ECB Language and Stock Returns – A Textual Analysis of ECB Press Conferences

Rouven Möller[+] **Doron Reichmann**[*+]

rouven.moeller@rub.de doron.reichmann@rub.de

Ruhr-Universität Bochum
Department of Finance and Banking

April 15, 2021

Abstract

This paper examines the language used by central bank officials in public press conferences and how it influences stock returns in the euro area. By proposing a sentiment mining approach that accounts for grammatical and syntactical cues, a distinction is drawn between (i) the general tone, (ii) uncertainty, and (iii) constraint expressed by ECB officials. The results show that as constraining language is often used to express policy commitment, press conferences with higher fractions of constraining language are associated with positive intraday stock price movements in times of unconventional monetary policy. In addition, we conclude that in times of crises, intraday returns are more sensitive towards the general tone of ECB officials as market participants may find it harder to grasp the future path of monetary policy. In further analyses, a distinction is made between sections within the press conferences that specifically address either the monetary analysis or the economic outlook. The results indicate that market participants interpret uncertain language in the economic outlook as a signal of expansive monetary policy decisions going forward as indicated by positive intraday stock returns. Finally, by proposing a novel rule-based approach to identify forward-looking statements of ECB press conferences, first evidence is provided in this paper that forward-looking answers given by ECB officials in the Q&A Sessions significantly affect euro area stock returns.

JEL-*Classification*: E44, E52, E58, G14

Keywords: Central Bank Communication; Forward Guidance; Textual Analysis

1 Introduction

The design of central bank communication has become a crucial element in the conduct of current monetary policy for all major central banks around the world (e.g., de Guindos, 2019). After reaching historically low levels of policy rates, a combination of several unconventional measures became increasingly important in order to provide additional stimulus for a stronger economic recovery. One important tool in times of unconventional monetary policy is explicit Forward Guidance (FG) on future monetary policy activity through central bank communication.[1]

The transparency created by FG is not only a requirement of central banks' accountability to the public (e.g., Hansen, McMahon and Prat, 2018), but also a manner by which central banks can manage market expectations which leading monetary economist and central bankers highlight as *the* task in central banking (e.g., Woodford, 2005; Bernanke, 2004). Furthermore, a survey by Blinder, Ehrmann, de Haan and Jansen (2017) shows that more than 70% of central bank governors and more than 85% of academics think that FG should remain an instrument in the central banks' "toolkit".

In this paper the objective is to analyse ECB FG from a linguistic perspective. ECB press conferences are highly anticipated events since monetary policy decisions are likely to influence future financing conditions of European companies. It is argued that market participants carefully process statements given in the press conferences to extract information about the future path of monetary policy. Therefore, the hypothesis is ventured that stock returns of European indices are likely to be driven by certain characteristics of language used in the press conferences. Following the literature on the effectiveness of monetary policy, an event study approach is applied by using high frequency data to calculate stock price movements in an 85-minute event window around ECB press conferences to infer the impact of ECB communication.

For the main analysis, a novel sentiment mining approach is proposed that is sensitive to grammatical and syntactical cues which can modify the perceived sentiment intensity of financial text. For this purpose, the word lists of Bodnaruk, Loughran and McDonald (2015), and Loughran and McDonald (LM) (2011) are combined with sentiment-

[1] For example, on December 16, 2008 the FOMC explicitly used Forward guidance for the first time by mentioning that economic conditions "are likely to warrant exceptionally low levels of the federal funds rate for some time." The FOMC continually used Forward guidance to foster expectation that the exceptionally low levels of the federal funds rate would likely to remain low: "for an extended period." (2009), "at least through mid-2013." (2011), at least until "late 2014" (2012).

heuristics proposed in Hutto and Gilbert (2014) so as to precisely measure three different sentiment dimensions (tone, uncertainty and constraint). Moreover, n-gram analyses are conducted for a deeper understanding of the words and contexts that act as drivers in the results obtained.

The findings suggest that in times of unconventional monetary policy, the ECB uses constraining language to express policy commitment. In line with this, Campbell, Evans, Fisher and Justiniano (2012) developed the concept of Odyssean FG to describe a situation where policy makers publicly commit to a future path of policy. Consequently, they constrain themselves much like the mythological Odysseus and his crew when they tied their hands to the mast of their ship to resist the siren calls. Hence, based on this analogy market participants have high appreciation for the future path of monetary policy being conditional on the achievement of known policy goals.

In addition, language within the monetary- and economic analysis of the introductory statements of press conferences is evaluated separately. Strong evidence is found that higher levels of uncertain language in the economic outlook have a positive effect on intraday stock returns. In other words, a vague economic outlook might signal more policy accommodation in the future. This finding supports the theoretical framework of Delphic FG. Named after the ambiguous oracle of Delphi, Campbell et al. (2012) define forecast-based FG that elaborates on likely or intended monetary policy actions. The latter follows the notion that policymakers reveal potentially superior information about future macroeconomic fundamentals and their own policy goals through economic forecasts.

Moreover, the baseline analysis applied suggests that in a period of high economic uncertainty, tone sensitivities of financial market participants increase as they find it hard to grasp the future path of monetary policy. The results obtained are robust, even after controlling for monetary surprises as developed by Gürkaynak, Sack and Swanson (2005a).

