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*Patrick Hirsch, Lars P. Feld, Ekkehard A. Köhler, Tobias Thomas*

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# "Whatever It Takes!" How Tonality of TV-News Affected Government Bond Yield Spreads during the European Debt Crisis

## Abstract

Were government bond risk premia affected by the media in addition to the effects of major events? Revisiting the European debt crisis, we analyze the role of television news in the rise and re-convergence of GIIPS bond spreads vis-à-vis Germany from 2007 to 2016. We use a dataset of more than one million human-coded news items from leading newscasts worldwide to identify over 25,000 news on the Eurozone and country-specific economic topics. Our findings emphasize the relevance of the tonality of news, such that an increasing share of positive (negative) news correlates with a decrease (increase) in spreads. Content-based endogenous clustering of news highlights the importance of news about institutions providing stability and "international financial support" to distressed countries in reducing bond spreads. Moreover, weekend news enables us to establish a causal link between country-specific news coverage and changes in spreads on the subsequent trading day.

JEL-Codes: E580, G120, L820.

Keywords: media coverage, TV newscast, tonality, Eurozone crisis, GIIPS bond yield spreads.

*Patrick Hirsch*
*Walter Eucken Institute and*
*University of Freiburg / Germany*
*hirsch@eucken.de*

*Lars P. Feld*
*Walter Eucken Institute and*
*University of Freiburg / Germany*
*feld@eucken.de*

*Ekkehard A. Köhler*
*Faculty III Economics*
*University of Siegen / Germany*
*ekkehard.koehler@uni-siegen.de*

*Tobias Thomas*
*DICE at Heinrich-Heine-*
*University Düsseldorf / Germany*
*thomas@dice.hhu.de*

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# 1 Introduction

In a celebrated study, Shiller (2017) highlights the importance of narratives for economic policy and economic outcomes. Accordingly, narratives, as such, have an impact beyond the actual economic event. Indeed, Draghi's to do "whatever it takes" to preserve the Euro significantly impacted financial markets, as it reassured investors and helped stabilize bond markets in the Eurozone. However, was this prime example of central bank communication a singular event, or is there a systematic impact of media coverage on bond yield spreads?

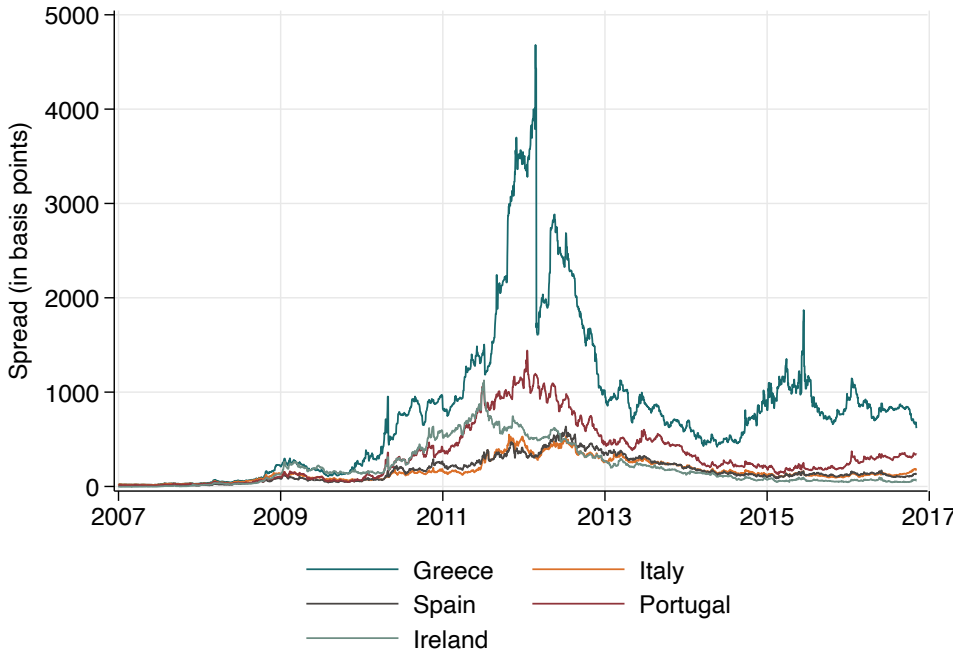
In this paper, we examine whether TV news coverage of economic issues related to EMU crisis countries or the Eurozone in general affected GIIPS interest rate differentials vis-à-vis Germany beyond the impact of major events during the European sovereign debt crisis.[1] The focus on TV news may be surprising, as investors are likely to derive their views and decisions from sources other than TV news. However, if the current study can confirm the impact of TV news on bond spreads, this could be important information for instance for central bank communication. In addition, existing studies on this subject often use newswire data, such as Reuters and Bloomberg, or media databases, like Factiva, and follow an identification strategy of simple word counts rather than full content analysis. These can cause several problems. On the one hand, these sources can be biased by insufficient indexing, so that not all relevant news is provided. On the other hand, they lead to shortcomings as they do not comprehend the content precisely, in particular when it comes to topical context and tonality (see, e.g., Grimmer and Stewart, 2013; Nelson et al., 2021; Van Atteveldt et al., 2021).[2]

In contrast, we draw on 1,147,119 hand-coded news items from a sample of evening news programs aired by the leading TV stations in France, Germany, Italy, Spain, Switzerland, the U.K., and the U.S., including 25,276 news items on economic topics related to GIIPS countries and the Eurozone from January 2007 to November 2016. The media data is unique in several respects: First, all news items within each newscast were systematically coded so that we observe the total number of news items on a given day. This allows us to calculate the share of news relevant to our research question proxying their importance. Second, the news programs were analyzed by human analysts who coded them based on a comprehensive set of variables, including the protagonist, topic group, topic,

[1] GIIPS is short for Greece, Italy, Ireland, Portugal, and Spain. We select these countries as they experienced a dramatic rise in yield spreads vis-à-vis Germany during the European sovereign debt crisis (see Figure 1).

[2] In communication science, the sentiment or tone of coverage is called tonality (see Haselmayer and Jenny, 2017). It refers to the qualitative assessment or characterization of the overall sentiment expressed in a media content and can be positive, negative, or neutral, and can vary in intensity.

FIGURE 1: GIIPS 10-YEAR GOVERNMENT BOND YIELD SPREADS VIS-À-VIS GERMANY




NOTES: This study covers the period before, during, and at the end of the European sovereign debt crisis, characterized first by a widening and then by a narrowing of government bond yield spreads.

source, and tone. Compared to approaches that rely solely on word counting or computational linguistics, this method ensures significantly higher accuracy, not least in capturing the tonality expressed in media messages. Consequently, we construct (sentiment) variables that effectively capture the importance, newsworthiness, precise content, and tone of the news, providing a comprehensive and accurate portrayal of (international) media content over the European sovereign debt crisis.

We follow a panel estimation approach to identify the effects, including a multitude of controls. Besides risk fundamentals, we control for a set of variables labeled "policy controls," which represent the most significant measures or decisions by institutions like the ECB to control the crisis, i.e., the events about which the media also likely report. The primary rationale is that the measured effect of our news variables should not proxy or be driven by extreme events. Instead, we are interested in media coverage's additional "noise" effect on yield spreads.[3]

[3]According to Black (1986, p. 529), people tend to treat "noise" as information; he argues that "a large number of small events is often a causal factor much more powerful than a small number of large events can be." In our context, the true value of certain information about potentially upcoming events or, in hindsight, the classification of events is often not clear. As a result, news (about events) that does not have significant informational content may nevertheless have an impact on bond prices simply because it is disseminated in the market.

However, despite the various controls included, we are aware of potential endogeneity problems. For example, it cannot be ruled out that the development of bond spreads is also covered in newscasts, leading to biased results due to reverse causality. In addition, both media coverage and bond spreads could depend on a third variable. Although we control for "policy" measures, we cannot fully rule out such an omitted variable bias.

To address the issue of causality and to isolate the impact of news coverage on government bond spreads, we utilize news broadcast over the weekend when financial markets are closed and measure its impact on the changes in yield spreads observed on Mondays.

Our main findings suggest that positive (negative) Eurozone and country-specific news were associated with decreasing (increasing) yield spreads during the European sovereign debt crisis. Controlling for a wide range of policies in the sample period, we interpret the effect to depend on "noise." Utilizing weekend news indicates that a one percentage point higher share of neutral to positive country-specific news to total news leads to -1.5 basis points lower bond spreads in the respective country.

The multidimensionality of the coded news items offers an opportunity for additional analysis. We combine data clustering methods with the established regression framework to exploratively identify news content and protagonists most relevant to changes in yield spreads. We employ the k-modes algorithm to identify self-informed clusters in the data, which are then used as explanatory news variables. Our results emphasize the importance of Eurozone news related to monetary policy and common fiscal institutions providing stability, as well as country-specific news pointing to international financial support to narrow yield spreads.

The remainder of this paper is organized as follows. Section 2 summarizes and discusses the main findings of the related literature. In Section 3 we describe the data and in Section 4 the empirical framework. Section 5 presents and discusses the empirical results. Section 6 concludes.

# 2 Related Literature

Given the numerous documented influences of media coverage on perceptions and human behavior,[4] it is hardly surprising that the relevance of the media for financial markets has also been the subject of extensive research. In the following, the literature review focuses on results of studies that investigate the link between media coverage and government bond yields in the run-up to and during the sovereign debt crisis in the EMU (e.g., Beetsma et al., 2013; Büchel, 2013; Gade et al., 2013;

[4]See, for instance, Bernhardt et al. (2023) for an overview.

Mohl and Sondermann, 2013; Falagiarda and Gregori, 2015; Apergis et al., 2016; Conrad and Zumbach, 2016). For a comprehensive overview of the methods, samples, and media classification used in these studies, please refer to Table A.1 in the Appendix.

All these studies find a significant effect of media coverage or communication on government bond yields or credit default swaps (CDS). However, the detailed findings differ across existing studies, although most studies emphasize the importance of distinguishing between negative and positive news. For instance, Beetsma et al. (2013) find that, on average, more news released on a country raises the interest rate spreads of the GIIPS countries, driven by bad news. Gade et al. (2013) conclude that positive communication can lead to a compression of spreads, whereas negative communication dedicated to fiscal policy can cause a widening of spreads. The research by Dergiades et al. (2015) indicates that Greek sovereign yield spreads were particularly susceptible to negative news discussed on social media. Apergis et al. (2016) report a significant impact of the tone of local news in major newspapers in the GIIPS on CDS spreads during the European sovereign debt crisis. Conrad and Zumbach (2016) present evidence that statements regarding periphery countries cause stronger market responses than statements focused on the Eurozone, particularly when the statements are negative.

According to Büchel (2013), communication by representatives of Germany, France, and the EU, as well as ECB Governing Council members, have an immediate impact on GIIPS CDS and bond yield spreads. In contrast, communication of representatives of the smaller Eurozone member countries has no effect. The analysis differentiates between policy signals and finds that "dovish" statements significantly lowered CDS and bond yield spreads compared to "hawkish" statements. Mohl and Sondermann (2013) find a positive effect of the number of Eurozone government statements on government bond spreads in EMU when statements are related to "restructuring" or "bailout." Finally, Falagiarda and Gregori (2015) identify significant differences in the impact of fiscal policy announcements by different Italian administrations over time.

The majority of previous studies obtain their news data from text-based agencies such as Bloomberg, Reuters, Dow Jones Newswire, and Market News International (Conrad and Zumbach, 2016; Falagiarda and Gregori, 2015; Mohl and Sondermann, 2013; Gade et al., 2013). Beetsma et al. (2013) use Eurointelligence, while Apergis et al. (2016) and Büchel (2013) retrieve their news data from Factiva, an online newspaper database that classifies articles by subject. Other studies focus on simple Google search queries or social media platforms like Twitter (e.g., Dergiades et al., 2015).

