and forecasting after using macroeconomic and firm-specific news sentiment as the explanatory factors. The concluding Section 5summaries the findings and proposes some suggestions for the research direction in the future.

2. Data

2.1 Bond Data

The data source of the corporate bonds we investigated is the Thomson Reuters DataScope. We investigated the corporate bonds issued by seven companies from three main countries in Europe and these companies are all listed in the Euro Stoxx 50 index. They are **Adidas AG**, **Deutsche Bank AG** and **Munich Re Group** from Germany; **Banco Santander, S.A.** and **BBVA S.A.** from Spain; **Enel** and **Eni S.p.A.** from Italy. All the corporate bonds we investigate are those issued after 1 January 2007. The time series of bond yields and news sentiment cover the period from 1 January 2007 to 15 May 2017.

Bond Variable	Company	Country	Bond Description	In-Sample Period	Out-of-Sample Period
ADIDAS	Adidas AG	Germany	0.250 06/14/19 CVT PUT	2012/03/20-2014/10/15	2014/10/16-2017/05/15
DBKG1	Deutsche Bank AG	Germany	2.500 03/31/09 MATd	2008/01/21-2008/08/19	2008/08/20-2009/03/25
DBKG2	Deutsche Bank AG	Germany	4.537 06/20/14 MATd	2009/10/14-2012/02/14	2012/02/15-2014/06/17
MUVG	Munich Re Group	Germany	7.625 06/21/28 '18 FRN	2007/01/02-2012/05/16	2012/05/17-2017/05/15
SAN1	Santander	Spain	4.250 05/06/13 MATd	2007/04/30-2010/05/06	2010/05/07-2013/04/30
SAN2	Santander	Spain	4.000 08/02/13 MATd	2011/08/05-2012/07/31	2012/08/01-2013/07/30
BBVA1	BBVA S.A.	Spain	6.200 07/04/23	2008/07/04-2011/09/13	2011/09/14-2014/11/04
BBVA2	BBVA S.A.	Spain	0.750 01/20/22	2015/01/15-2016/03/15	2016/03/16-2017/05/15
ENEL	Enel	Italy	5.250 01/14/15 MATd	2009/01/19-2012/01/18	2012/01/19-2015/01/12
ENI	Eni	Italy	1.064 06/29/15 FRN MATd	2009/09/28-2012/08/14	2012/08/12-2015/06/25

Table 2-2-1 Ten Bonds Used for Study

Table 2-1-1 listed the bonds used for the study, including coupon rate, maturity date, bond type and the periods for in-sample calibration and out-of-sample forecasting.

2.2 News Sentiment Data

As mentioned in section **2.1**, the sentiment data we use for the research is based on three news sentiment databases provided by RavenPack. The three databases cover the news sentiment in Germany, Spain and Italy and each of the three datasets is comprised of news sentiment data of several entities. RavenPack categorises all the entities involved in the news by COMP (company), ORGA (organisation), PEOP (people) and PLCE (place). For convenience, we name the three main databases as the Germany Sentiment Database, Spain Sentiment Database and Italy Sentiment Database separately. As

RavenPack has identified the entity involved in news, it would be convenient to extract firm-specific news sentiment data from the corresponding sub database. In addition to the firm-specific news sentiment, we can also extract macroeconomic news sentiment from the main database. Since most of the macroeconomic announcements are made by government organizations, this paper also examines the impact of news sentiment with different government ministries as the related entities.

Each sub database of news sentiment data includes but is not limited to the following information:

Year, **date** and **hour**: these three figures represent the time and date when the specific news was received by RavenPack.

Relevance: This is a relevance score which ranges from 0 to 100, indicating the extent to which the entity is related to the news item. The higher the value the stronger the relevance. In our analysis, we set the threshold to be 60, i.e. only the news sentiment with relevance score greater than 60 is considered as significantly relevant.

ESS-Event Sentiment Score: This score ranges from -1 to 1 in which a negative value represents the sentiment from a negative news story and a positive value represents positive sentiment. The greater the absolute value of **ESS** the stronger sentiment conveyed through the news story. When **ESS** is zero, it means the news sentiment is neutral.

What should be noted when using the raw data is that all bond trading date is presented according to UTC (coordinated universal time) standard, however the date listed in the news sentiment database is based on the local time of the country for which the news is listed. Therefore, it is necessary to adjust the date and time of news sentiment databases to a universal time zone. In addition, all the news originally occurring during holidays and weekends need to be shifted to the next working day. One important assumption in our research is that the opening time of the bond market is from 8.00 a.m. to 18.30 p.m. (UTC) in each working day. We assume, first, that the news breaks during holidays and weekends to be effective at 8.00 a.m. of the next working day and, second, that a piece of news pops up after 18.30 p.m. impacts the bond on the next working day.

The following table summarizes the databases regarding both macroeconomic sentiment and firm-specific sentiment databases we may use in the models.

Country code: Germany (DE), Spain (ES), Italy (IT)				
Germany News Sentiment Database				
Entity	***Entity Type***	***No. of data relevance >=60***	***R data frame***	***Database ID***
Germany	PLCE	165155	Germanynewssentiment1	E96159
Government of Germany	ORGA	62439	Germanynewssentiment2	D5F939
Parliament of Germany	ORGA	857	Germanynewssentiment5	7DE2A2
Central Bank of Germany	ORGA	343	Germanynewssentiment10	0425F5
Adidas AG	COMP	1531	Germanynewssentiment11	8876D6
Deutsche Bank	COMP	2401	Germanynewssentiment12	9B16D5
Munich Re Group	COMP	578	Germanynewssentiment13	314E5A
Spain News Sentiment Database				
Entity	***Entity Type***	***No. of data relevance >=60***	***R data frame***	***Database ID***
Spain	PLCE	97605	Spainnewssentiment1	986F1A
Government of Spain	ORGA	37480	Spainnewssentiment2	9B4ED8
Central Bank of Spain	ORGA	702	Spainnewssentiment4	8FD0DB
Banco Santander	COMP	7081	Spainnewssentiment13	BC8373
BBVA S.A.	COMP	5428	Spainnewssentiment14	789D88
Italy News Sentiment Database				
Entity	***Entity Type***	***No. of data relevance >=60***	***R data frame***	***Database ID***
Italy	PLCE	94163	Italynewssentiment1	847BDC
Government of Italy	ORGA	42984	Italynewssentiment2	09F9AD
Central Bank of Italy	ORGA	610	Italynewssentiment3	270709
ENEL	ORGA	2480	Italynewssentiment10	6E9442
ENI	ORGA	6836	Italynewssentiment11	AE0DB4

Table 2-2-2 News Sentiment Databases

3. Methodology

3.1 News Sentiment Data Aggregation

Since sentiment scores are categorized as positives and negatives and since this research is aimed at figuring out the effect of positive and negative news sentiment separately and aggregately, we transform and merge the news sentiment scores in the following ways for our experiments:

Case 1: sum up positive and negative sentiment scores in the same day separately. The associated formulas are

$$possum = \sum ESS^{+}$$

$$negsum = \sum ESS^{-}$$

In the above formula, ESS^{+} and ESS^{-}, individually, represent the positive and negative sentiment scores in a news sentiment database and the computing results are stored in the data frames of $possum$ and $negsum$.

Case 2: take the average of positive and negative sentiment scores (**ESS**) in the same day separately. The formulas are shown below:

$$posmean = \frac{\sum ESS^{+}}{N^{+}}$$

$$negmean = \frac{\sum ESS^{-}}{N^{-}}$$

Where N^{+}represents the number of positive **ESS**, and N^{-} is the number of negative **ESS**. What should be noted is that for some dates, there is no positive ESS or negative ESS, we consider the positive ESS or negative ESS for this date as 0 (neutral ESS).

Case 3: sum up all sentiment scores in the same day. This is:

$$aggregate = negsum + possum$$

This approach aggregates together the positive and negative sentiment scores (**ESS**) and allow for the offset of positives and negatives.

Case 4: Considering the exponential decay effect of news sentiment, we introduce a score which possesses a decay feature. We define such a score as impact score (**IS**) to differentiate it from **ESS**. The technique of decay was firstly introduced by Yu (2014). The exponential decay impact score calculation method in our model is inspired by the one introduced by Yu and Mitra (2016) and is of a form with **ESS** multiply by monotone decreasing exponential function:

$Impact\ score = ESS * e^{-\lambda(T-t)}$.

T represents the closing time of bond market (i.e. 18.30 p.m.) and t is the time news breaks. Therefore $(T-t)$ measures the difference between the time when news happens and the closing time of the bond market. This exponential decay effect causes a news story to only have half of the initial impact left after a specific time span. In our models, we specify this time span as 90 minutes, then the parameter λ can be determined from the expression: $1 * e^{-\lambda(90)} = \frac{1}{2} \Rightarrow \lambda = 0.007701635$.

Positive impact score and negative impact score can be calculated by replacing ESS with $ESS^{+}$and ESS^{-}. As in **Case 1**, positive impact scores and negative impact scores in the same trading day are summed up such that only one positive **IS** and one negative **IS**, individually, reflect the positive effect of good news and negative effect of bad news in a trading day.

$$posimpact = \sum(ESS^{+} * e^{-0.007701635*(T-t)})$$
$$negimpact = \sum(ESS^{-} * e^{-0.007701635*(T-t)})$$

Case 5: take the average of positive and negative impact scores (**IS**)in the same day separately. The formulas are shown below:

$$posimpactmean = \frac{posimpact}{n^{+}} = \frac{\sum(ESS^{+} * e^{-0.007701635*(T-t)})}{n^{+}}$$
$$negimpactmean = \frac{negimpact}{n^{-}} = \frac{\sum(ESS^{-} * e^{-0.007701635*(T-t)})}{n^{-}}$$

where n^{+}represents the number of positive impact scores, and n^{-} is the number of negative impact scores.

Case 6: Aggregate positive impact score and negative impact score. The expression for this data manipulation case is:

$$sumimpact = posimpact + negimpact$$

By summing up all impact scores in one trading day, the overall impact score allows us to find out the aggregate effect of positive news and negative news with exponential decay property on corporate bonds.