In additional analysis, a novel rule-based approach to identify forward-looking statements of ECB press conferences is proposed. In addition to the introductory statement, this approach is used to analyse the language of answers provided in the Q&A sessions following thereupon. Since the answers seem to contain a significant amount of information unrelated to the future path of monetary policy, applying this approach can greatly reduce noise in the textual analysis of Q&A sessions. Consequently, this paper is the first to provide evidence that the sentiment of forward-looking answers given in Q&A sessions of ECB press conferences affect intraday stock returns.

The remainder of this paper is structured as follows. Section 2 provides an overview on related literature in the field of central banks' FG. Section 3 describes the dataset used and the construction of communication variables. Section 4 presents the course of linguistic characteristics of press conferences over time. Section 5 offers the empirical results obtained, whereas in Section 6 additional analyses are discussed. Section 7 concludes this paper.

2 Literature Review

2.1 Effectiveness of monetary policy on asset prices

Kuttner (2001) was the first to address the effectiveness of monetary policy in influencing prices on financial markets in empirical research. He calculated unexpected interest rate changes (monetary surprises) on days of monetary policy activity from daily price changes of Fed Funds Futures. Using the same methodology, Bernanke and Kuttner (2005) demonstrated that stock prices react to unexpected interest rate changes. Accordingly, an unexpected interest rate cut by the FED of 25 basis points leads to an increase of 1 percentage point in a broad stock index. Rigobon and Sack (2004) find comparable effects but apply a heteroskedastic estimation procedure in which they use the co-movement of stock and bond yields to differentiate between asset price shocks and monetary policy shocks. Since then, numerous studies based on these methods have confirmed the effects of conventional and unconventional monetary policy measures on different asset prices.[2]

Some studies explain the effects on asset prices by changes in real short-run interest rate expectations induced by monetary policy decisions. Thus, central banks pass on private information about their own policies and economic fundamentals to the financial markets, which then influence the real interest rate expectations of investors (Nakamura and Steinsson, 2018; Campbell, Fisher, Justiniano and Melosi, 2017, Campbell, Sunderam and Viceira, 2017). Since investors' inflation expectations are not sufficiently anchored (Binder 2017), changes in short-term interest rate expectations may subsequently affect interest rates on the long-run (Gürkaynak, Sack and Swanson, 2005b).

Other studies argue that changing risk premia are the primary explanation for monetary policy effects on asset prices (Bernanke and Kuttner 2005). Bekaert, Hoerova and Lo Duca (2013) show that accommodative monetary policy is associated with declining risk aversion and decreasing uncertainty. Gertler and Karadi (2015) show that monetary policy surprises induce large changes in credit costs as they affect both maturity premiums and credit spreads. In this regard Hanson and Stein (2015), and Hanson, Lucca and Wright (2018) argue that when short-term interest rates fall, investors in search of yield induce

[2] Individual papers, also examine the firm-level effects of monetary policy. Ippolito, Ozdagli and Perez (2018) and Ehrmann and Fratzscher (2004) show that small firms, firms with low creditworthiness, high indebtedness, low cash holdings, high price-earnings ratios and high Tobin's q have a higher sensitivity to monetary surprises.

demand shocks in long-term bonds, thereby lowering maturity premiums. Studies focusing on the effectiveness of bond purchase programs confirm the effect on risk premia (Swanson, 2017; Krishnamurthy and Vissing-Jorgensen, 2015; Wright, 2012; Gagnon, Raskin, Remache and Sack, 2010).[3] This evidence is in line with the predictions of the literature on the risk-taking channel of monetary policy, which, commencing with Borio and Zhu (2012), attempts to integrate endogenous risk premia and the risk taking of the financial sector into the conduct of monetary policy (Drechsler, Savoy and Schnabl, 2018; Jiménez, 2014; Morris and Shin, 2014).[4]

2.2 Central bank communication

Given the focus on the language used for the ECB's FG, this paper also refers to the extensive literature on central bank communication.[5]

Based on Kuttner (2001), Gürkaynak, Sack and Swanson (2005a) (GSS) use high frequency yield changes in a narrow time window around FOMC announcements to determine monetary surprises using two latent factors. The first "target" factor reflects the unexpected changes in the Federal Funds rate due to the monetary policy decisions of the FED. The second "path" factor reflects changes in future policy and relates to the FOMC's FG via its press statements. The authors demonstrate that both factors have significant effects on asset prices with the target factor having a greater impact on short-term interest rates and the path factor primarily affecting long-term interest rates.

Several papers have used the GSS methodology to analyze the effects of the ECB's monetary policy. In the case of the ECB, a target- and a path factor are also extracted from Euro-specific high frequency yield changes. Overall, the ECB's FG shows similar effects to the FOMC's FG. It has significant effects on (i) medium- and long-term yields (Brand, Buncic and Turunen, 2010), (ii) the risk premiums of government bonds of the European periphery (Leombroni, Vedolin, Venter and Whelan., 2018), and (iii) industrial production, inflation and the US dollar/euro exchange rate (Kane, Rogers and Sun 2018).