Moreover, many existing studies rely on simple word counts or computer lin-

guistic approaches (e.g., Apergis et al., 2016; Gade et al., 2013). However, this approach has limitations, especially when using only keywords to determine the relevance of a report. It can result in relevant reports and statements being filtered out if the wording differs from the specified search string. Additionally, simple algorithms cannot capture contextualized information and therefore miss out on the full news content.

The reliance on newswire services introduces another potential source of misspecification. As highlighted by Ehrmann and Fratzscher (2007), newswire services can be selective in their reporting, leading to incorrect reporting or misinterpretation of statements made by policy-makers. Moreover, many studies are explicitly or implicitly based on the assumption that specific keywords are associated with "good" or "bad" outcomes for bond pricing (e.g., Büchel, 2013; Dergiades et al., 2015). However, the adequacy of word count methods or computer linguistics in accurately capturing news content, topical context, and tonality can be questioned. The limitations of computer linguistics in the social sciences are well-documented in the literature (Grimmer and Stewart, 2013; Nelson et al., 2021; Van Atteveldt et al., 2021). Consequently, there is (at least so far) no adequate substitute for human coding in media analysis.[5]

# 3 Data

The data used in this study focuses on five EMU member states: Greece, Italy, Ireland, Portugal, and Spain (referred to as GIIPS), which are the countries most affected by the Eurocrisis. For each variable introduced below, we use daily data from January 2007 to November 2016. The period covered is particularly interesting as it encompasses the entire financial and European sovereign debt crisis, which was characterized by rising as well as falling bond spreads for the countries most affected by the crisis. The following sections describe the dependent variable, our main explanatory media variables, and the controls.

**Dependent Variable: 10-Year Spreads.** Daily government bond yields are obtained from Thomson Reuters Datastream and represent end-of-day secondary market yields on bonds with a maturity of 10 years. To reflect what has been shown to be mainly risk premia during the European sovereign debt crisis (see, e.g., Afonso et al., 2014, 2015), but also including liquidity premia and inflation premia, among others, the dependent variable in our model is the daily *yield spread* of GIIPS government bonds vis-à-vis Germany, considered a safe asset in

[5]For a more detailed overview over the current state of comparative studies about human coding and automated methods see Section 3.

Table 1: Media Dataset

| TV News Shows | Country | Sample Period | Total News | Relevant News |
|---|---|---|---|---|
| TF 1 Le Journal de 20h | France | 04/07–11/16 | 98,684 | 492 |
| ARD Tagesschau | Germany | 01/07–11/16 | 72,624 | 2,249 |
| ARD Tagesthemen | Germany | 01/07–11/16 | 89,425 | 3,229 |
| ZDF heute | Germany | 01/07–11/16 | 82,876 | 1,857 |
| ZDF heute journal | Germany | 01/07–11/16 | 84,224 | 3,247 |
| RAI 1 TG1 | Italy | 01/07–11/16 | 132,175 | 4,396 |
| TVE 1 Telediario | Spain | 06/07–11/16 | 178,502 | 5,201 |
| SRF Tagesschau | Switzerland | 01/07–11/16 | 90,913 | 1,894 |
| BBC 1 Ten O'Clock News | U.K. | 01/07–11/16 | 72,932 | 1,078 |
| BBC 2 Newsnight | U.K. | 01/07–11/16 | 37,821 | 1,067 |
| NBC Nightly News | U.S. | 01/07–11/16 | 65,429 | 135 |
| CBS Evening News | U.S. | 01/07–11/16 | 63,970 | 118 |
| FOX Special Report | U.S. | 01/07–11/16 | 77,544 | 313 |
| Total | | | 1,147,119 | 25,276 |

Notes: The table provides an overview of the newscasts and the number of news items in the sample period. Relevant news includes news related to the ECB, news related to debt-related aspects of the economy in GIIPS countries, or news related to the Eurozone economy in general. The explanatory variables used in the regressions are lower due to the calculation as a share of relevant news to total news on a given day.

the European Monetary Union (e.g., Von Hagen et al., 2011). The variable is measured in basis points (see Figure 1).

**Main Explanatory Variables: Television News.** Media variables are derived from a dataset based on Media Tenor International's media content analysis.[6] Based on this media data, a growing number of research studies have been conducted and published in recent years.[7] The sample of media outlets comprises thirteen major TV news programs from seven countries (see Table 1). Their selection and the sample period are mainly based on the data available to us. However, the media set is also reasonable from a communication and media science perspective: First, TV News still have a by far higher reach than other media and can be seen as more influential than others. Second, this is particularly true for evening TV news which are more heavily watched than other news shows during the day. Hence, we focus on evening news only. Finally, the TV news selected are opinion leading in the sense that they are quoted more often by other media. This international composition of the media set allows us to infer general sentiment rather

[6] See www.mediatenor.com.

[7] Meanwhile, the publications based on Media Tenor's data cover a wide range of topics and high ranked journals such as Benesch et al. (2019), Berlemann and Thomas (2019), Bernhardt et al. (2023), Dewenter et al. (2016, 2019, 2020), Dräger (2015), Garz (2012, 2013, 2014), Tausch and Zumbuehl (2018), Ulbricht et al. (2017), and Von Gaudecker and Wogrolly (2022).

than overemphasize a national or any particular view.[8]

The TV news programs were coded by Media Tenor's human analysts based on a wide range of characteristics, as defined by Media Tenor in a binding coding manual ("codebook"). As the TV news programs were fully coded, no selection bias can occur with regard to the relevant news items in the news programs analyzed. Each news program was coded and categorized by topic (e.g., currency, public debt, unemployment, inflation), participating persons (e.g., entrepreneurs, managers, politicians), and institutions (e.g., central banks, companies, governments, political parties), region of reference (e.g., Europe, Germany, U.S., World), time reference (future, past, present), the source of information (e.g., expert, journalist, politician etc.), and other categories. In addition, the analysts captured whether the relevant protagonists and/or institutions receive "positive," "negative," or "neutral" coverage.[9] Newscasts are analyzed news item by news item; for each new topic, person, institution, region, time reference, or source of relevance, an additional news item is coded. The human analysts had to enter their coding into a computerized coding mask that listed all variables and possible values according to the codebook.

As indicated above, the advantage of hand-coded data in this analysis is that "compared to human-based coding, automated coding is less accurate in detecting the tone of each specific text analyzed" (Puglisi and Snyder, 2015, p. 656). For the human-coded data in the current study, Media Tenor guarantees a minimum accuracy of 0.85 compared to coding fully in line with the codebook. To achieve high accuracy and to avoid systematic bias in the coding, monthly standard tests and spot checks were reviewed by a team of trainers of Media Tenor, who coded the items themselves based on the codebook and then compared them with the initial coding. This procedure is standard and comparable to Van Atteveldt et al. (2021). In their comparative study, the authors define coding of a text by three coders based on a codebook with discussion of possible disagreements between them as the "gold standard" and compare it to other methods. The authors find that when coding sentiment (or tone), individual coders achieve an accuracy of

[8]Having all possible media in mind, it could be that the same information can be presented by different media in rather different ways. For instance, Dewenter et al. (2020), on the basis of a newly introduced Political Coverage Index (PCI), provide empirical evidence for media bias in political reporting of 35 different media outlets from Germany. However, the German TV News in the current study are identified to report in a rather balanced way. In addition, the authors find robust empirical hints that on average the German media investigated have the tendency to report more critically on the political party in power. With respect to US Newsshows Bernhardt et al. (2023) show that ABC News, CBS News and NBC News report slightly more critical on the Republicans whereas FOX News is criticizing the Democrats in a rather harsh way. In addition, where CBS News and NBC News show a government-critical bias depending which President runs office. In contrast, FOX News turns out to be always more critical to the Democrats.

[9]If "no clear tone" was attributed, we refer to the news as neutral.

0.82 and teams of three coders achieve an accuracy of 0.88. Both outperform the accuracy of human crowd coding (0.72–0.77), machine learning approaches (0.57–0.63), and automated dictionary-based methods (0.39–0.50) (Van Atteveldt et al., 2021, p. 128, Table 2).[10] Thus, the accuracy of hand-coded data in our analysis of at least 0.85 is consistent with the state of the art according to Van Atteveldt et al. (2021). The high accuracy of the media data allows us to focus specifically on the tone and content of the news in relation to the bond spreads.

Based on the media set in the sample period all 1,147,119 news items were coded. Out of the entire universe of news items, for the sake of our analysis, we focus on news items that either refer specifically to the Eurozone or that focus on the economies of the individual GIIPS countries. In addition, for the country-specific economic news, we consider all news about the European Union and the EU with reference to the respective country, as well as all news about the economic and fiscal situation of the respective country. This results in a total of 25,276 relevant news items. Throughout the analysis, we use a primal distinction between two types of news, those focusing on the Eurozone (16.6%) and those focusing on a specific GIIPS country (83.4%).[11]

For the empirical analysis, five distinct types of daily media variables are constructed to serve as explanatory variables (see Table A.2 in the Appendix for summary statistics of the main media variables). Each of these variables is calculated as a percentage of the total number of news items on a given day:

[10] Biswas et al. (2022) find an even higher accuracy of automated sentiment coding by applying lexicon-based method Afinn and the deep learning model BiLSTM to Twitter texts (both achieving an accuracy of 0.80). However, until now and to the best of our knowledge such high accuracy levels are not reached when it comes to more complex texts like economic or political news. For an outlook, on possible future developments in automated sentiment analysis see Bordoloi and Biswas (2023).

[11] As mentioned, the TV news programs were fully coded. Hence, no selection bias can occur with regard to the relevant news items in the news programs analyzed. In addition, the code book of Media Tenor structures the topic in a tree structure with nine overarching topic chapters (like "Internal Affairs News", "Foreign Affairs News", "Economy/Economic Policy News", "Company News" etc.). Each of the nine overarching topic chapters contains up to ten topic groups (like "Budget", "State of the Economy" etc.). Each of the topic groups contains theoretically up to 99 topics; practically most of the topic groups contain 10-20 topics (like "Budget deficit", "Budget surplus", "Debt brake","Revenues", ..., "Other"). As on the lowest level of the tree-structure each topic group is closed by a category "Other", no news item can remain without an assignment option. Among the topic groups we selected all, which make sure, that we consider all news about the European Union and the EU with reference to the respective country, as well as all news about the economic and fiscal situation of the respective country. The accuracy of the assignment of the topic were regularly checked with scientific state-of-the-art monthly standard tests and spot checks as described above. The two word clouds illustrated in Figure A.1 and Figure A.2 in the Appendix provide insights into which topics are most frequently covered in Eurozone and country-specific news.

$$Media_{i,t} = \frac{\text{No. of relevant news}_{i,t}}{\text{No. of total news}_t} \times 100.$$

(1) As noted above, the first set of variables comprises two straightforward measures: the share of *Eurozone* news coverage that is invariant across countries and the share of news that is *country-specific*, reflected in the subscript $i$. A similar differentiation of news is adopted by Conrad and Zumbach (2016).

(2) The second set of variables builds on the previous two by further distinguishing between the tonality of the news. This results in six daily variables: the share of *positive, neutral*, and *negative* news, both for the *Eurozone* and in the *country-specific* context. Figure 2 shows descriptive graphs illustrating these main explanatory variables. Note that the y-axis indicates the share of positive news downward and the share of negative news upward. This choice of orientation is based on the assumed relationship between negative news and rising bond spreads and positive news and falling bond spreads. The share of neutral news is not shown in the figures.