3.2 Bond Yield Spread Calculation Method

In finance, yield spread measures the difference between the yields of two assets with same maturity. In our study, the ECB yield rates published by European Central Bank, are used as the representative of benchmark bond yield. The Svensson parametric method (Svensson,1994) is adopted to calculate the yield spreads of the corporate bonds. Before obtaining the spread, the Svensson function is used to obtain the Svensson yield (spot rate of ECB AAA-rated bond with the same time-to-maturity as the corporate bonds):

$$Svensson\ Yield_t(\tau) = \beta_0 + \beta_1 \frac{1 - \exp\left(-\frac{\tau}{\lambda_1}\right) +}{\frac{\tau}{\lambda_1}} + \beta_2 \left[\frac{1 - \exp\left(-\frac{\tau}{\lambda_1}\right)}{\frac{\tau}{\lambda_1}} - \exp\left(-\frac{\tau}{\lambda_1}\right)\right] + \beta_3 [\frac{1 - \exp\left(-\frac{\tau}{\lambda_2}\right)}{\frac{\tau}{\lambda_2}} - \exp\left(-\frac{\tau}{\lambda_2}\right)]$$

where six parameters $(\beta_0, \beta_1, \beta_2, \beta_3, \lambda_1, \lambda_2)$, which are quoted by ECB, are utilized with the time-to-maturity (τ). Then the yield spread can be obtained by subtracting the spot rate of ECB AAA-rated bond (Svensson Yield) from the current corporate bond yield.

3.3 ARIMA model

ARIMA stands for auto-regressive integrated moving average. and models a time series based on the historical observed values. A typical ARIMA model is specified by three order parameters: $p,\ d,\ q$, in which p represents the order of the autoregressive (AR) part, d stands for the order of differencing and q denotes the order of moving-average (MA). An ARIMA model is denoted by ARIMA ($p,\ d,\ q$). For more details on ARIMA modelling, please see Tsay (2010).

A difference-stationary ARIMA model with the parameters of ($p,\ d,\ q$) in the report can be expressed as:

$$\varphi(L)(1 - L)^d Spread_t = \theta(L)\varepsilon_t$$

where $Spread$ is the dependent variable, φ is the coefficient set of past values of

$Spread$, L is a lag operator, θ is the coefficient set of past error terms and d is the order of differencing.

The procedure to fit an ARIMA model is the Box-Jenkins method (Box and Jenkins,1976), which contains three stages: model identification, parameter estimation and diagnostic test. Using a similar procedure to determine the model parameters, we use the Akaike information criterion (AIC) as the key criteria for selection of parameter orders. According to the approach introduced by Akaike (1974), AIC can be written as:

$$AIC = -2\log(L) + 2(p + q + k + 1)$$

where L is the likelihood of data, p and q are the parameters of AR and MA, and k is the number of parameters in the model (the number of explanatory variables plus one constant intercept). To avoid overfitting of the models, we select the candidate models with AR parameter p ranges from 0 to 6 and MA parameter q from 0 to 3. In addition, we determine the parameter of differencing d by increasing it from 0 and use the smallest possible d that makes the time series stationary. After deciding the differencing parameter d, we choose the candidate models with the smallest AIC. Since the purpose of this report is to examine whether a simple ARIMA model can be enhanced by adding news sentiment as external regressor (ARIMAX model), the parameter set of ARIMA should be as close as possible to that of the corresponding ARIMAX models.

The following table summarizes the sentiment data after manipulation, they are also the external variables in the models:

News Sentiment data manipulation (6 cases)										
Germany										
Macroeconomic Announcement										
Case 1		**Case 2**		**Case 3**	**Case 4**		**Case 5**		**Case 6**	**Entity**
G1possum	G1negsum	G1posmean	G1negmean	G1aggregate	G1posimpact	G1negimpact	G1posimpactmean	G1negimpactmean	G1sumimpact	country
G2possum	G2negsum	G2posmean	G2negmean	G2aggregate	G2posimpact	G2posimpact	G2posimpactmean	G2negimpactmean	G2sumimpact	Government
G5possum	G5negsum	G5posmean	G5negmean	G5aggregate	G5posimpact	G5posimpact	G5posimpactmean	G5negimpactmean	G5sumimpact	Parliament
G10possum	G10negsum	G10posmean	G10negmean	G10aggregate	G10posimpact	G10posimpact	G10posimpactmean	G10negimpactmean	G10sumimpact	Central Bank

Firm-specific news										
G11possum	G11negsum	G11posmean	G11negmean	G11aggregate	G11posimpact	G11negimpact	G11posimpactmean	G11negimpactmean	G11sumimpact	ADIDAS
G12possum	G12negsum	G12posmean	G12negmean	G12aggregate	G12posimpact	G12posimpact	G12posimpactmean	G12negimpactmean	G12sumimpact	Deutsche Bank
G13possum	G13negsum	G13posmean	G13negmean	G13aggregate	G13posimpact	G13posimpact	G13posimpactmean	G13negimpactmean	G13sumimpact	Munich Re Group
Spain										
Macroeconomic Announcement										
Case 1		**Case 2**		**Case 3**	**Case 4**		**Case 5**		**Case 6**	**Entity**
S1possum	S1negsum	S1posmean	S1negmean	S1aggregate	S1posimpact	S1negimpact	S1posimpactmean	S1negimpactmmean	S1sumimpact	Spain
S2possum	S2negsum	S2posmean	S2negmean	S2aggregate	S2posimpact	S2negimpact	S2posimpactmean	S2negimpactmmean	S2sumimpact	Government
S4possum	S4negsum	S4posmean	S3negmean	S3aggregate	S3posimpact	S3negimpact	S3posimpactmean	S3negimpactmmean	S3sumimpact	Central Bank
Firm-specific news										
S13posmean	S13negsum	S13posmean	S13negmean	S13aggregate	S13posimpact	S13negimpact	S13posimpactmean	S13negimpactmmean	S13sumimpact	Santander
S14posmean	S14negsum	S14posmean	S14negmean	S14aggregate	S14posimpact	S14negimpact	S14posimpactmean	S14negimpactmmean	S14sumimpact	BBVA
Italy										
Macroeconomic Announcement										
Case 1		**Case 2**		**Case 3**	**Case 4**		**Case 5**		**Case 6**	**Entity**
I1possum	I1negsum	I1posmean	I1negmean	I1aggregate	I1posimpact	I1negimpact	I1posimpactmean	I1negimpactmmean	I1sumimpact	Italy
I2possum	I2negsum	I2posmean	I2negmean	I2aggregate	I2posimpact	I2negimpact	I2posimpactmean	I2negimpactmmean	I2sumimpact	Government
I3possum	I3negsum	I3posmean	I3negmean	I3aggregate	I3posimpact	I3negimpact	I3posimpactmean	I3negimpactmmean	I3sumimpact	Central Bank
Firm-specific news										
I10possum	I10negsum	I11posmean	I11negmean	I11aggregate	I11posimpact	I11negimpact	I11posimpactmean	I11negimpactmmean	I11sumimpact	ENEL S.P.A
I11possum	I11negsum	I12posmean	I12negmean	I12aggregate	I12posimpact	I12negimpact	I12posimpactmean	I12negimpactmmean	I12sumimpact	ENI S.P.A

Table 3-1-1 Macroeconomic News and Firm-Specific Sentiment

3.4 ARIMAX model

An ARIMAX model refers to the autoregressive integrated moving average model with explanatory variable. As mentioned in section **3.1**, the explanatory variables include macroeconomic sentiment and firm-specific sentiment. To examine the forecasting accuracy of ARIMAX with one external variable and ARIMAX with multiple external variables, we design the experiments:

- Examine the forecasting accuracy with single external variables in **Table 3-1-1** and these models are specified as one-variable ARIMAX models which have the expression of:

$$\varphi(L)(1-L)^d Spread_t = \Theta(L)Sentiment_t + \theta(L)\varepsilon_t$$

  Θ is the parameter of the external variable $sentiment$. Note that $sentiment$ is a class of sentiment data, it can be replaced by the sentiment variables to construct an ARIMAX model. Comparing the prediction accuracy among one-variable ARIMAX models and comparing that between ARIMAX models and ARIMA model can provide a clue whether news sentiment is able to enhance the prediction of a bond spread or not.

- Expand the univariate ARIMAX model to a version with two external variables. In the first experiment of univariate ARIMAX model, positive and negative news sentiment are separately included as external explanatory variable of the univariate ARIMAX model. The expression for the multivariate ARIMAX model with two explanatory variables can be expressed as:

$$\varphi(L)(1-L)^d Spread_t = \Theta_1(L)Sentiment_{1t} + \Theta_2(L)Sentiment_{2t} + \theta(L)\varepsilon_t$$

  where Θ_1 and Θ_2 are the coefficient parameter of the two external variables $Sentiment_1$and $Sentiment_2$.

3.5 Augmented Dickey-Fuller Test

As one of the key condition for using ARIMA and ARIMAX model is that the time series data should be stationary, we apply an augmented Dickey–Fuller test (ADF) (Fuller, 1976) to detect the stationarity of the data. The null hypothesis of the augmented Dickey-Fuller test is that a time series exhibits the feature of a unit root process. The alternative hypothesis is that the time series sample is stationary or trend stationary, depending on the specific test used. In this study, we used the ADF test to see whether the time series sample is stationary.