Andrade and Ferroni (2018) split the path factor into two elements and use suitable rotations of the factor matrix to analyze the effect of Delphic and Odyssean FG. They show that restrictive Odyssean FG does not only have a significant impact on medium- and long-term interest rates (positive) and inflation expectations (negative). In addition,

[3] For a comprehensive overview of the effects of unconventional Fed measures on the financial markets, see Kuttner (2018).
[4] For a comprehensive literature review of the risk-taking channel, see Adrian and Liang (2018).
[5] Woodford (2001) and Blinder et al. (2008) are two comprehensive reviews of the literature on central bank communication.

restrictive Odyssean FG, in contrast to the path factor, has a significant negative impact on EuroStoxx returns. Swanson (2017) provides a second extension to the GSS approach. In addition to the target- and path factor, he extracts a factor for the FOMC's policy that reflects the unexpected yield changes due to unconventional measures in the QE phase from 2009 onwards. In contrast to GSS, Swanson (2017) shows that FG explains changes in short- to medium-term interest rates. Moreover, the effects last only 1-4 months while the QE factor affects long-term interest rates, corporate yields and interest rate uncertainty more persistently.

Altavilla, Brugnolini, Gürkayak, Motto and Ragusa (2019) use the ECB's two-tier announcement structure to determine monetary surprises separately: firstly, for the announcement of the monetary policy decision, and, secondly, for communication in the press conference that follows. In total, they extract four different factors from the yield changes for the two separate time windows. For the time window of the monetary policy decision, they extract only a target factor that reflects the changes for short-term interest rates with a maturity of one month whereas for the time window of the press conference, they extract three additional factors. Firstly, a timing factor that reflects the changes for short-term interest rates with a maturity of 3-6 months. Secondly, a FG factor that reflects changes for medium and long-term interest rates with a maturity of 1-5 years, and, thirdly, a QE factor that mainly affects long-term interest rates with a maturity of 10 years.

In line with expectations, the authors demonstrate that the target factor primarily explains interest rates at the short end. The factors from the conference window, in particular FG and QE, explain changes in medium- and long-term interest rates. The evidence on Spanish and Italian government bonds shows that the QE factor and, to a lesser extent, the FG factor narrow the interest rate spreads of these bonds. For all the factors in the conference window, the exchange rate effects are in line with expectations according to the uncovered interest parity. Restrictive monetary surprises result in an appreciation of the euro against the US dollar. Finally, the authors find significant negative effects on the returns of the EuroStoxx and a Euro-specific bank index for the target factor over the entire time period and before the financial crisis as well as for the timing and FG factor in the period 2014-2018. The lack of significance for the QE factor and the other subsamples is attributed to the presence of information shocks (Jarocinski and Karadi, 2018). For example, the effects of negative (Delphic) FG in press conferences (information shocks) counteract the positive effects of expansionary policies so that on average the effects for stocks are not significant.

While the previous papers measure the impact of central bank communication by extracting monetary surprises from changes in asset prices, some papers also analyze the content of central bank communication directly.

Following the narrative approach of Romer and Romer (1989, 2004), some early papers quantify central bank communication by manual coding. These early contributions focus on the assessment of the tone of central bank communication and transform it into a discrete variable (most often from very dovish to very hawkish). They show that central bank communication has an equally predictive ability as market-based expectations. Furthermore, unexpected elements of communication can significantly influence market expectations (Rosa and Verga, 2007), have a significant influence especially on short-term interest rates (Musard-Gies, 2006) and can explain interest rate decisions (Gerlach, 2007).[6]

Due to the subjectivity as well as the limited reproducibility of manual coding, more recent papers follow Tetlock (2007) and LM (2011) and use text analysis techniques such as dictionary-based word-count approaches to evaluate the tone of central bank communication. Jansen and de Haan (2007) find that the frequency with which the word *vigilance* is used in ECB press conferences has only a marginally negative effect on inflation expectations in the euro area. However, subsequent research has confirmed the importance of language for the impact of monetary policy. With the help of a self-developed field-specific dictionary, Picault and Renault (2017) show that the tone of the introductory statement of ECB press conferences can help to explain future policy decisions. Furthermore, the tone with which the ECB communicates its economic outlook has a negative impact on stock market volatility on the day after the press conference. In this context, Jegadeesh and Wu (2017) use a Latent Dirichlet Allocation model to identify eight different themes within the FOMC minutes. In subsequent analyses, they show that the tone used to communicate the themes "policy stance, inflation and employment" has significant negative effects on the volatilities of the S&P 500 and Libor. However, the tone of the themes “trade, consumption and investment” has hardly any significant

[6] Papers analyzing the orientation of monetary policy based on the content communicated within the introductory statements of the press conferences, show that monetary analysis was not an important determinant of the ECB's actions in its early years (Berger, de Haan and Sturm 2011). Only the communication on price stability in the euro area has a significant effect on the euro-dollar exchange rate (Conrad and Lamla 2010).

effects. Schmeling and Wagner (2019) find that negative changes in the fraction of negative words within the introductory statements of ECB press conferences have a positive influence on stock prices and a negative influence on volatility risk premia and credit spreads. They also show that the tone sensitivity of individual stocks depends on their systematic risk. Accordingly, the returns on higher beta stocks show an increased sensitivity to changes in the central bank tone.