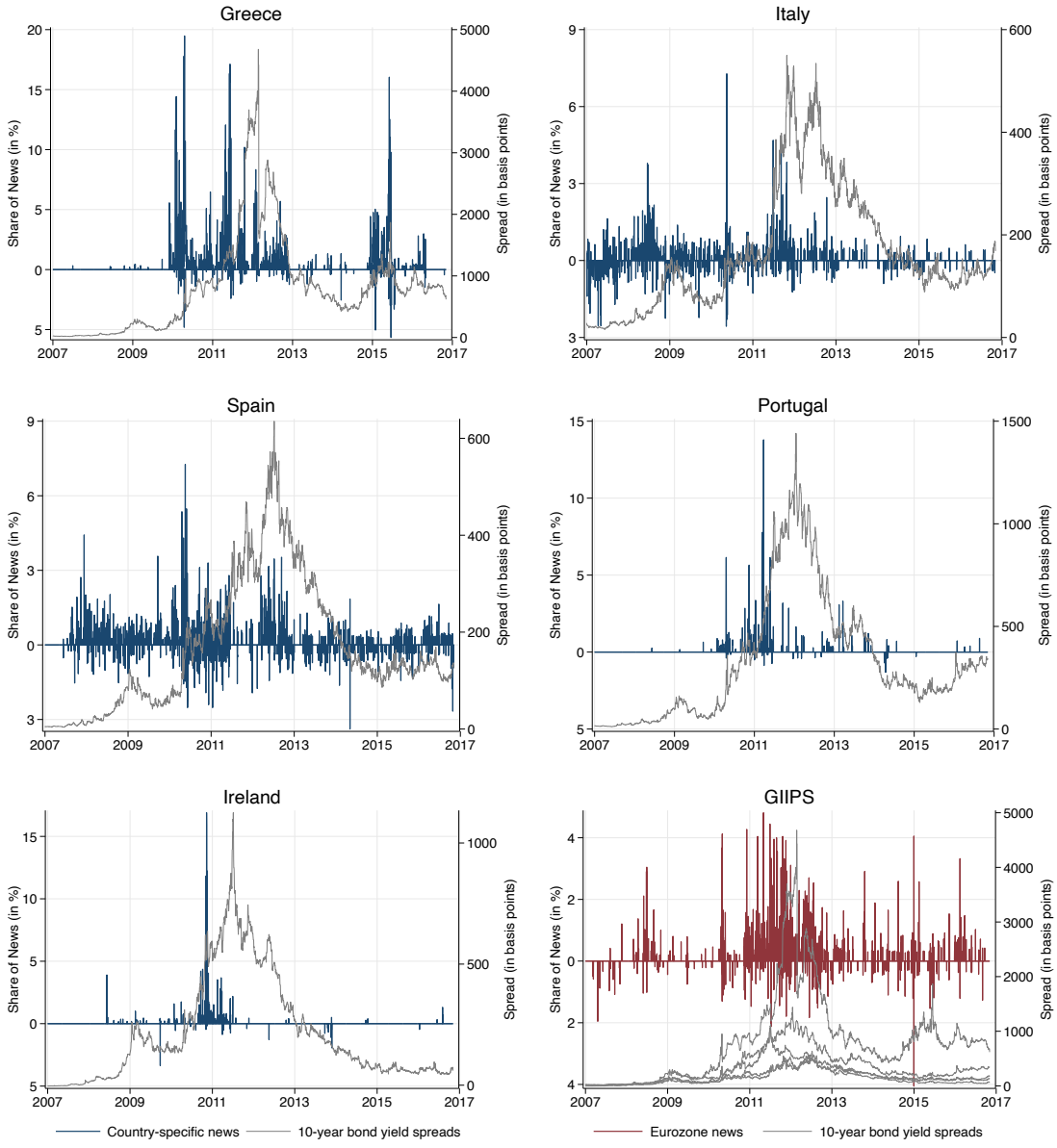
(3) To investigate a causal relationship between news coverage and bond spreads, we determine the share of *weekend news* for both *Eurozone* and *country-specific* economic news. As markets are closed for the weekend, this approach assumes that news will impact bond markets on the subsequent trading day.

(4) To explore the relevance of different media markets, we analyze the impact of news on bond spreads in markets directly related to crisis developments and in markets unrelated to them. The media dataset includes TV news from the four largest *EMU* countries, namely France, Germany, Italy, and Spain, as well as from the three *non-EMU* countries, Switzerland, the U.K., and the U.S. Accordingly, we calculate the shares of news of interest to us out of the total news, in the respective markets. The latter three countries are considered important financial centers worldwide.

(5) Lastly, we propose employing a machine-learning algorithm to *cluster* the raw media data. Through this exploratory approach, the sample is endogenously split into eight clusters, each containing news stories with similar content and protagonists. The objective is to create an additional set of explanatory variables based solely on the categorical news dataset, allowing informative inferences about the most important subjects for bond spreads. We use the *k-modes algorithm* by Huang (1997, 1998) with an initialization method proposed by Cao et al. (2009) for categorical data.[12] In short, this algorithm utilizes the dissimilarity between

[12]The k-modes clustering algorithm mirrors the prominent center-based k-means paradigm (one of the most popular data mining techniques) to cluster categorical text data. The choice of the number of clusters $k$ is a trade-off between the precision of clusters and usability in a regression

Figure 2: Country-Specific News and Eurozone News Contrasted with the Development of Yield Spreads




Notes: The share of news is displayed as a percentage of the total news on a given day. The positive news share is plotted downward on the left y-axis, and the negative news share is plotted upward. Neutral news is not included in the graphs, although it accounts for almost 50% of the news (see Table A.2 in the Appendix).

two observations meaning the number of categories within each news item where they differ. Each categorical difference enters the cost function, which is minimized by assigning the respective cluster to each news item observation. The categories

framework. We rely on the "elbow graph" method to determine an appropriate number of clusters. The results of the clustering process were validated using the *ROCK* clustering algorithm (Guha et al., 2000). Very similar results were observed. An adjusted rand index score of 0.94, which is used in data clustering as a measure of the similarity between two sets of data clusters, approves that the identified clusters in the data are congruent to a large extent.

from the raw media data that we include in the clustering exercise are "protagonist type," "protagonist," "topic group," "topic," and the "source label." However, we do not consider the categories "media market," "medium," "country" (that the report is about), and "tonality." Table A.3 in the Appendix provides a comprehensive overview of the structure and content breakdown across the endogenously determined clusters.[13] Note that the clustering does not separate news on the Eurozone from country-specific news. Each cluster therefore contains news for both news types so that both Eurozone and country-specific news for each cluster are used in the regression analysis, again as shares of all news for the day.[14]

We are confident that these five variable types provide a comprehensive representation of the (international) media landscape through the European sovereign debt crisis. The sample of evening news broadcasts provides a timely account of the most important developments, and human analysts' precise classification of news ensures accuracy, particularly in terms of tonality. Combined with the total number of news items reported each day, we construct sentiment indices that well reflect the importance and tonality of news.

**Control Variables: Fundamentals.** In the selection of control variables, we differ from studies such as Attinasi et al. (2009) or Gerlach et al. (2010) in that we choose not to include control variables at lower frequencies, such as quarterly GDP growth, (expected) debt-to-GDP ratios, or fiscal space, in our model for three reasons: First, we estimate the model in first differences with daily data, where the inclusion of such variables has less statistical relevance, unlike in models in levels and at lower frequencies where their inclusion might be warranted (see, e.g., Altavilla et al., 2017). Second, for forward-looking variables such as forecasts and projections, the literature has shown that they are of less empirical relevance (see, e.g., Afonso et al., 2015). Third, there is evidence that fundamental fiscal indicators have become less important over the period during which bond spreads widened in the Euro area. De Grauwe and Ji (2013, p. 27) point out that "[markets] tended to exaggerate the default risks." Therefore, we follow Codogno et al. (2003), who emphasize the role of various (international) risk measures in the evolution of yield spreads in selecting our fundamental control vector. According to asset pricing theory, a higher yield should compensate for an increase in risk.

[13]To determine the clusters, we use an additional 11,851 country-specific news items on the German economy. Additional data improves the segmentation of the clusters.

[14]Data clustering techniques have become an important strategy in statistical data analysis and data mining, especially when dealing with more dimensional observations. We came across the study of Mohamed et al. (2013) in the field of safety sciences that likewise follows a two-step clustering regression approach to identify types of accidents that are most severe for pedestrians. However, to our knowledge, categorical clustering to determine the explanatory variable prior to a regression analysis in economics is a novel approach to dealing with a large media dataset such as ours.

To measure financial turmoil in the European markets, we use the *EUROSTOXX Volatility Index* as a proxy (Arghyrou and Kontonikas, 2012; Falagiarda and Gregori, 2015; Glick and Leduc, 2012). It is derived from option prices on the EUROSTOXX 50 index, which tracks the performance of major European stocks and reflects investors' assessment of future price fluctuations. A higher value indicates greater market uncertainty. The data are taken from Thomson Reuters Datastream.

As an additional standard control in modeling yield spreads, we use a measure of international risk aversion in the financial sector (Afonso et al., 2014; Attinasi et al., 2009; Codogno et al., 2003; Gerlach et al., 2010). The variable, named as *AAA10Y*, is from the FRED database and represents the daily difference between the yield on AAA-rated U.S. corporate bonds and 10-year U.S. Treasury bonds.

We use *credit rating spreads* to control for changes in individual sovereign default risk. We follow the approach of Afonso et al. (2015) and compute a variable that ranges from 1 to 24 and represents daily sovereign ratings determined by a linear transformation of common investment grades, with the lowest value indicating a AAA rating. The credit ratings are calculated as the average of the three agencies: S&P, Moody's, and Fitch. Since we focus our analysis on the spread between GIIPS yields and Germany, credit ratings are also calculated as the respective spreads. Since Germany consistently receives the highest rating throughout the sample period, a higher rating spread indicates a greater credit risk for the country assessed by the rating agencies.

In order to account for short-term fluctuations in the countries' business climates, we employ the *national stock market index* as a proxy for investment tendencies in the GIIPS economies. Data series taken from Thomson Reuters Datastream are indexed and normalized.

Furthermore, changes in the main refinancing rate (*MRO rate*) are included as a control variable to capture the ECB's conventional monetary policy measures (e.g., Afonso et al., 2018; Beetsma et al., 2013).

Finally, note that during the European sovereign debt crisis, yield spreads and their volatility structurally increased relative to other periods (Costantini et al., 2014). Therefore, we include a *Eurocrisis* dummy variable for the respective crisis period.[15]

[15]The crisis dummy ranges from November 5, 2009, to July 26, 2012. Like most others in this field, we pick the start date of November 5, 2009, when the new Greek Prime Minister, Giorgos Papandreou, announced that Greece's annual budget deficit would be 12.7 percent of GDP – more than twice the previously announced figure. This event led to a cascade of events that culminated in Mario Draghi's famous words on July 26, 2012, when the ECB president gave an account of the Eurozone economy at a conference in London. By that time, bond yields of weak Euro-member governments were soaring, and traders doubted that national, Euro-, or EU-level institutions could get their act together to avert disaster. Draghi sought to convince

**Control Variables: Crisis Policies.** We additionally include a set of variables that we refer to as "policy controls." Besides increasing the fit of the model, the main reason for this is that the measured effect of our media variables should not be driven by extreme events in the context of the Eurocrisis. Instead, we are particularly interested in a more general "noise" effect of media coverage on yield spreads (Black, 1986). To account for this, we control for several well-identified measures and decisions taken by, among others, the ECB, the IMF, the ESM and its predecessors, and the European Council.[16] The control vector, comprising 71 measures and decisions, was taken from a dataset covering the Eurocrisis compiled by Köhler et al. (2024).[17]

The dataset is similar to that of De Santis (2014), who refers to the data as key economic news. However, the employed dataset exceeds that of De Santis (2014) in both time coverage and scope. The dataset includes dummy variables for events such as the announcement of unconventional monetary and fiscal policy measures (e.g., Draghi's speech or the announcement of the SMP), the signing of treaties (e.g., the fiscal compact), as well as information on the size of the ECB's daily bond purchases and the allocation of bailout funds to financially distressed countries, to name a few.