3.6 Model Performance Evaluation

In our study, we consider Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE) and Mean Absolute Scaled Error (MASE) as the main measures of prediction accuracy of the models. MAE and RMSE are scale-dependent error measures. The forecast error is denoted as $e_i = y_i - \widehat{y_i}$, MAE and RMSE can be expressed in terms of e_i:

$$MAE = mean|e_i| = \frac{\sum_{i=1}^{n}|e_i|_i}{n} = \frac{\sum_{i=1}^{n}|y_i - \widehat{y_i}|}{n}$$

$$RMSE = \sqrt{mean(e_i{}^2)} = \sqrt{\frac{\sum_{i=1}^{n}(e_i{}^2)}{n}} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{n}}$$

Both MAE and RMSE measure the prediction error of the models on average. The smaller the value of MAE and RMSE, the better the prediction performance of the models. What differs RMSE from MAE is that RMSE magnify large errors because of the square in the numerator, therefore RMSE penalizes large prediction errors. MAPE is associated with the percentage error $\mathrm{p}_i = 100 \times \frac{e_i}{y_i}$ and it can be expressed as:

$$MAPE = mean|p_i| = \frac{\sum_{i=1}^{n}|p_i|}{n} = \frac{\sum_{i=1}^{n}|\frac{e_i}{y_i}|}{n} \times 100 = \frac{\sum_{i=1}^{n}|\frac{y_i - \widehat{y_i}}{y_i}|}{n} \times 100.$$

Scaled errors were introduced by Hyndman and Koehler (2006). The main function of scaled errors is to compare prediction errors in different scales. For the non-seasonal time series, MASE can be expressed as:

$$MASE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|e_i|}{\frac{1}{n-1}\sum_{i=2}^{n}|y_i - y_{i-1}|}\right) = \frac{\sum_{i=1}^{n}|e_i|}{\frac{n}{n-1}\sum_{i=2}^{n}|y_i - y_{i-1}|}$$

4. Results and Discussion

4.1 Time Series Stationarity Test

The following table shows the ADF test results of 10 corporate bonds time series

Augmented Dickey–Fuller test		
Bond	p-value (original time series)	p-value (difference=1)
ADIDAS	0.99	0.01

DBKG1	0.8803	0.01
DBKG2	0.9194	0.01
MUVG	0.322	0.01
SAN1	0.8753	0.01
SAN2	0.4893	0.01
BBVA1	0.6679	0.01
BBVA2	0.1426	0.01
ENEL	0.8401	0.01
ENI	0.7109	0.01

Table 4-1 ADF Results

All the original time series data of the yield spread exhibit non-stationarity, therefore they cannot be applied directly into the models. However, they are all stationary when taking the difference for one lag. As discussed in **Section 3**, ARIMA and ARIMAX model includes a differencing parameter representing the maximum times of difference to make time series stationary. Based on the ADF results from **Table 4-1**, the differencing order d takes a value of 1 for all ARIMA and ARIMAX models.

4.2 ARIMA Results

The following table shows the in-sample calibration accuracy results of the ARIMA models for all the bonds:

ARIMA In-sample Result					
Result number	Bond	RMSE	MAE	MAPE	MASE
1	ADIDAS	0.107808	0.7840896	2.621932	0.9927379
2	DBKG1	0.04426089	0.02974929	2.900349	0.9632253
3	DBKG2	0.03307575	0.02292463	1.758099	0.9812305
4	MUVG	0.1401733	0.05545005	2.240148	0.999257
5	SAN1	0.05301667	0.03537848	4.517674	0.9569646
6	SAN2	0.08413574	0.05915032	1.772193	0.9679504
7	BBVA1	0.03801894	0.0270464	1.850272	0.9365825
8	BBVA2	0.02565777	0.01912145	4.491516	0.9331505
9	ENEL	0.08353927	0.0504008	3.389179	0.9842386
10	ENI	0.09560577	0.05754326	22.44376	0.9924139

Table 4-2 In-sample ARIMA Result

After training the ten ARIMA models with the sample time series data, we can forecast the future values of corporate bond spreads based on these fitted models. In the following **Table 4-3**, it shows the out-of-sample forecast accuracy of the ARIMA models.

ARIMA Out-of-sample Result					
Result number	Bond	RMSE	MAE	MAPE	MASE
1	ADIDAS	0.329982	0.2159288	2.846013	0.9903144
2	DBKG1	0.1814664	0.07442775	2.781292	1.135238
3	DBKG2	0.06647042	0.03052111	6.76793	0.9909216
4	MUVG	0.05694364	0.03769255	3.731598	0.9992715
5	SAN1	0.09450958	0.05471458	3.82397	1.065408
6	SAN2	0.05626798	0.03674345	2.549518	1.0417
7	BBVA1	0.105693	0.02638905	0.7899773	1.064833
8	BBVA2	0.02643522	0.01903804	3.474636	0.9477778
9	ENEL	0.06041881	0.03361491	2.465371	1.075527
10	ENI	0.04985906	0.02513168	4.691581	1.046831

Table 4-3 Out-of-sample ARIMA Result

4.3 ARIMAX Results

4.3.1 ARIMAX with Country News Sentiment

Firstly, we compare the model accuracy results of the ARIMAX models with the country macroeconomic news sentiment as external variables. Starting from the corporate bonds in Germany, the associated country macroeconomic news regarding the topics: balance-of-payments, business-activity, consumption, credit, crime, domestic product, elections, employment, foreign-relations, government, housing, industrial accidents, etc.

ADIDAS BOND ARIMAX with country news sentiment (in-sample)								
External Variable(s)	RMSE	Diff	MAE	diff	MAPE	diff	MASE	diff
G1possum	0.1067952	**-0.0010128**	0.0780503	**-0.70603928**	2.6083	**-0.013632**	0.988197	**-0.004541**
G1negsum	0.1068279	**-0.0009801**	0.0780492	**-0.70604042**	2.628827	0.006895	0.988183	**-0.004555**
G1posmean	0.106896	**-0.000912**	0.0779311	**-0.70615855**	2.622045	0.000113	0.986687	**-0.006051**
G1negmean	0.1068839	**-0.0009241**	0.0779101	**-0.70617948**	2.621585	**-0.000347**	0.986422	**-0.006316**
G1aggregate	0.1069102	**-0.0008978**	0.0779713	**-0.70611828**	2.624826	0.002894	0.987197	**-0.005541**
G1posimpact	0.1067833	**-0.0010247**	0.0778702	**-0.70621936**	2.616633	**-0.005299**	0.985917	**-0.006821**
G1negimpact	0.1068445	**-0.0009635**	0.0779795	**-0.7061101**	2.628502	0.00657	0.987301	**-0.005437**
G1sumimpact	0.1069147	**-0.0008933**	0.0780155	**-0.7060741**	2.626798	0.004866	0.987756	**-0.004981**
G1pos/negsum	0.1066845	**-0.0011235**	0.0778079	**-0.70628167**	2.616803	**-0.005129**	0.985128	**-0.007609**
G1pos/negimpact	0.1067441	**-0.0010639**	0.0778436	**-0.70624604**	2.618986	**-0.002946**	0.985579	**-0.007158**
G1posimpactmean	0.1069874	**-0.0008206**	0.0782388	**-0.70585077**	2.621965	3.3E-05	0.990584	**-0.002154**

G1negimpactmean	0.1069072	**-0.0009008**	0.0780584	**-0.70603124**	2.628563	0.006631	0.988299	**-0.004439**
G1pos/negimpactmean	0.1068889	**-0.0009191**	0.0780301	**-0.70605948**	2.627994	0.006062	0.987942	**-0.004796**

Table 4-4 In-sample model accuracy: ADIDAS Bond ARIMAX models with Country News Sentiment

In the above table, the first column represents the external variables in the ARIMAX models. What should be noted is that the columns with 'G1pos/negsum', 'G1pos/negimpact', 'G1pos/negimpactmean' are the multivariate ARIMAX models with two external variables. 'G1pos/negsum' represents two external variables in the multivariate ARIMAX model which are G1possum and G1negsum. 'G1pos/negimpact' corresponds to two external variables: G1posimpact and G1 negimpact, 'G1pos/negimpactmean' stands for G1posimpactmean and G1negimpactmean. 'diff' is the abbreviation of difference, which measures the gap between the error measure of ARIMAX model and that of corresponding ARIMA model. For example, in **Table 4-4**, the RMSE of ARIMAX model with G1possum as the external variable for ADIDAS bond is 0.1067952. Subtracting the RMSE of simple ARIMA model for ADIDAS bond yield spread (0.107808, as shown in **Table 4-2**) from 0.1067952 obtains the difference as -0.0010128. Therefore, when an ARIMAX with news sentiment improve the model accuracy, the value of diff is negative. From **Table 4-4**, it can be found that both positive country news sentiment and negative country news sentiment improve the in-sample model accuracy as they reduce RMSE, MAE and MASE of ARIMAX model. However, the improvement of in-sample model performance does not guarantee that forecast accuracy will be improved as well in the out-of-sample test. Out-of-sample model accuracy is a more straightforward measure when examining how much the prediction accuracy is enhanced by using ARIMAX models with news sentiment.

DBKG1 BOND ARIMAX with country news sentiment (In-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
G1possum	0.04422929	**-3.16E-05**	0.02974761	**-1.7E-06**	2.900547	0.000198	0.9631707	**-5.5E-05**
G1negsum	0.04420122	**-5.967E-05**	0.02977328	2.4E-05	2.900038	**-0.00031**	0.9640021	0.000777
G1posmean	0.04426027	**-6.2E-07**	0.02973715	**-1.2E-05**	2.899194	**-0.00115**	0.9628321	**-0.00039**
G1negmean	0.04385119	**-0.0004097**	0.02987522	0.000126	2.90936	0.009011	0.9673027	0.004077
G1aggregate	0.04415743	**-0.00010346**	0.02978072	3.14E-05	2.901125	0.000776	0.9642427	0.001017
G1posimpact	0.04399253	**-0.00026836**	0.02948207	**-0.00027**	2.878079	**-0.02227**	0.9545731	**-0.00865**
G1negimpact	0.04424745	**-1.344E-05**	0.02983814	8.88E-05	2.9083	0.007951	0.966102	0.002877

G1sumimpact	0.04408088	**-0.00018001**	0.02982825	7.9E-05	2.908269	0.00792	0.9657819	0.002557
G1pos/negsum	0.04415533	**-0.00010556**	0.0297769	2.76E-05	2.90048	0.000131	0.9641191	0.000894
G1pos/negimpact	0.04397708	**-0.00028381**	0.02957973	**-0.00017**	2.88683	**-0.01352**	0.9577353	**-0.00549**
G1posimpactmean	0.04410665	**-0.00015424**	0.02964479	**-0.0001**	2.88702	**-0.01333**	0.9598418	**-0.00338**
G1negimpactmean	0.04426087	**-2E-08**	0.02975078	1.49E-06	2.900482	0.000133	0.9632733	4.8E-05
G1pos/negimpactmean	0.04409636	**-0.00016453**	0.02974457	**-4.7E-06**	2.896088	**-0.00426**	0.9630725	**-0.00015**

Table 4-5 In-sample model accuracy: DBKG1 Bond ARIMAX models with Country News Sentiment