3 Data and Methodology

3.1 Stock returns

We follow the existing literature and apply an event study approach to analyse the effect of language used in ECB press conferences on Euro Area asset prices. Each press conference commences with the President reading out the introductory statement from 14:30-14:45 CET, followed by the Q&A session that usually lasts about 45 minutes. In order to assure a robust identification of asset price movements due to communication, high frequency data taken from the *Euro Area Monetary Policy Event-Study Database* (EA-MPD) provided by Altavilla et al. (2019) is relied upon. The database contains changes in the median quotes of various asset prices and yields from two separate time windows: firstly, the press-release window with median quotes from 13:25-13:35 CET (pre-release window) and 14:00-14:15 CET (post-release window), and, secondly, the press-conference-window with median quotes from 14:15-14:25 CET (pre-conference window) and 15:40-15:50 CET (post-conference window). The two separate event windows allow us to identify asset price reactions due to ECB communication unrelated to the interest rate decisions announced in the prior press-release window. Hence, the focus falls on the changes in median quotes of the STOXX50E and SX7E indices within the press conference window. Since Altavilla et al. (2019) noted that their intraday data prior to 2002 are noisy, the sample period ranges from 2002 to 2019.

3.2 ECB language

Raising the question whether the content from a popular *Wall Street Journal* column could be linked to investor psychology and sociology, Tetlock (2007) was first to provide evidence that media sentiment can predict stock market movements. Sentiment can be described as the feeling a certain thought, opinion, or idea is based on and has gained considerable attention in accounting and finance research (see LM (2016) for more details). As decisions made by the ECB can greatly impact the European economy, the hypothesis is postulated that the market carefully processes the content of ECB press conferences. While prior works construct proxies for central bank communication using monetary policy surprises measured as high frequency asset price reactions to communication events, we contribute to a strand of literature that aims to directly analyze the language of central bank communication. For instance, Schmeling and Wagner (2019) document that a more positive (negative) sentiment of ECB press conferences is associated with higher (lower) equity market returns. However, sentiment likely comes in shades that go well beyond simple means of positivity or negativity. Given the importance of monetary policy decisions, we believe that market participants will pick up on any cues that allow to draw inferences about the future path of monetary policy. Following this notion, we aim to provide a more comprehensive view on the linguistic characteristics of central bank communication and how they affect market prices by incorporating multiple dimensions of sentiment into our textual analysis while also controlling for policy surprises. Sentiment can be measured by using machine learning algorithms or dictionary-based approaches, the latter is often preferred as machine learning methods such as the Naïve Bayesian methodology lack of replicability (LM, 2016). The dictionary-based approach relies on certain word lists that share common sentiments (e.g., negative, positive, uncertain or constraining). The approach follows a simple notion: for instance, if a given text contains more negative words, it is more likely that the text conveys a negative feeling. Therefore, a substantial volume of literature commonly defines the sentiment of text as the word count of sentiment-labeled words scaled by the text's total word count (e.g., Schmeling and Wagner, 2019; Tsai, Lu and Hung, 2016; Hillert, Jacobs and Müller, 2014; Dougal, Engelberg, Garcia and Parsons, 2011; Tetlock, 2007). Thus, higher values of such scores indicate stronger (e.g., negative, positive, uncertain or constraining) sentiment. However, this rudimentary method is not sensitive to grammatical and syntactical cues which can modify the perceived sentiment intensity and may lead to misclassifications. To enhance the quality of the sentiment analysis and reduce the likelihood of potential misclassification in this paper, a comprehensive dictionary-based sentiment-mining approach is proposed. Therefore, the analysis is based on the positive and negative word lists proposed in LM (2011).[7] The LM (2011) word lists are deliberately selected for this paper. The dictionary generally suits the frame of this study as it was developed by using a sample of 10-K filings to create

[7] The positive word list counts 354 words, whereas the negative word list counts 2355 words.

word lists that incorporate the specifics of financial communication.[8] Alternatively, the option existed for us to compile our own dictionary for ECB communication. However, this approach would have greatly increased our control over the results of our empirical analysis. In order to adjust the sentiment-score based on grammatical and syntactical cues the so-called VADER method of Hutto and Gilbert (2014) is followed. The latter researchers used a sample of social media text snippets to identify generalizable heuristics humans use to assess sentiment intensity. Even though the heuristics are based on social media text, three heuristics are identified by us that are generalizable for almost every kind of natural language and, therefore, are highly applicable to this study:[9]

1) *Intensifiers*: Words that either increase or decrease the sentiment intensity (e.g., "the results are very bad" or "the results are marginally bad").
2) *Contrastive conjunctions*: The conjunction "but" shifts sentiment polarity with the sentiment conveyed after the conjunction being more dominant (e.g., "the preparation was good but the results are bad").
3) *Negations*: The negation of a sentence can "flip" the polarity of a text so that a negated sentence with a negative word is actually perceived as positive (e.g., "this was not a bad decision at all").

These heuristics are incorporated by using the openly available *nltk.sentiment.vader* module in *Python* provided by Hutto and Gilbert (2014). The predefined dictionary is edited and the sentiment word lists are imported, where positive (negative) words are assigned the value +1 (–1). The standardized sentiment score $VADER\_LM$ is measured as the sum of the heuristic-adjusted positive and negative words and ranges from –1 (extremely negative) to +1 (extremely positive). However, the VADER model works best for short text as it was initially made for social media content such as tweets. In order to make the VADER model applicable for longer texts, we calculate the sentiment score of each text i as the word-weighted sum of sentiment scores per sentence s.[10] The weighting scheme is based on sentences after stopword removal (e.g., *for, and, of, are,* etc.) and

[8] However, words that appear negative in the context of 10-K filings do not necessarily have to be negative in the setting of a press conference. Thus, to avoid potential bias, the occurrences of all positive and negative words that are prevalent in ECB press conferences are counted. Then the words that drive the sentiment score are carefully evaluated, finding that more than 20% of the negative word count can be attributed to the words "question/s". Since these words are neutral in press conferences, both words are excluded from the negative dictionary.