As one of their main variables of interest, Attinasi et al. (2009) also use dummies on the announcements of bank rescue packages, while Büchel (2013) includes a control vector of binary variables with value 1 on days of important policy decisions or macro releases. Gade et al. (2013, p. 13) control for "events related to political meetings or agreements."

# 4 Empirical Framework

As outlined above, our analysis is based on daily data covering the five GIIPS countries from January 2007 to November 2016. Throughout estimations, the dependent variable is the yield spread of 10-year government bonds of country $i$ vis-à-vis Germany at time $t$. These time series are highly persistent, as indicated by augmented Dickey-Fuller tests that cannot reject the presence of a unit root.

international investors that the region's economy was not as bad as it seemed. He then made the momentous remark, "Within our mandate, the ECB is ready to do whatever it takes to preserve the Euro. And believe me, it will be enough."

[16]This can be illustrated by an example: On March 12, 2012, when the second economic adjustment program for Greece was announced, the Greek government bond yield dropped by more than 2700 basis points (see Figure 2). The impact of such de facto crisis measures is not of primary interest to this study. However, since such dramatic events, both the announcement and the drop in bond yields, are newsworthy, we control for them.

[17]In addition to the outline of the dataset, Köhler et al. (2024) offer an analysis of the influence of various (fiscal) policy measures on GIIPS yield spreads. Further details about the dataset can be obtained upon request.

Therefore, we employ models in first differences, similar to the approach of Beetsma et al. (2013), with the $\Delta$-operator representing the change in the variables from $t-1$ to $t$.

**Panel Estimation.** The baseline panel model, estimated using feasible generalized least squares (FGLS), [18] is as follows:

$$\Delta spreads_{i,t} = \rho \Delta spreads_{i,t-1} + \beta X_{i,t} + \lambda^E Media_t^E + \lambda Media_{i,t} + \alpha_i + \gamma_d + \epsilon_{i,t} \quad (1)$$

with $i = 1, ..., 5$ denoting the GIIPS countries and $t = 1, ..., 2,587$ indexes the daily time dimension.[19] To account for the dynamic nature of yield changes that are likely to be affected by past changes, we include the lagged dependent variable as a regressor, also addressing autocorrelation to some extent. The model includes country fixed effects $\alpha_i$ to control for time-invariant unobserved differences in the panel dimension and day-of-the-week dummies $\gamma_d$, labeled "working-day FE," to control for weekly yield patterns.[20]

$X_t$ represents the set of (first-differenced) control variables described in Section 3, with some variables invariant across countries ($\Delta EUROSTOXX$ *volatility index,* $\Delta AAA10Y$, $\Delta MRO$ *rate*, and the *Eurocrisis* dummy), and others related to individual economies ($\Delta$*credit spread* and $\Delta$*national stock market index*). In most specifications, we additionally control for the "policy controls" vector.

The variables labeled *Media* refer to the set of main explanatory variables described in detail in Section 3. Each variable employed is measured as a percentage of the total news on a given day. Throughout estimations, we account for two different categories of news: $\lambda Media_{i,t}$ includes country-specific news, while $\lambda^E Media_t^E$ includes news that refers to the Eurozone as a whole and is considered invariant across countries in the model. Correlation coefficients between Eurozone and country-specific news variables indicate no issues with multicollinearity (see Table B.2 in the Appendix). Therefore, both types of variables are included in single regressions. Further differentiation concerns, for instance, tonality, i.e.,

[18] The Parks-Kmenta FGLS estimator is consistent for estimating models when there is groupwise heteroskedasticity, cross-sectional dependence (CD) between panels, and panel-specific AR(1) series correlation in the error term, particularly in cases where the time dimension is sufficiently large, i.e., having a large T and small N (Hoechle, 2007). In particular, financial data series are prone to these characteristics, which is confirmed in a residual analysis in Table B.1 in Appendix B for our panel. To test our findings' robustness, we employ a selection of alternative estimators and models commonly used in related studies. Table A.5 shows estimation results using a general fixed effects (FE) estimator with clustered standard errors, Driscoll and Kraay (1998) standard errors, and a GARCH(1,1) model. All of these estimators produce results in line with our baseline findings.

[19] Instead of holding yields constant during weekends, we exclude non-trading days from the regression, which reduces the number of observations in each cross-section from 3,623 to 2,587.

[20] We consider the Nickell-bias to be negligible, since the time dimension is sufficiently large (see, e.g., Baltagi, 2008; Hallerberg and Wolff, 2008).

consideration of the shares of positive, neutral, and negative country-specific and Eurozone news as well as the cluster variables.

We argue that a clustering exercise prior to a regression analysis can complement the latter, especially when raw data has many dimensions and complex linkages that cannot be used in a standard multivariate regression. The clustering algorithm allows us to use objective segmentation for variables in the regression analysis. The interpretation of the effect of news clusters in the regression is only difficult if the clusters are very fragmented. Homogeneous clusters with few categorical values are less of a concern. We refer to Table A.3 in the Appendix to determine essential topics and content in each cluster.

Further specifications include interactions with the Eurocrisis dummy variable and a dummy that divides the sample into times of high and low (policy) uncertainty. Both approaches should provide information as to whether broadcast news was of particular importance in times of crisis and high uncertainty. Finally, we subdivide the news coverage variable by differentiating whether the news was broadcast in EMU countries or non-EMU countries.

**Country-Specific Estimation.** In a further step, to allow for a cross-country comparison of the effects and to check the robustness of the panel results, we extend our analysis by estimating individual media effects for each country. For this purpose, we estimate the following time-series model:

$$\Delta spreads_t = \rho \Delta spreads_{t-1} + \beta X_t + \lambda^E Media_t^E + \lambda Media_t + \gamma_d + \epsilon_t \qquad (2)$$

where the main explanatory variables and the control vector are the same as in the panel regression. Newey-West standard errors are employed.

**Notes on Endogeneity.** Our news coverage data come from evening newscasts, which we assume provide comprehensive summaries of the day's major events, most of which occur before the markets close. These evening newscasts usually resemble the news reports that are already broadcast during the day. Given these considerations, our careful data preparation, and the large sample size, we are confident that the generated news variables are contemporaneously exogenous. This claim is also invoked and assumed by previous research (e.g., Büchel, 2013). Nevertheless, it must be acknowledged that reverse causality remains an important problem among the potential endogeneity issues that complicate the identification of the impact of media coverage on government bond yields.

To shed more light on the causal nature of the relation, we initially run Granger

causality tests for panel data as proposed by Lopez and Weber (2017).[21] In the baseline setup, we find some evidence in favor of bidirectional causality between news and changes in sovereign bond yield spreads (see Table B.3 in the Appendix). However, the link from news to spreads appears more distinct.

To investigate the causal relationship between news coverage and bond spreads in more detail, we leverage news data from non-trading days, i.e. weekends. Extending the baseline model as specified in Equation 1, we regress the changes in the yield spreads of the corresponding subsequent trading day on the share of news related to both the *Eurozone* and *country-specific* economic news from the preceding weekend. This allows us to measure the impact of (the tonality of) weekend news as reflected in the markets on the following trading day, thus addressing concerns about reverse causality.[22]

This identification is based on there being no specific pattern underlying the weekend news reporting and Monday's yield spread changes that is driven by the previous week's spread movements. We reject this on the basis of distinct regressions that regress the weekend news variables and Monday's yield changes on the previous week's cumulative spread changes, split into positive and negative. No significant effects or patterns are found (see Table B.4 in the Appendix).

# 5 Empirical Results

## 5.1 Baseline Findings

Table 2 shows the baseline results of estimating Equation 1 with the default main explanatory variables. The coefficients in Columns 1 and 3 represent the specifications that show the overall relationship between the share of *Eurozone* or *country-specific* coverage and bond spreads. The estimations in Columns 2 and 4, on the other hand, incorporate the tonality of the news. As a result, these specifications reveal the link between the shares of *positive*, *neutral*, and *negative* news and bond spreads. Unlike specifications 1 and 2, specifications 3 and 4 include policy controls, such as larger measures or announcements, for instance, by the ECB.

The control variables show the expected signs and align with previous empirical studies (e.g., Gerlach et al., 2010; Afonso et al., 2018). The lagged dependent variable is highly significant and positive, indicating a strong temporal relationship between bond spreads and their previous values. During the *Eurocrisis*, govern-

[21] Gade et al. (2013) and Falagiarda and Gregori (2015) also run Granger Causality tests. They find that results are in favor of causality running from news to spreads.

[22] Note that events from the policies control dataset are shifted to the next trading day if they occur or are publicly announced during a weekend.

Table 2: Link Between Media Coverage and GIIPS Bond Yield Spreads

| | (1) | (2) | | | (3) | (4) | | |
|---|---|---|---|---|---|---|---|---|
| Δ10-year bond yield spread$_{t-1}$ | 0.0931*** (0.00865) | 0.0824*** (0.00882) | | | 0.0209*** (0.00720) | 0.0191*** (0.00724) | | |
| *Tonality* | | *pos.* | *neut.* | *neg.* | | *pos.* | *neut.* | *neg.* |
| Eurozone news | -0.462*** (0.108) | -6.042*** (0.705) | -0.287 (0.199) | 0.762** (0.306) | -0.290** (0.125) | -4.915*** (0.847) | -0.270 (0.214) | 0.686** (0.328) |
| Country-specific news | 0.241*** (0.0739) | -0.538* (0.279) | -0.335** (0.148) | 1.026*** (0.142) | 0.282*** (0.0747) | -0.532* (0.273) | -0.358** (0.146) | 1.116*** (0.138) |
| Eurocrisis | 0.993*** (0.301) | 0.673** (0.305) | | | 0.718 (0.904) | 0.604 (0.896) | | |
| ΔCredit rating spread | -0.686 (1.256) | -1.257 (1.331) | | | -1.148 (1.232) | -1.650 (1.280) | | |
| ΔMRO rate | -3.400 (4.004) | -3.690 (3.942) | | | -2.357 (4.517) | -2.569 (4.454) | | |
| ΔNational stock market index | -0.702*** (0.0521) | -0.730*** (0.0540) | | | -0.624*** (0.0515) | -0.649*** (0.0526) | | |
| ΔEUROSTOXX Volatility index | 0.685*** (0.0724) | 0.610*** (0.0725) | | | 0.643*** (0.0731) | 0.592*** (0.0730) | | |
| ΔAAA10Y | -5.028 (3.807) | -4.416 (3.747) | | | -4.195 (3.881) | -4.072 (3.825) | | |
| Country FE | Yes | Yes | | | Yes | Yes | | |
| Working-day FE | Yes | Yes | | | Yes | Yes | | |
| Policy Controls | | | | | Yes | Yes | | |
| Goodness of Fit | 0.1635 | 0.1756 | | | 0.8044 | 0.8062 | | |
| No. of Observations | 12,935 | 12,935 | | | 12,935 | 12,935 | | |

Notes: The dependent variable is the Δ10-year bond yield spread of the GIIPS vis-à-vis Germany. The table reports coefficients estimated using FGLS. Standard errors in parentheses. Weekends are excluded from the regression. The Goodness of Fit measure is the correlation coefficient between the observed values of the dependent variable and the fitted values of the dependent variable.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ment bond yield spreads of the GIIPS vis-à-vis Germany increased by up to 1 basis point each day compared to before and after the crisis. However, the significance vanishes when controlling for crisis policies. The other fundamental controls are very stable across the estimated specifications. The relationship between the *EUROSTOXX volatility index* and bond yield spreads is consistently positive across all specifications. This implies that an increase in uncertainty and turmoil is associated with wider bond yield spreads. Additionally, the coefficient of the *national stock market index* indicates that an improvement in the economic situation of the countries is negatively correlated with bond yield spreads, aligning with theoretical expectations. However, the coefficients of the *credit rating spreads* and *AAA10y* are statistically insignificant, suggesting that individual credit risk of the GIIPS countries and overall risk aversion do not significantly affect European crisis coun-

tries' bond yield spreads. Furthermore, changes in the *MRO rate* do also not show significant coefficients in relation to bond yield spreads.