DBKG1 BOND ARIMAX with country news sentiment (Out-of-sample)								
External Varibale(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
G1possum	0.1818255	0.0003591	0.07445284	2.51E-05	2.77875	**-0.00254**	1.135621	0.000383
G1posmean	0.1814307	**-3.57E-05**	0.07441523	**-1.3E-05**	2.781334	4.2E-05	1.135047	**-0.00019**
G1negmean	0.1808681	**-0.0005983**	0.07417954	**-0.00025**	2.788869	0.007577	1.131452	**-0.00379**
G1aggregate	0.1821014	0.000635	0.0747986	0.000371	2.775641	**-0.00565**	1.140895	0.005657
G1posimpact	0.1826718	0.0012054	0.0743033	**-0.00012**	2.773576	**-0.00772**	1.13334	**-0.0019**
G1negimpact	0.1813182	**-0.0001482**	0.07435342	**-7.4E-05**	2.775602	**-0.00569**	1.134104	**-0.00113**
G1sumimpact	0.1816988	0.0002324	0.0740542	**-0.00037**	2.756752	**-0.02454**	1.129541	**-0.0057**
G1pos/negsum	0.1820783	0.0006119	0.07489974	0.000472	2.77841	**-0.00288**	1.142437	0.007199
G1pos/negimpact	0.1825001	0.0010337	0.07410882	**-0.00032**	2.762585	**-0.01871**	1.130374	**-0.00486**
G1posimpactmean	0.1815903	0.0001239	0.07397393	**-0.00045**	2.759834	**-0.02146**	1.128316	**-0.00692**
G1negimpactmean	0.1814557	**-1.07E-05**	0.07441574	**-1.2E-05**	2.78103	**-0.00026**	1.135055	**-0.00018**
G1pos/negimpactmean	0.181428	**-3.84E-05**	0.07378516	**-0.00064**	2.753941	**-0.02735**	1.125437	**-0.0098**

Table 4-6 Out-of-sample model accuracy: DBKG1 Bond ARIMAX models with Country News Sentiment

As observed in **Table 4-5** and **Table 4-6**, country news sentiment scores and impact scores improve the model accuracy and it is not limited to the in-sample model performance. Positive average sentiment score (G1posmean), negative average sentiment score (G1negmean), positive impact score (G1posimpact), overall impact score (G1sumimpact) and average positive impact score (G1posimpactmean) improve three of four performance measures. Negative impact score (G1negimpact), average negative impact score (G1negimpactmean) and a pair of variables: G1posimpactmean&G1negimpactmean enhance all the four model accuracy measures. Overall, these results (**Table 4-5** and **Table 4-6)** prove that using negative country sentiment as the external variable can improve the forecast of Deutsche Bank corporate bond yield spread.

DBKG2 BOND ARIMAX with country news sentiment (In-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
G1possum	0.0330072	**-6.855E-05**	0.02299	6.582E-05	1.761683	0.003584	0.984048	0.0028175

G1negsum	0.03304355	**-3.22E-05**	0.023006	8.092E-05	1.766524	0.008425	0.984694	0.0034638
G1posmean	0.03307572	**-3E-08**	0.022923	**-1.73E-06**	1.757887	**-0.000212**	0.981157	**-7.39E-05**
G1negmean	0.03299976	**-7.599E-05**	0.022896	**-2.9E-05**	1.756951	**-0.001148**	0.979988	**-0.001243**
G1aggregate	0.03307585	1E-07	0.022924	**-2.2E-07**	1.758067	**-3.2E-05**	0.981221	**-9.3E-06**
G1posimpact	0.03295679	**-0.000119**	0.022936	1.175E-05	1.757815	**-0.000284**	0.981733	0.0005029
G1negimpact	0.03292822	**-0.0001475**	0.022968	4.346E-05	1.763744	0.005645	0.983091	0.0018602
G1sumimpact	0.0330437	**-3.205E-05**	0.022947	2.272E-05	1.761202	0.003103	0.982203	0.0009725
G1pos/negsum	0.03299319	**-8.256E-05**	0.023033	0.0001081	1.76641	0.008311	0.985859	0.0046287
G1pos/negimpact	0.03286567	**-0.0002101**	0.022937	1.208E-05	1.760048	0.001949	0.981748	0.000517
G1posimpactmean	0.03306526	**-1.049E-05**	0.022874	**-5.08E-05**	1.754528	**-0.003571**	0.979058	**-0.002173**
G1negimpactmean	0.0329516	**-0.0001242**	0.022873	**-5.16E-05**	1.75236	**-0.005739**	0.979021	**-0.00221**
G1pos/negimpactmean	0.03294306	**-0.0001327**	0.022832	**-9.23E-05**	1.749506	**-0.008593**	0.97728	**-0.00395**

Table 4-7 In-sample model accuracy: DBKG2 Bond ARIMAX models with Country News Sentiment

DBKG2 BOND ARIMAX with country news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
G1posmean	0.06646696	**-3.46E-06**	0.030519	**-2.38E-06**	6.767676	**-0.000254**	0.990844	**-7.72E-05**
G1aggregate	0.06646545	**-4.97E-06**	0.030522	4.1E-07	6.767901	**-2.9E-05**	0.990935	1.35E-05
G1posimpactmean	0.0664315	**-3.892E-05**	0.030529	7.52E-06	6.766368	**-0.001562**	0.991166	0.0002443

Table 4-8 Out-of-sample model accuracy: DBKG2 Bond ARIMAX models with Country News Sentiment

Table 4-7 and **Table 4-8** present the model accuracy of the univariate ARIMAX models with country news sentiment for another Deutsche Bank bond. It can be found that average positive sentiment score (G1posmean), aggregate sentiment score (G1 aggregate) and average positive impact (G1posimpactmean) improve the forecast of Deutsche Bank bond. It seems that the results from DBKG1 bond and DBKG2 bond are opposite. However, these two results are acceptable when comparing the in-sample period and out-of-sample periods of these two bonds. As discussed in section **2.1**, the first Deutsche Bank corporate bond yield spread is modelled by using the data sample during 2008/01/21-2008/08/19, which is the early stage of recession period. It is reasonable that corporate bond spreads are sensitive to negative country news in a crisis period. Furthermore, Deutsche Bank belongs to the banking industry which is more vulnerable to the unfavorable news stories in that time period. The second bond is modelled with the sample data range from 2009/10/14 to 2012/02/14, when the shadow of financial crisis is fading and economy is recovering. In this stage, positive news sentiment has a significant positive impact on corporate bond yield spread.

MUVG BOND ARIMAX with country news sentiment (In-sample)

External Variable(s)	RMSE	diff	MAE	diff	MAPE	Diff	MASE	diff
G1possum	0.140167	**-6.5E-06**	0.055477	2.65E-05	2.241178	0.00103	0.999735	0.000478
G1negsum	0.140078	**-9.53E-05**	0.055497	4.71E-05	2.240834	0.000686	1.000105	0.000848
G1posmean	0.140078	**-9.55E-05**	0.055583	0.000133	2.249474	0.009326	1.001654	0.002397
G1negmean	0.140141	**-3.22E-05**	0.055439	**-1.2E-05**	2.242864	0.002716	0.999049	**-0.00021**
G1aggregate	0.140125	**-4.82E-05**	0.055443	**-7.2E-06**	2.239434	**-0.00071**	0.999127	**-0.00013**
G1posimpact	0.140164	**-9.4E-06**	0.055411	**-3.9E-05**	2.237451	**-0.0027**	0.998551	**-0.00071**
G1negimpact	0.140096	**-7.77E-05**	0.05547	2.04E-05	2.238471	**-0.00168**	0.999624	0.000367
G1sumimpact	0.140131	**-4.19E-05**	0.055498	4.77E-05	2.241905	0.001757	1.000117	0.00086
G1pos/negsum	0.140078	**-9.54E-05**	0.055499	4.9E-05	2.240908	0.00076	1.00014	0.000883
G1pos/negimpact	0.140095	**-7.86E-05**	0.055458	8.13E-06	2.237684	**-0.00246**	0.999403	0.000146
G1posimpactmean	0.140115	**-5.8E-05**	0.05544	**-1E-05**	2.240552	0.000404	0.999074	**-0.00018**
G1negimpactmean	0.140173	**-3E-07**	0.055465	1.48E-05	2.240981	0.000833	0.999523	0.000266
G1pos/negimpactmean	0.140019	**-0.000154**	0.055221	**-0.00023**	2.230686	**-0.00946**	0.995137	**-0.00412**

Table 4-9 In-sample model accuracy: MUVG Bond ARIMAX models with Country News Sentiment

MUVG BOND ARIMAX with country news sentiment (Out-of-sample)								
External Variable(s)	RMSE	Diff	MAE	diff	MAPE	diff	MASE	diff
G1possum	0.056849	**-9.44E-05**	0.037634	**-5.9E-05**	3.727977	**-0.00362**	0.997707	**-0.00156**
G1posmean	0.056839	**-0.000104**	0.037835	0.000142	3.740062	0.008464	1.003048	0.003776
G1posimpact	0.056848	**-9.56E-05**	0.037643	**-5E-05**	3.72783	**-0.00377**	0.997946	**-0.00133**
G1posimpactmean	0.056982	3.8E-05	0.037821	0.000129	3.730185	**-0.00141**	1.002687	0.003416
G1negimpactmean	0.056934	**-9.68E-06**	0.037682	**-1.1E-05**	3.730316	**-0.00128**	0.998981	**-0.00029**
G1pos/negimpactmean	0.056784	**-0.000159**	0.037718	2.5E-05	3.704889	**-0.02671**	0.999934	0.000663

Table 4-10 Out-of-sample model accuracy: MUVG Bond ARIMAX models with Country News Sentiment

It is observed in **Table 4-9** and **Table 4-10** that both positive and negative country news sentiment can enhance the modelling performance. The most significant improvement is observed when using multivariate ARIMAX model with average impact score (G1posimpactmean) and average negative impact score (G1negimpactmean) as two external variables. The out-of-sample performance result shows that RMSE is reduced by 0.000159, MAPE is reduced by 0.02671. The models for MUVG corporate bond yield spreads use the sample range from 2007/01/02 to 2012/05/16, which covers the financial crisis in 2008 and the economic recovery period. This result coincides with the results found from Deutsche Bank corporate bonds models.

The next four tables present the out-of-sample forecast performance of the ARIMAX models for the corporate bond yield spreads of four bonds in Spain.