[9] Additionally, Hutto and Gilbert (2014) also identify *Punctuation*, namely the exclamation mark (!) and the use of *ALL-CAPS* words to intensify sentiment. However, these heuristics are of less importance for the purposes of this study.

[10] Aggregating the sentiment scores on a sentence-level avoids potential bias arising from differences in the length of each press conference. Note, that the normalization used by Hutto and Gilbert (2014) is $\frac{x}{\sqrt{x^2+\alpha}}$, where x is the sum of the heuristic-adjusted sentiment words and α is a constant normalization parameter which is set to 15. Therefore, as x grows larger the sentiment score will get closer to its boundaries -1 and 1.

allows for the consideration of the actual length of each sentence as longer sentences are expected to account for a greater part of the overall sentiment score than shorter sentences:

$$Tone_i = \sum_{i=1}^{n} \frac{\#words\ in\ sentence_{i,s}}{\#total\ words_i} \cdot VADER\_LM_{i,s}$$

As this paper aims to provide the most comprehensive textual analysis of ECB press conferences to date, uncertainty (Unc) and constraining (Con) sentiment are also measured. Therefore, the same methodology is applied by using the word lists proposed in LM (2011) and Bodnaruk et al. (2015). The word list used to measure financial uncertainty includes 285 words emphasising the notion of imprecision rather than focusing on financial risk only (e.g., *approximate, depend, variability*) (LM, 2011). Higher values of the uncertainty score can indicate higher levels of imprecision expressed by the ECB Presidents, which might result in market movements. Bodnaruk et al. (2015) construct a unique word list of financially constraining words by analysing 10-K disclosures. The list includes 184 words such as *comply, limit* and *prohibit*. Therefore, higher scores of Con could indicate that the ECB is constrained by their current line or course, which might reduce uncertainties about future ECB decisions and impact market prices.

Since the precision of content discussed in ECB press conferences has remained unconsidered in prior works, this paper tests whether the market reacts to press conferences that contain more precise content. In order to measure the precision of press conferences the concept of Hope, Hu and Lu (2016) is applied. By employing Named Entity Recognition (NER) techniques using the *spaCy* module available for *Python* each word or phrase is assigned to a particular Named Entity.[11] The NER categories labelled as precise content are (1) names of persons, (2) names of locations, (3) names of organizations, (4) quantitative values in percentages, (5) money values, (6) times, and (7) dates.[12] Therefore, precision is measured as the total sum of precise information in each press conference divided by total words after stopword removal.

[11] Named-Entity Recognition (NER) is a subtask of information extraction that seeks to locate and classify so-called Named Entities mentioned in text into pre-defined categories.

[12] In *spaCy* the respective categories are (1) 'PERSON', (2) 'GPE', (3) 'ORG', (4) 'PERCENT', (5) 'MONEY', (6) TIME', and (7) 'DATE'. We also include 'CARDINAL', which are numerals that do not fall under another type as percentages in press conferences are often expressed in basis points (e.g., 100 basis points).

Consistent to prior work, we also control for other lexical features (Schmeling and Wagner, 2019). Following Li (2008) the Gunning-Fog index is calculated. The Gunning-Fog index estimates the number of years of education needed to understand a text on a first reading by considering the number of words per sentence and the percentage of complex words in a text.[13] However, since the effects of language on stock returns are being examined, we follow Kim, Whang and Zhang (2019), and the Gunning-Fog index is adjusted for financial terms that investors are unlikely to perceive as complex. Finally, as part of the robustness checks, we control for the similarity of two consecutive press conferences, because Bholat, Hansen, Santos and Schonhardt-Bailey (2015) and Ehrmann and Talmi (2019) suggest that markets might be affected differently if central bank communication deviates from previous communication. Similarity is calculated as the distance between two Euclidean vectors, while each vector consists of single word n-grams. Therefore, higher values indicate a greater deviation in the choice of words between to press conferences.

3.3 Controls

In order to focus on the linguistic effects of FG on asset prices, it was required to rule out the fact that linguistic effects matter for asset prices only because they capture unexpected information within communication events. Thus, the methodology of Altavilla et al. (2019) is adapted and latent factors from changes in OIS-rates at different maturities, from one-month to ten-years via principal components are extracted.[14] Using the Cragg and Donald (1997) test for number of significant factors, we consistently find three factors in our full sample. To give the resulting factors an economic interpretation, the same rotation matrix as Altavilla et al. (2019) is used. Hence, the factors are rotated so that the first factor is defined by orthogonality to the 1-month OIS change and the second factor is orthogonal to the first factor. Therefore, in total the two factors should explain most of the variance in OIS-rates. The third factor is orthogonal to the first two and the 1-month OIS and following explains the minimal share of the pre-crisis variance (Swanson, 2017). For the Euro Area dataset, this leads to a factor that explains only OIS-rates movement at the long-term end of the yield curve after 2014. Using these rotations, the three factors reported by Altavilla et al. (2019) are extracted: firstly, a factor called $Timing$ which

[13] Complex words are defined as words with more than two syllables. However, common suffixes (such as -es, -ed, or -ing) are not included as a syllable.
[14] For a formal illustration of the principal component analysis and the related factor rotation, the reader is referred to Altavilla et al (2019).

captures monetary policy surprises about the near future by shifting the expected policy action between the current and subsequent meetings, leaving long-term policy expectations unchanged; secondly, a factor called $ForGui$ that accounts for changes in market expectations about the future path of policy rates unrelated to the current policy surprise; and, thirdly, a factor called $QuantE$ that has only been active after 2014 and explains only OIS-rates movement at the long-term end of the yield curve.