Regarding our main explanatory variables, undifferentiated by tonality, we find that a higher share of news on the Eurozone as a whole is negatively associated with GIIPS yield spreads. As depicted in Column 1 of Table 2, a one percentage point higher share of Eurozone news is linked to -0.46 basis points lower GIIPS bond yield spreads. When controlling for policies, the link diminishes to -0.29 basis points. However, taking the tonality of the news into account, we obtain a more differentiated picture. In Column 2, the share of positive Eurozone news is negatively connected with the GIIPS yield spreads, whereas the share of negative Eurozone news is linked to increasing spreads. In contrast, country-specific news is significantly linked to bond spreads throughout all specifications. While both positive and neutral news is linked to lower bond spreads, negative country-specific news is associated with higher spreads. This follows the intuition. Importantly, even after controlling for various policies (see Table 2, Columns 3 and 4) and additionally considering macroeconomic data and fiscal releases (see Table A.6 in the Appendix), these results remain robust. This empirical evidence suggests that our findings are not solely influenced by specific measures and decisions taken by institutions like the ECB and fundamentals. Rather, spreads move with ongoing coverage – "noise" – that affects investor expectations in line with Black (1986). Based on these results, we conclude that the sentiment variables are meaningful predictors of spreads during the sample period.

These results are reinforced by examining country-specific effects (see Table A.4 in the Appendix). Most notably, positive Eurozone news shows substantial and statistically significant negative coefficients across all countries except Greece, indicating a strong association with decreasing bond spreads. Conversely, negative country-specific news shows a positive and statistically significant relationship with changes in spreads for most countries. Interestingly, the coefficients do not vary significantly across countries, indicating a relatively consistent relation of news with bond spreads.

One explanation for the greater importance of (positive) Eurozone news in comparison to country-specific news in bringing down yields might be as follows: As investors cast doubt on their pre-crisis expectation that the governing institutions of the Euro area would buy up their bonds during financial distress (Eichengreen et al., 1998), central bank communication and news on the Eurozone calmed down markets that were tempered by uncertainty. Regardless of whether one sees this as a useful function of a monetary union or not, from the financial market's perspective, the Eurozone can be seen as insurance for the countries' bonds. As long as the Eurozone exists, the risk of a total default of the bonds is seen as rather

limited. This underscores the likely imperfect credibility of the no-bailout clause, reinforcing the findings of previous studies by Bernoth et al. (2012), Manganelli and Wolswijk (2009) and Schuknecht et al. (2009), which highlight that a country's risk of default was no longer a significant factor in the bond pricing process since the inception of the common currency. Consequently, positive news on the Eurozone might be perceived as a trustworthy indicator for such a limited default risk and an implicit burden-sharing agreement. Further, while Eurozone news is dominated by topics like "Euro stability funds," the "EURO" in general, and the "role of central banks," country-specific news frequently covers news related to "budget policy, debt of nation or region" and "budget deficit" (see Figures A.1 and A.2 in the Appendix).

## 5.2 Establishing Causality

In order to examine causality between media coverage and bond spreads, we analyze the impact of weekend news on the following trading day. We compare the results of this approach, as presented in Table 3, with the use of lagged news variables. The estimation results for lagged news variables generally do not exhibit significant coefficients, except for a reversal effect observed in the case of negative Eurozone news.

As neutral news are not indicating a critical development, we combine both non-negative (i.e., positive and neutral news) into a single variable in the regressions incorporating *weekend news*. Additionally, the consistent direction of the coefficients for these two variables in the baseline estimations further validates this approach from an econometric perspective.

The results in Columns 3 and 4 of Table 3 show that (rather) positive reporting does indeed have a causal impact on yield spreads on the subsequent trading day. After controlling for policy decisions, we find that a one percentage point increase in country-specific reporting leads to a 1.5 basis point reduction in yield spreads. However, the effect of Eurozone news dissipates when controlling for the policy vector. This is consistent with the observation that a number of significant decisions by EU leaders and institutions occurred on weekends.

The country-specific estimates presented in Table A.4 in the Appendix provide further evidence for the causal relationship between (positive) country-specific news and bond spreads. The estimates reveal that negative country-specific news coverage on weekends leads to higher spreads on Monday for Greece, Italy, and Spain. This effect is particularly pronounced in Greece, which can be attributed to the substantial widening of spreads compared to the other countries. Furthermore, positive weekend news on the Greek economy significantly reduces their

## Table 3: Effects of Lagged and Weekend News

| | (1) incl. Lagged news | | | (2) incl. Lagged news | | | (3) incl. Weekend news | | | (4) incl. Weekend news | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Tonality* | *pos.* | *neut.* | *neg.* | *pos.* | *neut.* | *neg.* | *pos.* | *neut.* | *neg.* | *pos.* | *neut.* | *neg.* |
| Eurozone news | -6.052*** | -0.143 | 0.837*** | -4.920*** | -0.212 | 0.688** | -5.917*** | -0.186 | 0.820*** | -4.887*** | -0.292 | 0.705** |
| | (0.710) | (0.205) | (0.309) | (0.850) | (0.217) | (0.330) | (0.712) | (0.202) | (0.308) | (0.854) | (0.216) | (0.330) |
| Country-specific news | -0.473* | -0.235 | 1.074*** | -0.463* | -0.279* | 1.154*** | -0.528* | -0.302** | 1.033*** | -0.525* | -0.343** | 1.138*** |
| | (0.282) | (0.153) | (0.149) | (0.276) | (0.150) | (0.143) | (0.288) | (0.153) | (0.149) | (0.286) | (0.153) | (0.146) |
| Eurozone news$_{t-1}$ | 0.703 | -0.136 | -1.013*** | -0.272 | 0.160 | -0.875*** | | | | | | |
| | (0.724) | (0.215) | (0.323) | (0.747) | (0.223) | (0.334) | | | | | | |
| Country-specific news$_{t-1}$ | -0.191 | -0.357** | 0.0178 | -0.322 | -0.373*** | 0.0992 | | | | | | |
| | (0.302) | (0.145) | (0.149) | (0.295) | (0.141) | (0.143) | | | | | | |
| *Tonality* | | | | | | | *pos./neut.* | *neg.* | | *pos./neut.* | *neg.* | |
| Weekend Eurozone news$_{d=Mon.}$ | | | | | | | -3.123* | -3.537*** | | 2.462 | -0.524 | |
| | | | | | | | (1.690) | (1.356) | | (1.863) | (1.407) | |
| Weekend Country-specific news$_{d=Mon.}$ | | | | | | | -1.358** | 0.282 | | -1.514** | 0.508 | |
| | | | | | | | (0.611) | (0.509) | | (0.599) | (0.492) | |
| Country FE | Yes | | | Yes | | | Yes | | | Yes | | |
| Working-day FE | Yes | | | Yes | | | Yes | | | Yes | | |
| Fundamental Controls | Yes | | | Yes | | | Yes | | | Yes | | |
| Policy Controls | | | | Yes | | | | | | Yes | | |
| No. of Observations | 12,935 | | | 12,935 | | | 12,935 | | | 12,935 | | |

Notes: The dependent variable is the $\Delta$10-year bond yield spread of the GIIPS vis-à-vis Germany. The table reports coefficients estimated using FGLS. Standard errors in parentheses. Weekends are excluded from the regression. However, weekend news is included in the estimated model reported in Columns 3 and 4 and indicates the (causal) effect on the change in the yield spread on the following Monday ($d = Mon.$).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

yield spreads by about 25 basis points per percentage point increase in coverage.

## 5.3 Further Specifications and Content Clustering

We extend our analysis and subdivide the media variables to investigate the link between media coverage and bond spreads in more detail. Specifically, we examine (1) the variations in effects during the ongoing Eurocrisis compared to before and after, (2) the effects during periods of heightened uncertainty, and (3) potential differences in effects across different media markets (see Table 4). In addition, we utilize content media clusters. By examining these dimensions, we aim at empirically identifying the environment and topics that matter most for the relationship between news coverage and bond spreads.

By incorporating an interaction term of news variables with the dummy variable *Eurocrisis*, we examine the relevance of news at the time of greatest distress during the European sovereign debt crisis for bond spreads. The estimates reveal that during this narrower crisis period, a one percentage point increase in the share of positive Eurozone news is associated with a substantial reduction of 7.4 basis points in GIIPS yield spreads (see Column 1 Table 4). In contrast, the relationship is only half as strong before and after the acute crisis period. Similarly, the link between country-specific news and bond spreads is much more pronounced and highly significant during the crisis period.

Periods of high uncertainty also appear to affect the relationship between media coverage and bond yields. In the specification denoted in Column 2, we interact news with a country-specific dummy variable that measures policy uncertainty (inspired by Baker et al., 2016). It equals 1 if the standard deviation of country-specific news over the last five days exceeds twice the standard deviation over the entire sample period. The results show that a one percentage point increase in the share of positive news on the Eurozone in periods of high uncertainty is associated with a 13.2 basis point decline in bond spreads, compared with a 4.3 basis point decline during more certain times. The relationship between country-specific news and bond spreads also appears to be more pronounced and of higher statistical significance in periods of high uncertainty.

In addition, in Column 3 we examine whether the relationship between news and bond spreads varies by the location of the media market. We distinguish between the *EMU* market and *non-EMU* markets. The results reveal that the coefficients differ between media markets. Specifically, they indicate a stronger relationship for news broadcast in non-EMU markets. This is likely since only important and noteworthy news about GIIPS countries and the Eurozone is broadcast in these media markets. Descriptive statistics of the news variables confirm

Table 4: Further Specifications

| | (1) Eurocrisis | | | (2) Uncertainty | | | (3) Media Market | | |
|---|---|---|---|---|---|---|---|---|---|
| *Tonality* | *pos.* | *neut.* | *neg.* | *pos.* | *neut.* | *neg.* | *pos.* | *neut.* | *neg.* |
| Eurozone news | -3.488*** | 0.175 | 0.746 | -4.337*** | -0.315 | 0.685** | -1.306*** | -0.246*** | 0.467*** |
| | (1.161) | (0.388) | (0.640) | (0.852) | (0.214) | (0.329) | (0.323) | (0.0900) | (0.143) |
| Country-specific news | -0.230 | -0.191 | 0.478* | -0.389 | -0.00614 | 1.080*** | -0.118 | -0.110* | 0.301*** |
| | (0.375) | (0.226) | (0.278) | (0.330) | (0.183) | (0.217) | (0.0993) | (0.0566) | (0.0636) |
| | *eurocrisis = 0* | | | *uncertainty low* | | | *EMU markets* | | |
| | *eurocrisis = 1* | | | *uncertainty high* | | | *Non-EMU markets* | | |
| Eurozone news | -7.484*** | -0.462* | 0.661* | -13.29*** | 0.572 | 0.530 | -4.266*** | 0.519* | -0.466 |
| | (1.293) | (0.258) | (0.385) | (1.773) | (0.455) | (0.585) | (1.007) | (0.272) | (0.303) |
| Country-specific news | -1.027** | -0.554*** | 1.402*** | -0.629 | -1.246*** | 1.389*** | -2.381*** | -0.122 | 0.609*** |
| | (0.457) | (0.210) | (0.168) | (0.624) | (0.310) | (0.195) | (0.869) | (0.366) | (0.154) |
| Eurocrisis | | 0.659 | | | | | | | |
| | | (0.905) | | | | | | | |
| Uncertainty | | | | | 0.503 | | | | |
| | | | | | (0.584) | | | | |
| Country FE | | Yes | | | Yes | | | Yes | |
| Working-day FE | | Yes | | | Yes | | | Yes | |
| Fundamental Controls | | Yes | | | Yes | | | Yes | |
| Policy Controls | | Yes | | | Yes | | | Yes | |
| No. of Observations | | 12,935 | | | 12,935 | | | 12,935 | |

Notes: The dependent variable is the $\Delta$10-year bond yield spread of the GIIPS vis-à-vis Germany. The table reports coefficients estimated using FGLS. Standard errors in parentheses. Weekends are excluded from the regression.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

this; as expected, the mean value of country-specific news broadcast in non-EMU media markets is significantly lower than the mean value of country-specific news broadcast in the European media market.