SAN1 BOND ARIMAX with country news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	Diff	MAPE	Diff	MASE	diff
S1negmean	0.0944791	**-3.052E-05**	0.0546984	**-1.62E-05**	3.823579	**-0.00039**	1.065092	**-0.000316**
S1posimpactmean	0.0944708	**-3.881E-05**	0.0548322	0.0001176	3.846613	0.022643	1.067698	0.00229
S1negimpactmean	0.0944459	**-6.372E-05**	0.0546908	**-2.38E-05**	3.822997	**-0.00097**	1.064944	**-0.000464**
S1pos/negimpactmean	0.0944175	**-9.205E-05**	0.0548045	8.989E-05	3.844933	0.020963	1.067159	0.001751

Table 4-11 Out-of-sample model accuracy: SAN1 Bond ARIMAX models with Country News Sentiment

SAN2 BOND ARIMAX with country news sentiment (Out-of-sample)								
External Variable(s)	RMSE	Diff	MAE	Diff	MAPE	Diff	MASE	diff
S1possum	0.0555011	**-0.00076693**	0.0363472	**-0.000396**	2.550476	0.000958	1.030465	**-0.011235**
S1negsum	0.0562744	6.42E-06	0.0367332	**-1.03E-05**	2.553928	0.00441	1.041409	**-0.000291**
S1negmean	0.056314	4.602E-05	0.0367059	**-3.76E-05**	2.542578	**-0.00694**	1.040634	**-0.001066**
S1aggregate	0.0560616	**-0.0002064**	0.036521	**-0.000222**	2.559233	0.009715	1.035392	**-0.006308**
S1posimpact	0.0556724	**-0.0005956**	0.0367861	4.262E-05	2.5571	0.007582	1.042908	0.001208
S1sumimpact	0.0561974	**-7.055E-05**	0.0367901	4.666E-05	2.560074	0.010556	1.043023	0.001323
S1pos/negsum	0.055159	**-0.001109**	0.0360762	**-0.000667**	2.530981	**-0.018537**	1.022782	**-0.018918**
S1pos/negimpact	0.0555673	**-0.00070071**	0.0370319	0.0002885	2.575867	0.026349	1.049879	0.008179

Table 4-12 Out-of-sample model accuracy: SAN2 Bond ARIMAX models with Country News Sentiment

BBVA1 BOND ARIMAX with country news sentiment (Out-of-sample)								
External Variable(s)	RMSE	Diff	MAE	diff	MAPE	Diff	MASE	diff
S1pos/negimpactmean	0.1061405	**-0.000232**	0.0268598	**-0.0004142**	0.803647	**-0.009524**	1.08383	**-0.016713**

Table 4-13 Out-of-sample model accuracy: BBVA1 Bond ARIMAX models with Country News Sentiment

BBVA2 BOND ARIMAX with country news sentiment (Out-of-sample)								
External Variable(s)	RMSE	Diff	MAE	Diff	MAPE	Diff	MASE	diff
S1possum	0.026417	**-1.822E-05**	0.0190084	**-2.962E-05**	3.468441	**-0.006195**	0.9463037	**-0.00147**
S1negsum	0.02627988	**-0.00015534**	0.0189607	**-7.734E-05**	3.464999	**-0.009637**	0.943928	**-0.00385**
S1negmean	0.02643375	**-1.47E-06**	0.019046	7.98E-06	3.475935	0.001299	0.9481752	0.000397
S1aggregate	0.02642596	**-9.26E-06**	0.0190193	**-1.872E-05**	3.47119	**-0.003446**	0.9468461	**-0.00093**
S1posimpact	0.02644177	6.55E-06	0.0190048	**-3.326E-05**	3.469971	**-0.004665**	0.9461222	**-0.00166**
S1negimpact	0.02633415	**-0.00010107**	0.0190084	**-2.968E-05**	3.475015	0.000379	0.9463006	**-0.00148**
S1pos/negsum	0.02625775	**-0.00017747**	0.0189378	**-0.0001002**	3.461608	**-0.013028**	0.9427893	**-0.00499**
S1posimpactmean	0.0263607	**-7.452E-05**	0.0187348	**-0.0003033**	3.417428	**-0.057208**	0.9326792	**-0.0151**
S1pos/negimpactmean	0.02635634	**-7.888E-05**	0.0187269	**-0.0003112**	3.416036	**-0.0586**	0.932288	**-0.01549**

Table 4-14 Out-of-sample model accuracy: BBVA2 Bond ARIMAX models with Country News Sentiment

In Spain, country news sentiment data can be used to enhance the forecast of corporate bond yield spread as well. In **Table 4-11**, average negative sentiment (S1negmean) and average negative impact score (S1negimpactmean) used as external variables in ARIMAX model increase all four model performance measures. Comparable to

DBKG1 corporate bond yield spread, we used the sample data before the economic downturn when predicting corporate bond yield spread of SAN1 bond. A similar result suggests that negative news sentiment increases the forecast accuracy of the corporate bond yield spreads before the economic recession. The findings from **Table 4-12** and **Table 4-13** suggest that multivariate ARIMAX model with both positive and negative country news sentiment data can enhance the prediction of SAN2 and BBVA1 corporate bond yield spreads. The common feature of the yield spreads of SAN2 and BBVA1 is that the spreads change dramatically from in-sample period to out-of-sample period: SAN2 has its yield spreads decreases dramatically and BBVA1 has its yield spreads increase greatly. In **Table 4-14**, the modelling results for BBVA2 also suggests using multivariate ARIMAX model in predicting corporate bond yield spreads and preferring negative country news sentiment.

4.3.2 ARIMAX with Government News Sentiment

Secondly, we compare the out-of-sample model performance of ARIMAX model with the government macroeconomic news sentiment as external variables.

DBKG1 BOND ARIMAX with government news sentiment (Out-of-sample)								
External Variable(s)	RMSE	Diff	MAE	diff	MAPE	diff	MASE	diff
G2possum	0.1813338	**-0.0001326**	0.07430372	**-0.00012**	2.781107	**-0.00019**	1.133346	**-0.00189**
G2posmean	0.1814413	**-2.51E-05**	0.07435303	**-7.5E-05**	2.776743	**-0.00455**	1.134099	**-0.00114**
G2negmean	0.1808201	**-0.0006463**	0.07426214	**-0.00017**	2.782508	0.001216	1.132712	**-0.00253**
G2posimpact	0.1801367	**-0.0013297**	0.07293078	**-0.0015**	2.734623	**-0.04667**	1.112405	**-0.02283**
G2sumimpact	0.1812326	**-0.0002338**	0.07393925	**-0.00049**	2.764949	**-0.01634**	1.127787	**-0.00745**
G2pos/negimpact	0.1802388	**-0.0012276**	0.07297465	**-0.00145**	2.735725	**-0.04557**	1.113074	**-0.02216**
G2posimpactmean	0.1808013	**-0.0006651**	0.07392818	**-0.0005**	2.764062	**-0.01723**	1.127618	**-0.00762**
G2negimpactmean	0.1813064	**-0.00016**	0.07428592	**-0.00014**	2.771233	**-0.01006**	1.133075	**-0.00216**
G2pos/negimpactmean	0.1807149	**-0.0007515**	0.07387129	**-0.00056**	2.758059	**-0.02323**	1.126751	**-0.00849**

Table 4-15 Out-of-sample model accuracy: DBKG1 Bond ARIMAX models with government News Sentiment

DBKG2 BOND ARIMAX with government news sentiment (Out-of-sample)								
External Variable(s)	RMSE	Diff	MAE	diff	MAPE	diff	MASE	diff
G2posmean	0.06646899	**-1.43E-06**	0.030572	5.11E-05	6.774728	0.006798	0.992581	0.0016592
G2negmean	0.06646346	**-6.96E-06**	0.030529	8.19E-06	6.768363	0.000433	0.991188	0.000266
G2posimpact	0.06646551	**-4.91E-06**	0.030516	**-5.14E-06**	6.767209	**-0.000721**	0.990755	**-0.000167**
G2posimpactmean	0.06645765	**-1.277E-05**	0.03053	8.94E-06	6.76909	0.00116	0.991212	0.0002903
G2negimpactmean	0.06647803	7.61E-06	0.030518	**-2.74E-06**	6.767882	**-4.8E-05**	0.990833	**-8.89E-05**

G2pos/negimpactmean	0.06644696	-2.346E-05	0.030526	4.48E-06	6.76952	0.00159	0.991067	0.0001457

Table 4-16 Out-of-sample model accuracy: DBKG2 Bond ARIMAX models with government News Sentiment

In **Table 4-15**, DBKG1 ARIMAX model results suggest that both positive and negative Germany government news sentiment can be incorporated in the forecasting models to improve the model performance. They also suggest that positive government news sentiment, in general, is better than negative one in terms of increasing forecast accuracy as its RMSE, MAE, MAPE and MASE are much smaller. However, DBKG2 ARIMAX model results show that it is not necessary that positive Germany government news sentiment is a better input in the ARIMAX model than the negative news sentiment. RMSE can be reduced most by using both average positive impact score (G2posimpactmean) and average negative impact score (G2negimpactmean). However, to reduce MAE, MAPE and MASE, using positive government impact score is a better option than negative government impact score.

MUVG BOND ARIMAX with government news sentiment (Out-of-sample)								
External Variable(s)	RMSE	Diff	MAE	diff	MAPE	diff	MASE	diff
G2posmean	0.056914	-2.932E-05	0.037652	-4.103E-05	3.726412	-0.00519	0.998184	-0.00109
G2negmean	0.056844	-0.0001	0.037618	-7.417E-05	3.724966	-0.00663	0.997305	-0.00197
G2negimpactmean	0.056942	-1.51E-06	0.037721	2.87E-05	3.738231	0.006633	1.000032	0.000761

Table 4-17 Out-of-sample model accuracy: MUVG Bond ARIMAX models with government News Sentiment

MUVG Bond results (**Table 4-17**) suggest that negative government news sentiment is a better external regressor for ARIAMX in forecasting yield spreads than positive government news sentiment.