Following Cieslak and Vissing-Jorgensen (2018) and Schmeling and Wagner (2019) we control for lagged stock market returns ($LagRet$) from the previous PC to the day before the current PC in order to control for the possibility that the ECB might mechanically adjust its general tone to recent market conditions.[15] In addition, we control for policy rate changes with a dummy variable $RateCh$, which is 1 if the ECB announced a change in its policy rate, and 0 otherwise. $UncovMP$ denotes a dummy variable that equals 1 if the event is associated with an unconventional monetary decision and 0 otherwise. Furthermore, like Altavilla et al. (2019) we control for surprises in the Initial Jobless Claims (IJC) issued on a weekly basis during the press conference window since the employment situation is an important macroeconomic indicator that may affect asset prices. Finally, we include two dummy variables for the financial crisis period (01/2008 – 06/2013) and the QE period (07/2013 – 06/2019).[16]

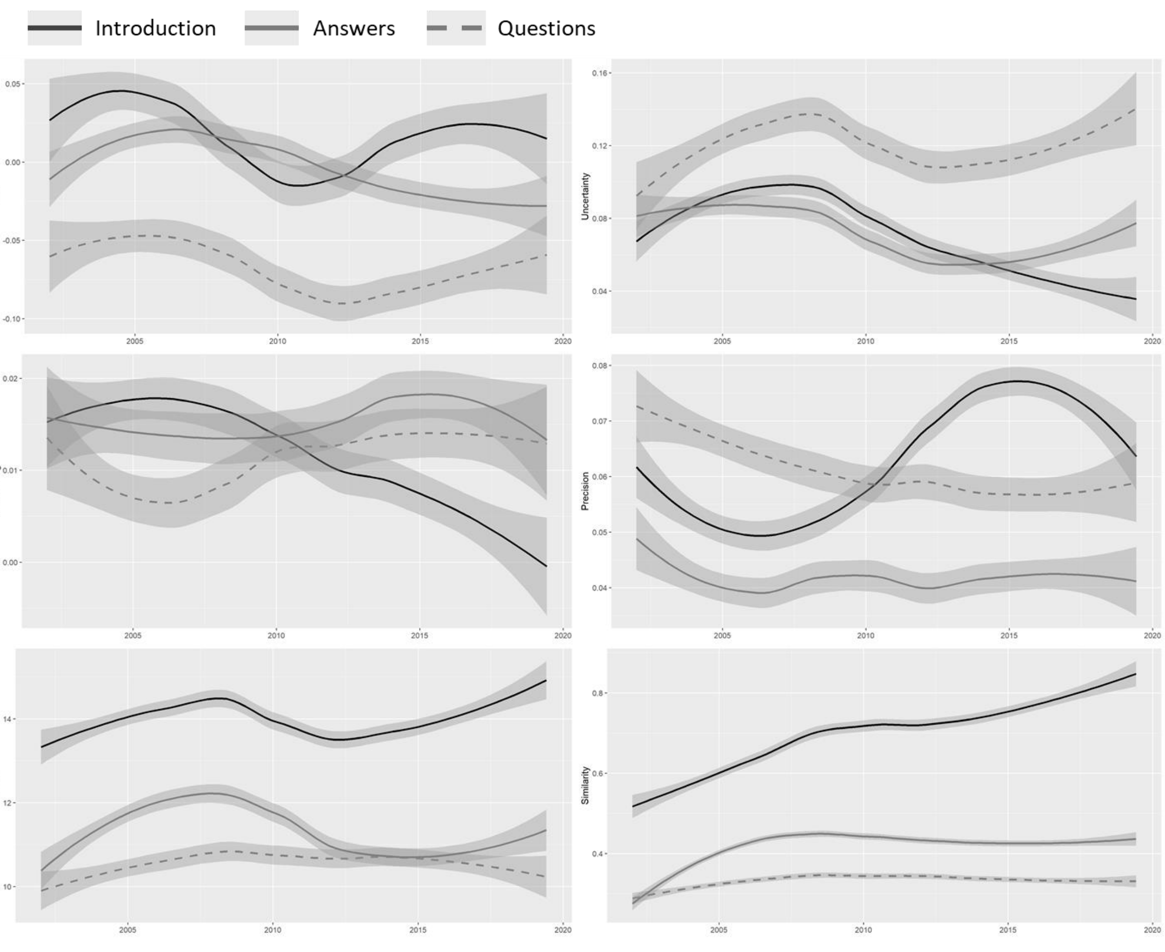
4 Linguistic Characteristics of ECB Press Conferences

ECB press conferences consist of three major segments which we distinguish based on their respective textual dimensions. Each conference begins with a pre-written introductory statement which is generally considered to be the most important part of the press conference (e.g., Berger, de Haan and Sturm, 2011) as it gives insights on monetary policy decisions, the monetary- and the economic analysis conducted by the ECB. On average, the introductory statement makes up about 28% of the total transcript. The introductory statement is followed by a Q&A session between journalists and the ECB President. The questions and answers make up 21% and 51% of the total transcript respectively.