The endogenous division of news into homogeneous clusters helps identify relevant content associated with changes in government bond yields over the observed period. Regression results in Table 5 show that five of the eight clusters we use as explanatory variables are of particular relevance: Clusters 1, 2, 4, 5, and 6; all others are not significantly correlated with yield spreads in any specification.[23] Especially when tonality is taken into account – again distinguishing only between negative and positive/neutral news (see Section 5.2) –, we confirm the results from the baseline regression: Positive news is associated with reductions in spreads, while negative news is associated with increases in spreads.

However, one coefficient related to Cluster 5 contradicts this interpretation. Yet, the negative and highly significant effect of negative country-specific news has an unusual explanation. Around 94.5% of the news comprising this variable

[23]See Table A.3 in the Appendix for an overview of the composition of each cluster.

Table 5: Cluster Regressions

| | (1) | (2) | |
|---|---|---|---|
| *Tonality* | | *pos./neut.* | *neg.* |
| Eurozone news | | | |
| Cluster 1 | 0.189 | -1.020 | 1.164 |
| | (0.410) | (1.191) | (0.815) |
| Cluster 2 | -0.593*** | -2.767*** | 1.937*** |
| | (0.204) | (0.543) | (0.611) |
| Cluster 3 | -0.389 | 0.548 | -0.677 |
| | (0.551) | (1.802) | (0.949) |
| Cluster 4 | -1.405 | -2.306 | -1.643 |
| | (0.971) | (2.306) | (2.072) |
| Cluster 5 | -0.795 | 1.037 | -4.878 |
| | (1.555) | (3.886) | (3.489) |
| Cluster 6 | 4.959 | 13.11 | 1.210 |
| | (3.344) | (9.744) | (4.735) |
| Cluster 7 | 3.454 | 5.211 | 2.790 |
| | (3.634) | (10.53) | (5.198) |
| Cluster 8 | 0.757 | 0.559 | 0.599 |
| | (0.758) | (2.030) | (1.581) |
| Country-Specific news | | | |
| Cluster 1 | 0.552*** | -0.854** | 1.830*** |
| | (0.112) | (0.353) | (0.212) |
| Cluster 2 | 1.514*** | 1.575 | 3.338** |
| | (0.458) | (1.263) | (1.433) |
| Cluster 3 | -0.00949 | 0.462 | -0.357 |
| | (0.514) | (1.596) | (0.900) |
| Cluster 4 | -0.472 | -6.250*** | 3.307* |
| | (0.764) | (2.144) | (1.764) |
| Cluster 5 | -2.250** | -12.66*** | -3.929*** |
| | (0.928) | (4.141) | (1.403) |
| Cluster 6 | -2.617*** | -9.891*** | 1.486 |
| | (0.733) | (2.124) | (1.423) |
| Cluster 7 | 0.470 | 0.937 | 0.393 |
| | (0.442) | (1.546) | (0.766) |
| Cluster 8 | 0.0497 | 0.516 | -0.268 |
| | (0.550) | (1.264) | (2.540) |
| Country FE | Yes | Yes | |
| Working-day FE | Yes | Yes | |
| Fundamental Controls | Yes | Yes | |
| Policy Controls | Yes | Yes | |
| No of. Observations | 12,935 | 12,935 | |

Notes: The dependent variable is the $\Delta$10-year bond yield spread of the GIIPS vis-à-vis Germany. The table reports coefficients estimated using FGLS. Standard errors in parentheses. Weekends are excluded from the regression. Clusters are calculated using the k-modes algorithm for categorical data (Huang, 1997, 1998; Cao et al., 2009). See Table A.3 in the Appendix for an overview of the structure and content breakdown across clusters.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

revolves around topics such as "international financial support," "debt relief" or "restructuring of debt." It is further noteworthy that commentators and speakers in the German media market, which accounts for 80.9% of the observations in this cluster (variable), tend to report negatively on these issues. Interestingly, while such indications of international support were portrayed very suspiciously on German television, the financial markets seemed to respond favorably.

Based on the remaining cluster-regression results, we draw the following conclusions: News on central public finance issues, such as "public budget, debt, revenue in general" or "budget policy, debt of nation or region," are relevant to bond markets when the news are country-specific (Clusters 1 and 6). Additionally, news related to "international financial support" is also particularly relevant in country-specific contexts (Clusters 4 and 5). These results thus complement those of Mohl and Sondermann (2013), who fail to present a conclusive picture of the effect of statements on financial support. The relatively large negative coefficients on positive news from Clusters 4 and 6 are most likely due to the news being mostly focused on Greece, where larger changes in spreads were observed, conditioning stronger effects.

On the other hand, Eurozone news regarding "EURO stability funds," "Monetary Policy" and the "EURO" play a crucial role in decreasing bond yield spreads when the primary protagonists involved are European institutions, including the ECB (Cluster 2). We interpret these results as evidence that financial markets positively respond to news that involves, among other things, efforts to stabilize the Euro area markets through the establishment of crisis institutions and signs that the ECB is expanding its measures. These findings add to results by Büchel (2013, p. 426), who claims that especially statements by ECB officials "on government bond purchases and the collateral framework moved financial markets." Conversely, when such news is negative, the spreads increase.

Additional news on monetary policy focusing on its primary mandate of price stability (Cluster 3) as well as on other topics more general than the ECB's core objective(s) (Cluster 7) shows no significant relationship with the development of yield spreads. General economic EU topics are also irrelevant (Cluster 8).

The cluster-regression analysis additionally provides insights into causality. Specifically, the relevance of country-specific news on "international financial support" and the relevance of "EURO stability funds" in Eurozone news, associated with a notable reduction in yield spreads of GIIPS vis-à-vis Germany, allows us to draw an important conclusion. It suggests that we can rule out reverse causality (at least for these types of news), since financial support or debt restructuring are not policy actions that are typically discussed and taken in response to a decline in sovereign yields.

# 6 Conclusion

In this paper, we examine whether sentiment indices derived from television news affect GIIPS interest rate spreads vis-à-vis Germany. We draw from a sample of over one million human-coded news items from newscasts aired by leading TV stations worldwide. Among them, we identify 25,276 news items on economic topics related to the Eurozone and the GIIPS countries from January 2007 to November 2016. The sample thus covers both periods of rising and falling spreads during the European sovereign debt crisis.

To investigate the link, we employ panel estimation techniques and incorporate a range of fundamental and policy controls. Across various specifications, we find significant correlations between the share of Eurozone and country-specific news with crisis countries' yield spreads. This underscores the importance of media as a valuable complement to models based on financial or fiscal fundamentals. The magnitude and direction of the effect depend on the tonality of the news. A higher share of positive (negative) news is associated with decreasing (increasing) GIIPS yield spreads.

Additionally, we uncover that the magnitude of the effect is more pronounced for Eurozone news compared to country-specific news. This aligns with the notion that the existence of the Eurozone serves as a form of insurance for member countries' bonds. Positive news on the Eurozone is assumed to be an indicator of limited default risk, i.e., an implicit joint liability of the Euro Member States is anticipated.

Content clusters employed in the regression analysis further support these findings, revealing that certain clusters, such as those dominated by topics related to "international financial support" and "EURO stability funds," drive the observed reducing effects on yield spreads. Conversely, negative country-specific news related to the countries' debt situation increases them.

Our results hold after controlling for various key events and policy measures during the debt crisis. This suggests that media coverage exerts a "noise" effect on bond spreads. By leveraging weekend coverage, we establish a causal relationship, particularly concerning positive country-specific news and its impact on bond spreads of the subsequent trading day. Specifically, a one percentage point increase in the share of positive news is associated with a 1.5 basis point decline in yield spreads. Country-specific analyses support this causal link.

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# A Additional Figures and Tables

Table A.1: Literature Overview

| Authors | Dependent Variable | News Source | Classification of News |
|---|---|---|---|
| Apergis et al. (2016) | GIIPS 5y sovereign CDS | Factiva (articles that discuss sovereign debt issues) | Word counting of positive and negative words associated with the Eurocrisis. A word is considered negative if it was preceded within five words by one of several negation terms. It was possible within an article to track both negative and positive words, although in the case of a negative article, positive words could hardly be tracked. |
| Beetsma et al. (2013) | GIIPS 5y and 10y gov. bonds | Eurointelligence (briefings on euro-area news based on European media) | Classification into bad, good and unclassified news by the author. "By 'bad news,' ('good news') we mean news that we expect to lead to a tightening (relaxation) of the government's inter-temporal budget constraint or news that we expect to lead to a rise (fall) in the interest rate." (Beetsma et al., 2013, 89) |
| Büchel (2013) | GIIPS 5y, 10y, and 30y gov. bond spreads and sovereign CDS | Factiva (Reuters, Dow Jones Newswires, Agence France-Press, Associated Press Newswires, and Market News International) | Classification of reports on seven distinct topics into both "dovish" and "hawkish" statements by decision-makers using signaling words. Binary variables; Counts per date. |
| Conrad and Zumbach (2016) | Eurozone 10y gov. bonds and USD-EUR exchange rate | Reuters; Statements of European politicians | If statements imply a positive outlook for countries, new austerity measures or suggest joint liability they are coded with +1, and as -1 otherwise |
| Dergiades et al. (2015) | Eurozone 10y gov. bond spreads | Google searches as well as Twitter, Facebook and Google blogs | Two indices are constructed. They are determined by (1) search queries, that are connected to the Greek crisis such as "Greece crisis" or "Greek debt crisis," and (2) Grexit mentions in Social Media. Due to their setup, Dergiades et al. (2015, 411) claim, that having chosen variables that are "linked to rising spreads, it is important to select a sample period where released news ... disclose predominantly negative information." |
| Falagiarda and Gregori (2015) | Italian 10y gov. bond spreads | ECB Real Time Information System; News media releases from Bloomberg, Dow Jones News Wire, Market News International, and Reuters | Public finance and fiscal policy announcements from Italian government members: +1 if the announcement signals a future deterioration (budget improvements), 0 if the announcement is budget-neutral, -1 if the announcement signals a future budget consolidation. |
| Gade et al. (2013) | GIP 10y gov. bonds | ECB real-time information system; News media releases from Bloomberg, Dow Jones News Wire, Market News International, and Reuters | An algorithm searches in politicians' statements for predetermined words regarding public finance in combination with words that have either a positive or negative connotation. |
| Mohl and Sondermann (2013) | GIIPS 10y gov. bonds | ECB real-time information system; News media releases from Bloomberg, Dow Jones News Wire, Market News International and Reuters | No classification into positive or negative statements. Focus on the keywords "restructuring," "bailout," and "EFSF." |