SAN1 BOND ARIMAX with government news sentiment (Out-of-sample)								
External Variable(s)	RMSE	Diff	MAE	diff	MAPE	diff	MASE	diff
S2negsum	0.0943485	-0.000161	0.0544954	-0.000219	3.818407	-0.00556	1.06114	-0.004268
S2aggregate	0.0943434	-0.0001661	0.0545516	-0.000163	3.820006	-0.00396	1.062235	-0.003173
S2posimpact	0.0945708	6.121E-05	0.0547935	7.894E-05	3.828757	0.004787	1.066945	0.001537
S2negimpact	0.094371	-0.0001386	0.0545636	-0.000151	3.829043	0.005073	1.062468	-0.00294
S2sumimpact	0.0943548	-0.0001548	0.0545538	-0.000161	3.826772	0.002802	1.062278	-0.00313
S2pos/negsum	0.0943458	-0.0001638	0.0546639	-5.07E-05	3.822513	-0.00146	1.064421	-0.000987
S2pos/negimpact	0.0943952	-0.0001144	0.0545974	-0.000117	3.831777	0.007807	1.063125	-0.002283

Table 4-18 Out-of-sample model accuracy: SAN1 Bond ARIMAX models with government News Sentiment

SAN2 BOND ARIMAX with government news sentiment (Out-of-sample)								
External Variable(s)	RMSE	Diff	MAE	diff	MAPE	diff	MASE	diff
S2possum	0.0563199	5.194E-05	0.036619	**-0.000124**	2.54952	2E-06	1.038171	**-0.003529**
S2negsum	0.0562882	2.024E-05	0.0367296	**-1.39E-05**	2.549052	**-0.000466**	1.041307	**-0.000393**
S2aggregate	0.0562826	1.461E-05	0.0367393	**-4.18E-06**	2.549451	**-6.7E-05**	1.041582	**-0.000118**
S2posimpact	0.056213	**-5.497E-05**	0.0367617	1.821E-05	2.553779	0.004261	1.042216	0.000516
S2negimpact	0.0562861	1.816E-05	0.0367352	**-8.3E-06**	2.549152	-0.000366	1.041465	**-0.000235**
S2sumimpact	0.0562928	2.48E-05	0.0367336	**-9.89E-06**	2.548449	-0.001069	1.04142	**-0.00028**
S2pos/negsum	0.0563308	6.278E-05	0.0366083	**-0.000135**	2.548928	**-0.00059**	1.037867	**-0.003833**
S2pos/negimpact	0.0562325	**-3.553E-05**	0.0367537	1.02E-05	2.553443	0.003925	1.041989	0.000289

Table 4-19 Out-of-sample model accuracy: SAN2 Bond ARIMAX models with government News Sentiment

BBVA1 BOND ARIMAX with government news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
S2negsum	0.1063646	**-7.5E-06**	0.027251	**-2.299E-05**	0.812626	**-0.000545**	1.099615	**-0.000928**
S2posimpact	0.1061298	**-0.000242**	0.0277602	0.00048615	0.82076	0.0075897	1.12016	0.019617
S2sumimpact	0.1062983	**-7.38E-05**	0.0272186	**-5.539E-05**	0.81205	**-0.00112**	1.098308	**-0.002235**

Table 4-20 Out-of-sample model accuracy: BBVA1 Bond ARIMAX models with government News Sentiment

BBVA BOND 2 ARIMAX with government news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
S2possum	0.02631244	**-0.00012278**	0.0189936	**-4.446E-05**	3.464351	**-0.010285**	0.9455646	**-0.00221**
S2negmean	0.02632156	**-0.00011366**	0.0188351	**-0.0002029**	3.442756	**-0.03188**	0.9376758	**-0.0101**
S2aggregate	0.0264215	**-1.372E-05**	0.0190129	**-2.517E-05**	3.470019	**-0.004617**	0.9465249	**-0.00125**
S2posimpact	0.02642269	**-1.253E-05**	0.0190325	**-5.51E-06**	3.473618	**-0.001018**	0.9475036	**-0.00027**
S2negimpact	0.02629472	**-0.0001405**	0.0189536	**-8.444E-05**	3.461171	**-0.013465**	0.9435745	**-0.0042**
S2sumimpact	0.02641204	**-2.318E-05**	0.0188349	**-0.0002032**	3.436276	**-0.03836**	0.9376625	**-0.01012**
S2pos/negsum	0.02632425	**-0.00011097**	0.0190012	**-3.681E-05**	3.46579	**-0.008846**	0.9459456	**-0.00183**
S2pos/negimpact	0.02631312	**-0.0001221**	0.0189616	**-7.642E-05**	3.462945	**-0.011691**	0.9439734	**-0.0038**
S2negimpactmean	0.0262893	**-0.00014592**	0.0188886	**-0.0001495**	3.448782	**-0.025854**	0.9403363	**-0.00744**
S2pos/negimpactmean	0.02646021	2.499E-05	0.0189595	**-7.856E-05**	3.465176	**-0.00946**	0.9438672	**-0.00391**

Table 4-21 Out-of-sample model accuracy: BBVA2 Bond ARIMAX models with government News Sentiment

From **Table 4-18** to **Table 4-21**, results from the modelling of SAN1 and BBVA2 yield spreads suggest using negative government sentiment in the ARIMAX model, however, the models for SAN2 and BBVA1 yield spreads suggest applying both positive and negative government sentiment as two external variables in the ARIMAX model to enhance prediction accuracy of corporate bond yield spread.

For the government news sentiment in Italy, the results show that using negative Italian government news sentiment data as external variables in the ARIMAX model can improve the forecast of ENEL and ENI corporate bond yield spread. In addition to the government news sentiment, we also investigate the parliament news sentiment in Germany. All the ARIMAX models with positive parliament news sentiment enhance the forecast of corporate bond yield spreads of Germany corporate bonds.

4.3.3 ARIMAX with Central Bank News Sentiment

Thirdly, we compare the out-of-sample model performance of ARIMAX model with the central bank macroeconomic news sentiment as external variables.

DBKG1 BOND ARIMAX with Central Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
G10negsum	0.1813968	**-6.96E-05**	0.07502644	0.000599	2.826585	0.045293	1.14437	0.009132
G10negmean	0.1813968	**-6.96E-05**	0.07502644	0.000599	2.826585	0.045293	1.14437	0.009132
G10aggregate	0.1814474	**-1.9E-05**	0.07435474	**-7.3E-05**	2.77972	**-0.00157**	1.134125	**-0.00111**
G10negimpact	0.1814663	**-1E-07**	0.07442273	**-5E-06**	2.781328	3.6E-05	1.135162	**-7.6E-05**
G10negimpactmean	0.1814663	**-1E-07**	0.07442273	**-5E-06**	2.781328	3.6E-05	1.135162	**-7.6E-05**

Table 4-22 Out-of-sample model accuracy: DBKG1 Bond ARIMAX models with Central Bank News Sentiment

DBKG2 BOND ARIMAX with Central Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
G10possum	0.0664684	**-2.02E-06**	0.030519	**-2.15E-06**	6.767854	**-7.6E-05**	0.990852	**-6.98E-05**
G10negsum	0.06646004	**-1.038E-05**	0.030521	3.2E-07	6.768603	0.000673	0.990932	1.06E-05
G10posmean	0.06625666	**-0.0002138**	0.03054	1.84E-05	6.76885	0.00092	0.991519	0.0005977
G10negmean	0.0664617	**-8.72E-06**	0.030533	1.183E-05	6.773902	0.005972	0.991306	0.0003842
G10aggregate	0.0665022	3.178E-05	0.030498	**-2.32E-05**	6.766917	**-0.001013**	0.99017	**-0.000752**
G10posimpact	0.06646807	**-2.35E-06**	0.030547	2.588E-05	6.766324	**-0.001606**	0.991762	0.0008405
G10sumimpact	0.06646944	**-9.8E-07**	0.030555	3.434E-05	6.766324	**-0.001606**	0.992037	0.0011151
G10pos/negsum	0.06646949	**-9.3E-07**	0.030517	**-4.39E-06**	6.768587	0.000657	0.990779	**-0.000142**
G10pos/negimpact	0.06649378	0.00002336	0.030571	4.976E-05	6.767571	**-0.000359**	0.992537	0.0016158
G10posimpactmean	0.06640694	**-6.348E-05**	0.030503	**-1.77E-05**	6.761818	**-0.006112**	0.990348	**-0.000574**
G10negimpactmean	0.06646497	**-5.45E-06**	0.030506	-1.5E-05	6.765801	**-0.002129**	0.990435	**-0.000486**
G10pos/negimpactmean	0.06640291	**-6.751E-05**	0.030487	**-3.43E-05**	6.759283	**-0.008647**	0.989807	**-0.001115**

Table 4-23 Out-of-sample model accuracy: DBKG2 Bond ARIMAX models with Central Bank News Sentiment

MUVG BOND ARIMAX with Central Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
G10negsum	0.056962	1.862E-05	0.037684	**-8.37E-06**	3.730235	**-0.00136**	0.99905	**-0.00022**
G10negmean	0.057009	6.555E-05	0.037687	**-5.77E-06**	3.729357	**-0.00224**	0.999118	**-0.00015**
G10aggregate	0.056978	3.465E-05	0.037703	1.009E-05	3.73134	**-0.00026**	0.999539	0.000267
G10pos/negsum	0.057107	0.00016307	0.037734	4.154E-05	3.730559	**-0.00104**	1.000373	0.001101
G10negimpactmean	0.056847	**-9.615E-05**	0.037735	4.215E-05	3.736468	0.00487	1.000389	0.001117

Table 4-24 Out-of-sample model accuracy: MUVG Bond ARIMAX models with Central Bank News Sentiment

Table 4-22, **Table 4-23** and **Table 4-24** suggest that both positive and negative Germany central bank news sentiment can enhance ARIMAX model accuracy, but the negative news sentiment is even more useful for predicting DBKG1 and Munich Rep Group corporate bond yield spread and positive news sentiment is more effective in the prediction of DBKG2 corporate bond yield spread.