[15] As one might argue that the ECB should ultimately be more concerned with macroeconomic rather than financial stability, it was decided to replace the lagged returns variable with the Economic Sentiment Indicator of Eurostat as an additional robustness check. Including the Economic Sentiment Indicator does not change any of the main results.

16 Please note that the results of our subsample analysis regarding the QE-Period should be interpreted cautiously as we could only cover a rather short time period with 54 observations.

Figure 1 shows the trend lines as well as the individual characteristics of each text-mining variable over time for the introductory statement, the questions and answers. The abscissa presents the years of the press conference under review whereas the ordinate measures the intensity of the respective text-mining variables. The first three plots show the heuristic-adjusted scores for (i) the overall sentiment, measured using the positive and negative LM (2011) word lists, (ii) uncertainty sentiment based on the LM (2011) uncertainty word list and (iii) constraining sentiment using the word list proposed in Bodnaruk et al. (2015). The fourth plot (iv) shows the fraction of precise content for each part of the transcript, followed by (v) the Gunning-Fog index capturing the complexity of texts. Finally, the sixth graph (vi) presents the similarity of each consecutive press conference. All graphs show smoothed trends and confidence intervals displayed in light grey.



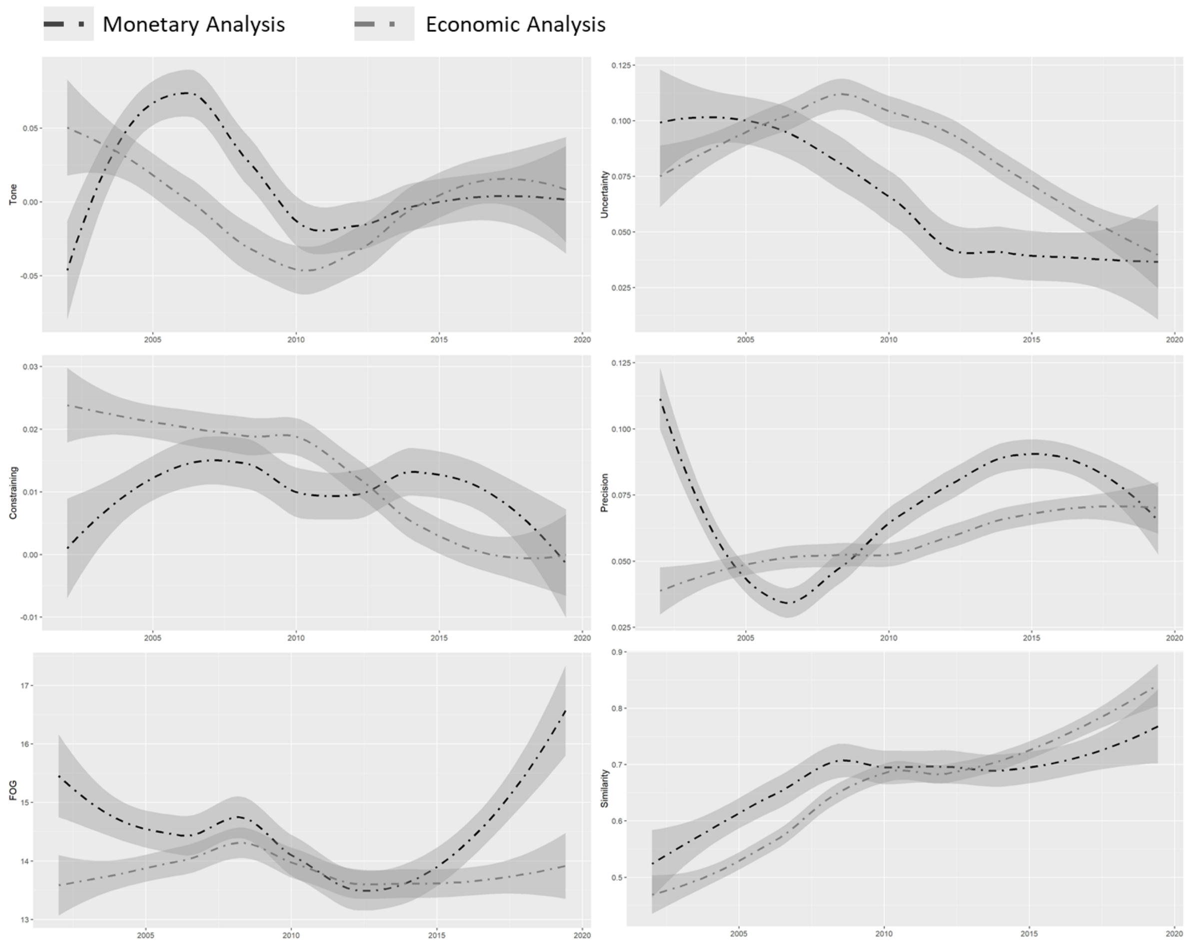
In line with expectations, the three different segments of the ECB press conferences clearly differ in almost every textual dimension. First, the graphs display some interesting differences concerning the choice of words in the Q&A session. The sentiment scores indicate that journalists ask rather critical questions, whereas the ECB Presidents tend to answer in a more neutral manner. An n-gram analysis of the uncertainty score shows that the higher level of uncertain language in the questions is driven by a higher fraction of weak modal verbs which might be due to the formal nature of questions ("*could* you please tell…"). Interestingly, the answers are considerably less precise than the introductory statement and the questions, indicating that the ECB aims to provide relevant information through their introductory statements. Moreover, the answers show a higher level of similarity than the questions, indicating that the ECB Presidents tend to answer questions in a more standardized manner.