TABLE A.2: SUMMARY STATISTICS MAIN NEWS VARIABLES

| News Variable (shares) | No. of Observations (of 2,587) | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Eurozone** | 803 | 1.459 | 1.758 | 0.151 | 12.16 |
| *positive* | 188 | 0.553 | 0.443 | 0.150 | 4.054 |
| *neutral* | 604 | 1.122 | 1.261 | 0.153 | 7.265 |
| *negative* | 437 | 0.892 | 0.812 | 0.151 | 4.444 |
| *Weekend pos./neut.* | 88 | 0.338 | 0.338 | 0.076 | 2.292 |
| *Weekend negative* | 53 | 0.535 | 0.521 | 0.151 | 2.405 |
| **Greece** | 657 | 2.924 | 4.065 | 0.169 | 25.37 |
| *positive* | 135 | 0.841 | 0.862 | 0.149 | 5.660 |
| *neutral* | 420 | 1.515 | 1.727 | 0.150 | 11.31 |
| *negative* | 533 | 2.198 | 3.002 | 0.169 | 19.48 |
| *Weekend pos./neut.* | 91 | 0.671 | 1.076 | 0.057 | 6.948 |
| *Weekend negative* | 109 | 1.305 | 2.055 | 0.140 | 11.26 |
| **Italy** | 1,115 | 0.865 | 0.872 | 0.152 | 10.54 |
| *positive* | 251 | 0.555 | 0.423 | 0.149 | 2.545 |
| *neutral* | 858 | 0.698 | 0.607 | 0.152 | 5.286 |
| *negative* | 355 | 0.639 | 0.717 | 0.148 | 7.280 |
| *Weekend pos./neut.* | 199 | 0.301 | 0.348 | 0.061 | 2.764 |
| *Weekend negative* | 66 | 0.403 | 0.319 | 0.137 | 1.893 |
| **Spain** | 1,115 | 0.979 | 0.969 | 0.152 | 9.437 |
| *positive* | 382 | 0.560 | 0.428 | 0.151 | 3.385 |
| *neutral* | 641 | 0.661 | 0.542 | 0.152 | 4.624 |
| *negative* | 612 | 0.742 | 0.711 | 0.146 | 7.263 |
| *Weekend pos./neut.* | 115 | 0.295 | 0.443 | 0.057 | 3.787 |
| *Weekend negative* | 86 | 0.485 | 0.419 | 0.114 | 1.916 |
| **Portugal** | 196 | 1.308 | 2.123 | 0.148 | 15.17 |
| *positive* | 22 | 0.403 | 0.283 | 0.158 | 1.316 |
| *neutral* | 88 | 0.794 | 1.058 | 0.151 | 8.026 |
| *negative* | 145 | 1.226 | 2.008 | 0.148 | 13.79 |
| *Weekend pos./neut.* | 20 | 0.174 | 0.091 | 0.057 | 0.378 |
| *Weekend negative* | 24 | 0.858 | 0.816 | 0.184 | 3.502 |
| **Ireland** | 173 | 1.401 | 2.549 | 0.169 | 20.66 |
| *positive* | 16 | 0.524 | 0.278 | 0.153 | 1.278 |
| *neutral* | 74 | 0.965 | 1.123 | 0.177 | 4.904 |
| *negative* | 127 | 1.280 | 2.216 | 0.169 | 15.87 |
| *Weekend pos./neut.* | 16 | 0.605 | 0.773 | 0.086 | 2.475 |
| *Weekend negative* | 16 | 1.638 | 2.621 | 0.155 | 8.447 |

NOTES: Each observation relates to a (trading) date where the corresponding variable is unequal to zero. Eurozone, as well as country-specific news, are calculated as a share of total news on that day and quoted in percent. Eurozone news is invariant across countries in the panel and, therefore, only denoted once. The sum of news by tonality does not necessarily have to add up to the total number of observations; some might relate to the same date. Eurozone news: 15.3% positive, 49.1% neutral, 35.6% negative. Country-specific news: 19.1% positive, 44.4% neutral, 36.6% negative

FIGURE A.1: TOPICS COVERED BY EUROZONE NEWS


NOTES: The figure shows the topics covered in Eurozone news, with the size of each topic indicating the frequency of its appearance in the news. Topics that appear less than ten times are not included in the plot.

FIGURE A.2: TOPICS COVERED BY COUNTRY-SPECIFIC NEWS


NOTES: The figure shows the topics covered in country-specific news, with the size of each topic indicating the frequency of its appearance in the news. Topics that appear less than ten times are not included in the plot.

Table A.3: Top three Categories of Clusters

| Cluster | No. of News Items | Protagonist Type | Protagonist | Topic Group | Topic | Source Label |
|---|---|---|---|---|---|---|
| 1 | 14,363 | State of the economy (75.2%), Institution (6.0%), Person (5.4%) | State of the economy (75.3%), Country (4.9%), other economical protagonist (3.1%) | Budget (94.3%), State of the economy (3.9%), EU (1.9%) | Public budget, debt, revenue in general (62.9%), Budget policy, Debt of nation or region (19.3%), Budget deficit (7.1%) | Journalist (69.9%), Government (2.6%), Protesters (1.5%) |
| 2 | 3,376 | Institution (78.7%), Person (11.7%), Greece (2,9%) | European Union (25.2%), ECB (22.6%), European Council of Ministers (5.5%) | Currency/ EURO/ Monetary policy (66.1%), EU (21.3%), International Economy (7.3%) | EURO stability funds (26.6%), Monetary policy/ EURO/ Inflation (13.8%), EURO (11.3%) | Journalist (80.6%), Mario Draghi (2.8%), Angela Merkel (0.8%) |
| 3 | 1,456 | State of the economy (98.0%), Spain (1.0%), Italy (0.7%) | State of the economy (98.0%), Consumers (0.8%), Country (0.7%) | Currency/ EURO/ Monetary policy (100%) | Monetary policy/ EURO/ Inflation (24.8%), Price indicators (e.g. inflation rate) in general (20.5%), Increasing inflation or high level (20.1%) | Journalist (68.2%), ECB (6.7%), Government (5.9%) |
| 4 | 1,960 | Greece (54.5%), Institution (13.0%), Person (7.8%) | Country (54.5%), Government (15.8%), European Council of Ministers (3.3%) | International economy (66.7%), EU (15.2%), Budget (9.4%) | International financial support (54.0%), Budget policy, Debt of nation or region (7.5%), EU: Relationship between EU and member countries or their institutions (5.9%) | Journalist (82.7%), Alexis Tsipras (1.6%), European Union (1.6%) |
| 5 | 1,365 | State of the economy (100%) | State of the economy (100%) | International economy (100%) | International financial support (76.8%), Debt relief (10.1%), Restructuring of debt (4.3%) | Journalist (81.5%), Angela Merkel (2.2%), Protesters (1.8%) |
| 6 | 1,008 | Greece (67.6%), Italy (11.8%), Portugal (5.3%) | Government (99.2%), Parliament in general (0.2%), Germany (0.2%) | Budget (95.9%), EU (1.3%), Currency/ EURO/ Monetary policy (0.4%) | Public budget, debt, revenue in general (88.5%), Budget policy, Debt of nation or region (4.5%), EU budget in general (1.3%) | Journalist (87.0%), Protesters (5.4%), Wolfgang Schaeuble (0.8%) |
| 7 | 751 | State of the economy (87.0%), Spain (8.8%), Greece (1.9%) | State of the economy (87.0%), other economical protagonist (5.5 %), Country (2.4%) | Currency/ EURO/ Monetary policy (100%) | Monetary policy, other (100%) | Journalist (77.4%), Government (7.5%), Mariano Rajoy (2.6%) |
| 8 | 997 | Person (57.4%), Institution (9.0%), Ireland (7.9%) | Angela Merkel (10.1%), Matteo Renzi (8.7%), Voters (5.3%) | EU (89.9%), State of the economy (3.1%), Currency/ EURO/ Monetary policy (3.1%) | EU in general, other topic (22.3%), EU: Relationship between EU and member countries or their institutions (15.0%), European elections (11.3%) | Journalist (66.2%), Matteo Renzi (4.7%), Mario Draghi (2.9%) |

## Table A.4: Country-Specific Effects

| | (1) Greece | | | (2) Italy | | | (3) Spain | | | (4) Portugal | | | (5) Ireland | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Tonality* | *pos.* | *neut.* | *neg.* | *pos.* | *neut.* | *neg.* | *pos.* | *neut.* | *neg.* | *pos.* | *neut.* | *neg.* | *pos.* | *neut.* | *neg.* |
| Eurozone news | -8.711 | -0.666 | 3.704 | -5.063*** | -0.256 | 0.558 | -4.842*** | -0.129 | 0.509 | -7.131*** | 0.252 | -0.198 | -4.570*** | -0.371 | 0.879 |
| | (6.361) | (1.521) | (2.918) | (1.540) | (0.352) | (0.507) | (1.780) | (0.352) | (0.488) | (2.352) | (0.542) | (0.977) | (1.710) | (0.466) | (0.711) |
| Country-specific news | -5.778 | -4.832 | 2.831*** | -1.279 | -0.281 | 2.979*** | -1.685** | -0.372 | 1.062*** | -1.237 | -2.311 | 0.887 | -1.043 | 0.152 | 0.585 |
| | (7.363) | (3.830) | (1.092) | (0.829) | (0.434) | (1.068) | (0.684) | (0.472) | (0.364) | (5.029) | (1.712) | (0.992) | (3.762) | (1.179) | (0.917) |
| *Tonality* | *pos./neut.* | | *neg.* | *pos./neut.* | | *neg.* | *pos./neut.* | | *neg.* | *pos./neut.* | | *neg.* | *pos./neut.* | | *neg.* |
| Weekend Eurozone | 18.40 | | -12.34 | 4.194 | | 0.278 | 2.243 | | -1.572 | 1.821 | | 22.80 | -0.183 | | -1.405 |
| $\text{news}_{d=Mon.}$ | (14.07) | | (14.23) | (3.648) | | (3.115) | (3.408) | | (3.097) | (5.821) | | (15.25) | (4.083) | | (1.999) |
| Weekend Country-specific | -25.48** | | 19.22** | -6.783 | | 4.843* | -0.853 | | 3.544** | -5.709 | | -0.627 | 0.360 | | -1.869 |
| $\text{news}_{d=Mon.}$ | (11.06) | | (9.643) | (4.637) | | (2.796) | (1.573) | | (1.525) | (13.99) | | (1.481) | (1.475) | | (1.354) |
| Working-day FE | Yes | | | Yes | | | Yes | | | Yes | | | Yes | | |
| Fundamental Controls | Yes | | | Yes | | | Yes | | | Yes | | | Yes | | |
| Policy Controls | Yes | | | Yes | | | Yes | | | Yes | | | Yes | | |
| No. of Observations | 2,587 | | | 2,587 | | | 2,587 | | | 2,587 | | | 2,587 | | |