SAN1 BOND ARIMAX with Central Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
S4posimpact	0.0945064	**-3.17E-06**	0.0547075	**-7.13E-06**	3.824281	0.000311	1.065269	**-0.000139**
S4posimpactmean	0.0945094	**-2.2E-07**	0.0547129	**-1.69E-06**	3.824104	0.000134	1.065375	**-3.3E-05**

Table 4-25 Out-of-sample model accuracy: SAN1 Bond ARIMAX models with Central Bank News Sentiment

SAN2 BOND ARIMAX with Central Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
S4negsum	0.0562862	1.82E-05	0.0366561	**-8.73E-05**	2.533493	**-0.016025**	1.039225	**-0.002475**
S4negmean	0.056395	0.00012699	0.0368008	5.735E-05	2.540976	**-0.008542**	1.043326	0.001626
S4negimpact	0.0563076	3.959E-05	0.0367389	**-4.51E-06**	2.548477	**-0.001041**	1.041572	**-0.000128**
S4sumimpact	0.0562507	**-1.724E-05**	0.0367624	1.89E-05	2.551535	0.002017	1.042236	0.000536
S4pos/negsum	0.0564291	0.00016109	0.0367476	4.17E-06	2.536715	**-0.012803**	1.041818	0.000118

Table 4-26 Out-of-sample model accuracy: SAN2 Bond ARIMAX models with Central Bank News Sentiment

BBVA1 BOND ARIMAX with Central Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
S4possum	0.106358	**-1.41E-05**	0.0272547	**-1.935E-05**	0.812027	**-0.001144**	1.099762	**-0.000781**

Table 4-27 Out-of-sample model accuracy: BBVA1 Bond ARIMAX models with Central Bank News Sentiment

BBVA2 BOND ARIMAX with Central Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
S4possum	0.02643497	**-2.5E-07**	0.0190399	1.88E-06	3.475069	0.000433	0.9478716	9.38E-05

S4posmean	0.02643429	-9.3E-07	0.0190394	1.37E-06	3.474981	0.000345	0.9478461	6.83E-05
S4aggregate	0.0262793	-0.00015592	0.0187698	-0.0002682	3.422546	-0.05209	0.9344245	-0.01335
S4posimpact	0.02643237	-2.85E-06	0.019038	-9E-08	3.474728	9.2E-05	0.9477736	-4.2E-06
S4pos/negsum	0.02624374	-0.00019148	0.0187257	-0.0003123	3.416012	-0.058624	0.9322289	-0.01555
S4pos/negimpact	0.02625159	-0.00018363	0.0187305	-0.0003075	3.417056	-0.05758	0.9324685	-0.01531
S4posimpactmean	0.02643221	-3.01E-06	0.0190378	-2.1E-07	3.474707	7.1E-05	0.9477677	-1E-05
S4pos/negimpactmean	0.02625552	-0.0001797	0.0187367	-0.0003013	3.418033	-0.056603	0.9327777	-0.015

Table 4-28 Out-of-sample model accuracy: BBVA2 Bond ARIMAX models with Central Bank News Sentiment

As observed in **Table 4-25**, **Table 4-26**, **Table 4-27** and **Table 4-28**, both positive and negative Spain central bank news sentiment are helpful in enhancing the prediction model of corporate bond yield as well.

ENEL BOND ARIMAX with Central Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
I3possum	0.060421	1.86E-06	0.033614	-4.6E-07	2.465119	-0.00025	1.075512	-1.5E-05
I3posmean	0.060428	9.53E-06	0.033607	-7.7E-06	2.464256	-0.00112	1.075282	-0.00024
I3posimpactmean	0.06045	3.13E-05	0.033617	1.95E-06	2.464636	-0.00074	1.075589	6.2E-05

Table 4-29 Out-of-sample model accuracy: ENEL Bond ARIMAX models with Central Bank News Sentiment

ENI BOND ARIMAX with Central Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
I3possum	0.04978285	-7.62E-05	0.025041	-9.05E-05	4.676238	-0.015343	1.043061	-0.00377
I3posmean	0.04984532	-1.37E-05	0.025085	-4.64E-05	4.684412	-0.007169	1.044898	-0.001933
I3negmean	0.04987098	1.192E-05	0.025151	1.892E-05	4.694306	0.002725	1.04762	0.000789
I3aggregate	0.04973907	-0.00012	0.024971	-0.000161	4.667402	-0.024179	1.040123	-0.006708
I3posimpact	0.04983584	-2.32E-05	0.025104	-2.72E-05	4.68699	-0.004591	1.045697	-0.001134
I3negimpact	0.04983686	-2.22E-05	0.025093	-3.87E-05	4.687748	-0.003833	1.045046	-0.001785
I3sumimpact	0.04982536	-3.37E-05	0.025089	-4.29E-05	4.685537	-0.006044	1.045046	-0.001785
I3pos/negimpact	0.04981408	-4.5E-05	0.025078	-5.37E-05	4.684445	-0.007136	1.044595	-0.002236
I3posimpactmean	0.04984546	-1.36E-05	0.025104	-2.77E-05	4.687983	-0.003598	1.045676	-0.001155
I3negimpactmean	0.04963184	-0.000227	0.02509	-4.18E-05	4.665761	-0.02582	1.045093	-0.001738
I3pos/negimpactmean	0.04985183	-7.23E-06	0.02515	1.857E-05	4.692461	0.00088	1.047605	0.000774

Table 4-30 Out-of-sample model accuracy: ENI Bond ARIMAX models with Central Bank News Sentiment

The evidence from Italian bond yield spreads ARIMAX models proves that Italian central bank news sentiment enhances the performance of ARIMAX model (See **Table 4-29** and **Table 4-30**). Positive news sentiment increases ARIMAX model performance when forecast the future yield spreads of ENEL bond. Both positive and negative central bank news sentiment boost the model performance for ENI corporate bond. Overall, central bank news sentiment is of value to corporate bond yield spread prediction. Like country news sentiment, positive central bank news sentiment seems more helpful in the prediction of yield spreads during the economic recovering period and negative central bank news sentiment are more likely to be useful in enhancing the prediction when economy has recovered.

4.3.4 ARIMAX with Firm-Specific News Sentiment

Finally, we compare the out-of-sample model performance of ARIMAX model with the firm-specific news sentiment as external variables.

DBKG1 BOND ARIMAX with Deutsche Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
G12negsum	0.1815108	0.0000444	0.07416898	**-0.00026**	2.771208	**-0.01008**	1.131291	**-0.00395**
G12posmean	0.1814341	**-3.23E-05**	0.07427582	**-0.00015**	2.773017	-0.00828	1.132921	**-0.00232**
G12negmean	0.1810765	**-0.0003899**	0.07442417	**-3.6E-06**	2.782636	0.001344	1.135184	**-5.4E-05**
G12aggregate	0.1814595	**-6.9E-06**	0.07445948	3.17E-05	2.781699	0.000407	1.135722	0.000484
G12posimpact	0.1814147	**-5.17E-05**	0.07427274	**-0.00016**	2.771831	**-0.00946**	1.132874	**-0.00236**
G12sumimpact	0.1814272	**-3.92E-05**	0.07432018	**-0.00011**	2.775049	**-0.00624**	1.133597	**-0.00164**
G12pos/negsum	0.1815201	5.37E-05	0.0743603	**-6.7E-05**	2.782107	0.000815	1.134209	**-0.00103**
G12pos/negimpact	0.1814444	**-2.2E-05**	0.07438738	**-4E-05**	2.777852	**-0.00344**	1.134622	**-0.00062**
G12posimpactmean	0.1814262	**-4.02E-05**	0.07440331	**-2.4E-05**	2.780244	**-0.00105**	1.134865	**-0.00037**
G12negimpactmean	0.1814557	**-1.07E-05**	0.07439336	**-3.4E-05**	2.780484	**-0.00081**	1.134714	**-0.00052**
G12pos/negimpactmean	0.1814264	**-4E-05**	0.07437876	**-4.9E-05**	2.779787	**-0.00151**	1.134491	**-0.00075**

Table 4-31 Out-of-sample model accuracy: DBKG1 Bond ARIMAX models with Company News Sentiment

DBKG2 BOND ARIMAX with Deutsche Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
G12possum	0.06652141	5.099E-05	0.030552	3.09E-05	6.767826	**-0.000104**	0.991925	0.0010034
G12negsum	0.06637158	**-9.884E-05**	0.030424	**-9.68E-05**	6.737376	**-0.030554**	0.987778	**-0.003143**
G12posmean	0.0664647	**-5.72E-06**	0.030522	1.31E-06	6.768079	0.000149	0.990964	4.26E-05
G12negmean	0.06647031	**-1.1E-07**	0.030528	6.88E-06	6.768584	0.000654	0.991145	0.0002234
G12aggregate	0.06638931	**-8.111E-05**	0.030463	**-5.81E-05**	6.754191	**-0.013739**	0.989036	**-0.001886**

G12posimpact	0.06644448	**-2.594E-05**	0.030561	3.963E-05	6.772564	0.004634	0.992208	0.0012867
G12pos/negsum	0.06640745	**-6.297E-05**	0.030439	**-8.23E-05**	6.738256	**-0.029674**	0.98825	**-0.002672**
G12posimpactmean	0.0664583	**-1.212E-05**	0.030597	7.638E-05	6.778589	0.010659	0.993402	0.0024799

Table 4-32 Out-of-sample model accuracy: DBKG2 Bond ARIMAX models with Company News Sentiment

MUVG BOND ARIMAX with Munich RE Group news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
G13negsum	0.056938	**-5.39E-06**	0.037688	**-4.55E-06**	3.731116	**-0.00048**	0.999151	**-0.00012**
G13negmean	0.056916	**-2.746E-05**	0.037661	**-3.189E-05**	3.72822	**-0.00338**	0.998426	**-0.00085**
G13negimpact	0.056861	**-8.277E-05**	0.037634	**-5.83E-05**	3.728563	**-0.00304**	0.997726	**-0.00155**
G13posimpactmean	0.056952	8.62E-06	0.037684	**-8.16E-06**	3.731782	0.000184	0.999055	**-0.00022**
G13negimpactmean	0.056919	**-2.504E-05**	0.037677	**-1.506E-05**	3.730797	**-0.0008**	0.998872	**-0.0004**
G13pos/negimpactmean	0.056926	**-1.772E-05**	0.037669	**-2.349E-05**	3.730974	**-0.00062**	0.998649	**-0.00062**

Table 4-33 Out-of-sample model accuracy: MUVG Bond ARIMAX models with Company News Sentiment

SAN1 BOND ARIMAX with Banco Santander news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
S13possum	0.0944969	**-1.265E-05**	0.0547115	**-3.05E-06**	3.803129	**-0.02084**	1.065349	**-5.9E-05**
S13negsum	0.0947227	0.00021308	0.0547509	3.632E-05	3.80666	**-0.01731**	1.066115	0.000707
S13posmean	0.0944732	**-3.635E-05**	0.0547456	3.1E-05	3.821869	**-0.0021**	1.066012	0.000604
S13negmean	0.0945783	6.867E-05	0.0547682	5.365E-05	3.815714	**-0.00826**	1.066453	0.001045
S13aggregate	0.0943814	**-0.0001282**	0.0546831	**-3.14E-05**	3.829988	0.006018	1.064796	**-0.000612**
S13pos/negsum	0.0946515	0.00014193	0.0547722	5.76E-05	3.821905	**-0.00206**	1.06653	0.001122
S13pos/negimpact	0.094811	0.00030137	0.0552922	0.0005776	3.821388	**-0.00258**	1.076655	0.011247
S13posimpactmean	0.0944598	**-4.974E-05**	0.0547195	4.93E-06	3.825346	0.001376	1.065504	9.6E-05
S13negimpactmean	0.0945146	4.99E-06	0.0546783	**-3.63E-05**	3.818245	**-0.00572**	1.064702	**-0.000706**
S13pos/negimpactmean	0.0944691	**-4.047E-05**	0.0546849	**-2.96E-05**	3.819758	**-0.00421**	1.064831	**-0.000577**

Table 4-34 Out-of-sample model accuracy: SAN1 Bond ARIMAX models with Company News Sentiment

SAN2 BOND ARIMAX with Banco Santander news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
S13posimpactmean	0.0562537	**-1.428E-05**	0.036718	**-2.55E-05**	2.543799	**-0.005719**	1.040978	**-0.000722**
S13negimpactmean	0.0562525	**-1.547E-05**	0.0367324	**-1.11E-05**	2.54957	5.2E-05	1.041386	**-0.000314**
S13pos/negimpactmean	0.0562333	**-3.47E-05**	0.0367081	**-3.53E-05**	2.544042	**-0.005476**	1.040698	**-0.001002**

Table 4-35 Out-of-sample model accuracy: SAN2 Bond ARIMAX models with Company News Sentiment

BBVA2 BOND ARIMAX with Central Bank news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff

S14negsum	0.02642661	**-8.61E-06**	0.0190376	**-4.7E-07**	3.474407	**-0.000229**	0.9477548	**-2.3E-05**
S14posmean	0.02643906	3.84E-06	0.0190816	4.351E-05	3.482222	0.007586	0.9499439	0.002166
S14negmean	0.026383	**-5.222E-05**	0.0189483	**-8.971E-05**	3.466734	**-0.007902**	0.9433117	**-0.00447**
S14aggregate	0.02654944	0.00011422	0.0191477	0.00010961	3.495748	0.021112	0.9532346	0.005457
S14posimpact	0.02642468	**-1.054E-05**	0.0190269	**-1.119E-05**	3.472351	**-0.002285**	0.947221	**-0.00056**
S14negimpact	0.02627114	**-0.00016408**	0.0187497	**-0.0002884**	3.419178	**-0.055458**	0.9334211	**-0.01436**
S14sumimpact	0.02643351	**-1.71E-06**	0.0190239	**-1.418E-05**	3.47185	**-0.002786**	0.9470723	**-0.00071**
S14pos/negimpact	0.02626163	**-0.00017359**	0.0187486	**-0.0002895**	3.419399	**-0.055237**	0.9333665	**-0.01441**
S14posimpactmean	0.0264121	**-2.312E-05**	0.0190237	**-1.434E-05**	3.472296	**-0.00234**	0.9470643	**-0.00071**
S14negimpactmean	0.02630732	**-0.0001279**	0.0187672	**-0.0002709**	3.424921	**-0.049715**	0.9342942	**-0.01348**
S14pos/negimpactmean	0.02642502	**-1.02E-05**	0.0190166	**-2.142E-05**	3.471206	**-0.00343**	0.9467116	**-0.00107**

Table 4-36 Out-of-sample model accuracy: BBVA2 Bond ARIMAX models with Company News Sentiment

ENI BOND ARIMAX with ENI S.P.A. news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
I11posmean	0.04989429	3.523E-05	0.025121	**-1.1E-05**	4.692444	0.000863	1.046372	**-0.000459**
I11negmean	0.04987657	1.751E-05	0.025131	**-7.1E-07**	4.695559	0.003978	1.046802	**-2.9E-05**
I11posimpact	0.04983814	**-2.09E-05**	0.025112	**-1.96E-05**	4.690841	**-0.00074**	1.046016	**-0.000815**
I11negimpact	0.04986136	2.3E-06	0.025113	**-1.84E-05**	4.693477	0.001896	1.046065	**-0.000766**
I11sumimpact	0.04984854	**-1.05E-05**	0.025125	**-6.83E-06**	4.690457	**-0.001124**	1.046547	**-0.000284**
I11pos/negimpact	0.0498432	**-1.59E-05**	0.025096	**-3.53E-05**	4.692916	0.001335	1.045361	**-0.00147**
I11posimpactmean	0.04985206	**-7E-06**	0.025135	3.62E-06	4.69611	0.004529	1.046982	0.000151
I11negimpactmean	0.0498288	**-3.03E-05**	0.025149	1.758E-05	4.690447	**-0.001134**	1.047564	0.000733
I11pos/negimpactmean	0.04981886	**-4.02E-05**	0.025159	2.688E-05	4.695694	0.004113	1.047951	0.00112

Table 4-37 Out-of-sample model accuracy: ENI Bond ARIMAX models with Company News Sentiment

ENEL BOND ARIMAX with ENEL news sentiment (Out-of-sample)								
External Variable(s)	RMSE	diff	MAE	diff	MAPE	diff	MASE	diff
I10possum	0.060406	**-1.3E-05**	0.033604	**-1.1E-05**	2.472333	0.006962	1.075168	**-0.00036**
I10negsum	0.060818	0.000399	0.033749	0.000134	2.463094	**-0.00228**	1.079824	0.004297
I10posmean	0.060418	**-1.1E-06**	0.033614	**-9.1E-07**	2.46538	9E-06	1.075498	**-2.9E-05**
I10negmean	0.060611	0.000193	0.033541	**-7.4E-05**	2.44643	**-0.01894**	1.07316	**-0.00237**
I10aggregate	0.06048	6.15E-05	0.033614	**-1.2E-06**	2.479014	0.013643	1.07549	**-3.7E-05**

Table 4-38 Out-of-sample model accuracy: ENEL Bond ARIMAX models with Company News Sentiment

From **Table 4-31** to **Table 4-38**, we can see the performance accuracy of ARIMAX models with company specific news for the corporate bonds. It is suggested that both positive and negative company news sentiment reduces the forecast error when predicting Deutsche Bank and ENEL corporate bond yield spread, but the effect of negative company news sentiment is more evident than that of positive news sentiment. MUVG corporate bond yield spread is affected by negative company news sentiment mostly. ENI bond, one BBVA bond and two Banco Santander corporate bonds are sensitive to both positive and negative sentiment.

5. Results and Discussion

This report examines the effect of macroeconomic news sentiment and firm-specific news sentiment on European corporate bonds. Using ARIMAX model with news sentiment as external variables improve the forecast performance compared to a simple ARIMA model. Positive country news sentiment is more effective in the economic recovery period,while negative country news sentiment predicts well the corporate bond yield spreads in a period of recession. Both positive and negative government news sentiment can enhance the one-step ahead forecast of spreads. Positive Germany parliament news sentiment enhances the prediction of Germany corporate bond but the effect of negative parliament news sentiment is limited. The effect of Central Bank news sentiment is mixed, but, overall, it also suggests that negative central bank news sentiment predicts the corporate bond yield spreads well in the recession period and positive central bank news sentiment do better in the recovery period. Compared to positive firm-specific news sentiment, in most cases, negative firm-specific news sentiment improves the prediction of corporate bond yields. For further research, we plan to investigate the combined effect of various categories of news sentiment in predicting corporate bond yield spread.

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References

Akaike, H. (1974). A new look at the statistical model identification. IEEE transactions on automatic control, 19(6), pp.716-723.

Apergis, N. (2015). Forecasting Credit Default Swaps (CDSs) spreads with newswire messages: Evidence from European countries under financial distress. Economics Letters, 136, pp.92-94.

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. The Journal of Finance, 61(4), pp.1645-1680.

Bank for International Settlements (2016). Electronic Trading in Fixed Income Markets, January.

Box, G.E. and Jenkins, G.M. (1976). Time series analysis: forecasting and control, revised ed. Holden-Day.

diBartolomeo, D. (2016). Credit Risk Assessment of Corporate Debt using Sentiment and News. Chapter 17 in Handbook of Sentiment Analysis in Finance (2016). Eds: Mitra, G. and Yu, X.

Fernandes, C., Gama, P.M. and Vieira, E. (2016). Does local and Euro area sentiment matter for sovereign debt markets? Evidence from a bailout country. Applied

Economics, 48(9), pp.816-834.

Fuller, W.A. (1976). Introduction to statistical time series, New York: John Wiley & Sons.

Greenwich Associates (2014). European fixed income study, July.

Greenwich Associates (2015). The Continuing Corporate Bond Evolution, December.

Hyndman, R.J. and Koehler, A.B. (2006). Another look at measures of forecast accuracy. International journal of forecasting, 22(4), pp.679-688.

Laborda, R., Olmo, J. (2014). Investor sentiment and bond risk premia. Journal of Financial Markets, 18, pp. 206–233.

MarketAxess (2016). 4Q 2015 Fact Sheet. Available from: https://www.marketaxess.com/mediacenter/docs/MAFactSheet_4Q2015.pdf. [Accessed 25th August 2017]

McKinsey & Company and Greenwich Associates (2013). Corporate bond e-trading: same game, new playing field, August.

Nayak, S. (2010). Investor sentiment and corporate bond yield spreads. Review of Behavioral Finance, 2(2), pp.59-80.

Svensson, L.E. (1994). Estimating and Interpreting Forward Interest Rates: Sweden 1992-1994 (No. w4871). National Bureau of Economic Research.

Tsay, R (2010) Analysis of Financial Time Series, 3rd ed., New Jersey: John Wiley & Sons.

Yu, X. (2014). ‘Analysis of news sentiment and its applications to finance’. Ph.D. Thesis, Brunel University London, UK.

Yu, X., Mitra, G. (2016) An Impact Measure for News: its use in (daily) trading strategies, The Handbook of Sentiment Analysis in Finance. pp. 288–309.