Notes: The dependent variable is the $\Delta$10-year bond yield spread of the GIIPS vis-à-vis Germany. The table reports coefficients estimated using OLS. Newey-West standard errors in parentheses. Weekends are excluded from the regression. However, weekend news is included and indicates the (causal) effect on the change in the yield spread on the following Monday ($d = Mon.$).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.5: ALTERNATIVE ECONOMETRIC SPECIFICATIONS

| | (1) OLS Clustered SE | | | (2) OLS Driscoll-Kraay SE | | | (3) GARCH(1,1) | | |
|---|---|---|---|---|---|---|---|---|---|
| Δ10-year bond yield spread$_{t-1}$ | 0.0413 | | | 0.0413 | | | 0.158*** | | |
| | (0.0204) | | | (0.0434) | | | (0.00780) | | |
| *Tonality* | *pos.* | *neut.* | *neg.* | *pos.* | *neut.* | *neg.* | *pos.* | *neut.* | *neg.* |
| Eurozone news | -5.899*** | -0.375** | 1.132 | -5.899** | -0.375 | 1.132 | -0.393*** | -0.000173 | 0.255*** |
| | (0.496) | (0.0997) | (0.555) | (2.085) | (0.489) | (0.739) | (0.127) | (0.0427) | (0.0525) |
| Country-specific news | -3.168** | -2.649 | 2.880** | -3.168 | -2.649 | 2.880** | -0.00591 | 0.0494 | 0.227*** |
| | (1.107) | (1.281) | (0.798) | (2.468) | (1.725) | (0.784) | (0.0746) | (0.0488) | (0.0499) |
| Eurocrisis | 0.395 | | | 0.395 | | | 0.525*** | | |
| | (0.360) | | | (0.868) | | | (0.179) | | |
| ΔCredit rating spread | -0.977 | | | -0.977 | | | 0.257 | | |
| | (2.065) | | | (5.603) | | | (0.625) | | |
| ΔMRO rate | 4.226 | | | 4.226 | | | -0.214 | | |
| | (5.994) | | | (5.829) | | | (0.634) | | |
| ΔNational stock market index | -1.064*** | | | -1.064*** | | | -0.0337*** | | |
| | (0.118) | | | (0.156) | | | (0.00524) | | |
| ΔEUROSTOXX Volatility index | 0.672* | | | 0.672** | | | 0.221*** | | |
| | (0.253) | | | (0.236) | | | (0.0114) | | |
| ΔAAA10Y | 4.237 | | | 4.237 | | | 3.060*** | | |
| | (5.581) | | | (5.990) | | | (0.542) | | |
| Arch$_{t-1}$ | | | | | | | 0.268*** | | |
| | | | | | | | (0.00462) | | |
| Garch$_{t-1}$ | | | | | | | 0.813*** | | |
| | | | | | | | (0.00217) | | |
| Country FE | Yes | | | Yes | | | Yes | | |
| Working-day FE | Yes | | | Yes | | | Yes | | |
| Policy Controls | Yes | | | Yes | | | Yes | | |
| No. of Observations | 12,935 | | | 12,935 | | | 12,935 | | |

NOTES: The dependent variable is the Δ10-year bond yield spread of the GIIPS vis-à-vis Germany. Standard errors in parentheses. Weekends are excluded from the regression.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Robustness Checks Utilizing Surprise Components from Macro and Fiscal Releases

| | (1) | (2) | | |
|---|---|---|---|---|
| Δ10-year bond yield spread$_{t-1}$ | 0.0204*** | 0.0182** | | |
| | (0.00720) | (0.00724) | | |
| *Tonality* | | *pos.* | *neut.* | *neg.* |
| Eurozone news | -0.294** | -4.953*** | -0.263 | 0.668** |
| | (0.125) | (0.847) | (0.214) | (0.327) |
| Country-specific news | 0.283*** | -0.550** | -0.348** | 1.113*** |
| | (0.0751) | (0.275) | (0.147) | (0.138) |
| Production improved | 0.109 | | 0.0823 | |
| | (0.443) | | (0.470) | |
| Production worse | 0.0316 | | -0.0741 | |
| | (0.492) | | (0.522) | |
| Sales improved | 0.274 | | 0.237 | |
| | (0.427) | | (0.453) | |
| Sales worse | 0.333 | | 0.301 | |
| | (0.515) | | (0.547) | |
| Unemployment rate improved | -1.025* | | -0.938 | |
| | (0.583) | | (0.616) | |
| Unemployment rate worse | -0.0504 | | -0.0623 | |
| | (0.515) | | (0.628) | |
| Growth improved | 0.675 | | 0.648 | |
| | (0.655) | | (0.688) | |
| Growth worse | -0.594 | | -0.644 | |
| | (0.702) | | (0.739) | |
| GDP forecast improved | 0.620 | | 0.805 | |
| | (2.022) | | (2.085) | |
| GDP forecast worse | 1.004 | | 1.106 | |
| | (1.801) | | (1.858) | |
| Debt-to-GDP forecast improved | 0.377 | | 0.616 | |
| | (1.909) | | (1.957) | |
| Debt-to-GDP forecast worse | 0.226 | | 0.0734 | |
| | (1.828) | | (1.864) | |
| Release EDP | -3.860* | | -3.870* | |
| | (2.011) | | (2.094) | |
| Country FE | Yes | | Yes | |
| Working-day FE | Yes | | Yes | |
| Fundamental Controls | Yes | | Yes | |
| Policy Controls | Yes | | Yes | |
| No. of Observations | 12,935 | | 12,935 | |

Notes: The dependent variable is the Δ10-year bond yield spread of the GIIPS vis-à-vis Germany. The table reports coefficients estimated using FGLS. Standard errors in parentheses. Weekends are excluded from the regression.
The additional control variables compared to the baseline in Table 2 are dummy variables that denote surprises from macro data releases as in Büchel (2013) as well as European Commission (EC) forecasts, showing whether the projection shows an improvement or worsening compared to preceding figures, and Excessive Debt Procedure (EDP) announcements, where event dates are coded to indicate EC decisions to initiate an EDP against a country. Sources are the Economic Calendar at Bloomberg and the EC. The results indicate that our baseline results are very robust to their inclusion.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# B Residual Analysis and Tests

**Testing for Unit Roots, Cross-Sectional Dependence, Heteroscedasticity, and Autocorrelation** Prior to examining the presence of a unit root process in each individual time series, the ideal lag length for each panel cross-section is determined using Akaike's information criterion. Subsequently, an Augmented Dickey-Fuller test is performed. The null hypothesis of non-stationarity cannot be rejected for government bond spreads and most financial controls in levels.[24] Therefore, a model in first differences is selected to avoid spurious regression concerns. As for the media data, the tests reject the presence of a unit root for all (sub-)samples.

To specify a correct and consistent model using an efficient estimator, we test for panel-specific concerns in the following model:

$$\Delta spreads_{i,t} = \rho \Delta spreads_{i,t-1} + \beta X_t + \alpha_i + \gamma_d + \epsilon_{i,t} \tag{B.1}$$

with $i = 1, ..., 5$ denoting the GIIPS countries and $t = 1, ..., 2,587$ indexes the daily time dimension. The control vector $X_t$ equals our baseline model depicted in Equation 1. The model is estimated using OLS.

First, a Breusch-Pagan Lagrange Multiplier test for cross-sectional independence in the residuals of Equation B.1 is conducted, following Baum (2001) and Breusch and Pagan (1980). The test is valid for large $t$ and small $i$. The null hypothesis of no cross-sectional dependence is rejected for the 10-year government bond yield spreads at the 1% significance level (see Table B.1, Column 1). This implies cross-sectional dependence of the residuals. Second, a modified Wald statistic for groupwise heteroscedasticity in the residuals of Equation B.1 is calculated, following Baum (2001). Homoscedasticity is the null hypothesis of this test, which is rejected at the 1% significance level for the dependent variable (see Table B.1, Column 2). Third, a Wald test for serial correlation in the idiosyncratic errors, discussed by Drukker (2003), is conducted. The null hypothesis of no serial correlation is rejected for the 10-year bond yield spreads at 5% (see Table B.1, Column 3).

[24] Test results available upon request.

Table B.1: Test Results Residual Analysis

| | Cross-Sectional Dependence* | Groupwise Heteroskedasticity** | Serial Correlation*** |
|---|---|---|---|
| Δ10-year bond yield spreads | 3883.95 | 99196.19 | 55614.81 |
| | (0.0000) | (0.0000) | (0.0000) |

Notes: Values for the individual test statistics are displayed, p-values are reported in parentheses.

* CD is tested with the Breusch and Pagan (1980) LM test. The resulting test statistic is $\chi^2(d)$ distributed, where: $d = N_g \cdot (N_g - 1)/2)$, under the null hypothesis of cross-sectional independence.

** Groupwise heteroscedasticity in the residual of a fixed-effects regression model is tested with a Modified Wald test. It tests that $\sigma^2(i) = \sigma$ for $i = 1, ..., N_g$, where $N_g$ is the number of cross-sectional units. The resulting test statistic is distributed $\chi^2(N_g)$ under the null hypothesis of homoscedasticity.

*** Wooldridge Wald F tests the null hypothesis of no first-order serial correlation.

Table B.2: Correlation Coefficients between Eurozone and Country-Specific News

| | Country-specific news | | | | | |
|---|---|---|---|---|---|---|
| | Overall | Greece | Ireland | Italy | Portugal | Spain |
| Eurozone news | 0.1008 | 0.1395 | 0.0421 | 0.1257 | 0.1597 | 0.1093 |

Notes: The table displays correlation coefficients between the Eurozone news variable, which is invariant across countries, and country-specific news in the panel (overall) and for each country individually, to test the appropriateness of including them simultaneously in a regression model.

**Testing for the causal direction of the effect of media coverage on bond yields** To shed light on the causal relationship between news coverage and changes in government bond yield spreads, we conduct the causality tests for stationary panel data as proposed by Lopez and Weber (2017). Granger causality tests using individual countries remained inconclusive in the paper by Gade et al. (2013), while Falagiarda and Gregori (2015) rule out Granger causality from sovereign spreads to fiscal policy announcements. According to our results, we cannot rule out bidirectional causality at reasonable significance levels. Still, the existence of causality from news to changes in bond yield spreads is particularly well documented for both Eurozone and country-specific news. A causal link in the opposite direction, between spreads and news, cannot be rejected. Yet, it appears to be much weaker. Causality between spreads and some subsamples (e.g., positive country-specific news) can be ruled out. We are aware that Granger causality analysis is not without controversy if rational expectations prevail (Sargent and Wallace (1976) or Buiter (1984)).

Table B.3: Test Results Granger Causality

| Dependent Variable | Explanatory Variable | Granger Non-Causality Test Results | | | |
|---|---|---|---|---|---|
| | | | *pos.* | *neut.* | *neg.* |
| Δ10-year bond yield spread | Eurozone news | 16.4795 | 3.5883 | 16.5919 | 9.0685 |
| | | (0.0000) | (0.0003) | (0.0000) | (0.0000) |
| Δ10-year bond yield spread | country-specific news | 9.0707 | -1.1311 | 8.9357 | 4.3844 |
| | | (0.0000) | (0.2580) | (0.0000) | (0.0000) |
| Eurozone news | Δ10-year bond yield spread | 0.9594 | 4.1271 | 1.0222 | 1.4520 |
| | | (0.3374) | (0.0000) | (0.3067) | (0.1465) |
| country-specific news | Δ10-year bond yield spread | 2.6873 | 0.8941 | 5.1879 | 1.6649 |
| | | (0.0072) | (0.3713) | (0.0000) | (0.0959) |

Notes: Values obtained for the Z-bar statistic are displayed, p-values are reported in parentheses. The test procedure is based on the work by Dumitrescu and Hurlin (2012). To test for Granger-causality in panel data the procedure by Lopez and Weber (2017) is applied. The null hypothesis of the test is that the explanatory variable does not Granger-cause the dependent variable. We include one lag in the tests.

Table B.4: Role of Previous Week's Spread Changes for Identification Based on Weekend News

| | (1) Weekend country-specific news | (2) Weekend Eurozone news | (3) Δ 10-year bond yield spread |
|---|---|---|---|
| Previous week cumulative spread change (positive)$_{d=Mon.}$ | -0.000124 | -6.74e-08 | -0.000898 |
| | (0.000202) | (0.00000164) | (0.0128) |
| Previous week cumulative spread change (negative)$_{d=Mon.}$ | 0.0000438 | 3.03e-08 | 0.00580 |
| | (0.000160) | (0.00000124) | (0.0114) |
| Country FE | Yes | Yes | Yes |
| Working-day FE | Yes | Yes | Yes |
| Fundamental Controls | No | No | Yes |
| No. of Observations | 12,925 | 12,925 | 12,915 |

Notes: The dependent variable is indicated above each column. The main explanatory variables are the cumulative positive or negative spread changes in one week in two separate variables used to explain the dependent variable (weekend news or subsequent spread changes) on the following Monday (hence $d = Mon.$). The table reports coefficients estimated using FGLS. Standard errors in parentheses. Weekends are excluded from the regression. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$