Second, we find interesting trends in language used in the introductory statement: the prewritten nature of the introductory statement is reflected in its high similarity score and its high Gunning-Fog index, measuring the complexity of texts.[17] This indicates that due to the higher degree of standardization in the introductory statement, ECB officials can carefully consider their choice of words, leading to texts with on average longer sentences and more "complex words". The overall sentiment score on average is positive, showing lower scores during the financial crises. Interestingly, starting with the financial crisis in 2008 the ECB continually reduces words expressing uncertain sentiment, while it simultaneously increases the precision in its introductory statement. Coenen et al. (2017) emphasise the increased importance of clarity in central bank communication, suggesting that central bank statements which are not sufficiently clear, can generate noise in communication. Therefore, reducing imprecise words and increasing the fraction of specific information could be an attempt of the ECB to enhance the effectiveness of their FG. Moreover, the introductory statement shows a strong tendency towards a higher level of standardization, which may reduce the uncertainty about the content of future press conferences. In contrast, it is still worthwhile noticing that the precision score of the introduction shows a downward trend starting around 2015.

For a deeper understanding of ECB communication, the introductory statement is separated into two sections concerning (i) the monetary analysis and (ii) the economic

[17] Given the increase in similarity and complexity over time, one could raise the question whether the empirical analysis conducted by us might be biased by these trends. This would especially be the case if there is a causal link between higher Gunning-Fog or similarity scores and either one of the sentiment dimensions. Given these concerns, research in the field of accounting and finance was carefully reviewed. However, to the best of our knowledge, there is no research that suggests a causal relationship between certain sentiment dimensions and readability or similarity which could raise serious concerns about the empirical analysis as such.

analysis. To avoid subjectivity, each introductory statement is separated based on its clear structure. Paragraphs containing and following bold words such as “key interest rate” or “monetary analysis/policy” are labeled as monetary analysis texts whereas paragraphs containing and following bold words such as “economic analysis”, “structural policies” and “fiscal policies” are labeled as economic analysis sections. Paragraphs containing a “cross-check” of the monetary policy and the economic analysis are not considered in the analysis. All bold words are identified based on their HTML-code. Figure 2 shows the textual dimensions for both parts of the introductory statement.



Firstly, some trends such as lower uncertainty scores over time, the tendency towards higher standardization and the impact of the financial crisis on the overall tone are found by us to be consistent with our findings mentioned above. However, the decrease in the fraction of constraining words are mainly driven by the choice of words in the economic outlook. This seems plausible as the expansive monetary policy of the ECB should not constrain firms but open new possibilities that encourage economic growth. Consistently, the negative trend in constraining language is in line with a more positive sentiment in the economic analysis. As presented by the precision score, the ECB gradually increases the fraction of specific information over time whereas the blue graph shows a strong decrease starting in 2002 followed by an increase during the financial crisis until it decreases again in 2015. The high precision scores in the beginning of the observed period are due to a different structure of the introductory statement in which the text concerning monetary policy was usually one paragraph long but still loaded with specific information.[18] While the increase of specific information is consistent with the ECB using FG as a policy tool more often during the period of the lower zero bound, it is however worth mentioning that the decrease of specific content in the monetary policy section after 2015 is accompanied by a sharp increase in complexity measured by the Gunning-Fog index. This might indicate that monetary policy decisions become more complex to communicate when the economy is stuck at the zero-lower bound.

5 Empirical Results

In our baseline analysis, we focus on the introductory statements of the ECB press conferences as market participants perceive these statements to be most informative for the future path of monetary policy decisions (e.g., Conrad and Lamla, 2010). Table 1 presents the empirical results of a regression model, where we regress intraday returns calculated within the press conference window for the STOXX50 (model 1) and SX7E (model 2) on the text-mining variables, the monetary surprise factors, as well as the other control variables. The regression models for each textual dimension as well as for the full model are estimated separately.

The variable $Tone$ is significantly positive on the 5% level for both indices, indicating that a more positive (negative) language is associated with higher (lower) intraday returns. This finding is generally consistent with evidence proposed in Schmeling and Wagner (2019). However, the estimates of $Tone$ indicate a greater impact of sentiment on the SX7E index compared to the STOXX50 index. This result seems plausible, as banks' business models are inherently more interest rate sensitive. Therefore, market expectations about the future path of monetary policy are likely to have a greater impact

[18] We identify a structural break between the two press conferences on the 03/04/2003 and on the 08/05/2003. This is consistent with the rapid decrease shown in the blue graph.

on financial firms, e.g., banks. These effects also have economic significance given the fact that a standard deviation increase (decrease) of one in $Tone$ translates into a positive (negative) return of around 12 basis points on press conference days. Keeping in mind that the ECB holds between 10 to 12 press conferences a year, this amounts to a return of 1.2 to 1.4 percent p.a.. This hypothesis finds support from the control variables FG and RC, indicating that FG monetary policy surprises and interest rate changes negatively affect the bank-specific index SX7E, whereas the coefficients for the STOXX50 are only significant on a 10% level.

We are first to analyse the effects of constraint- and uncertainty-related language as well as the fraction of precise content captured by the variables Unc, Con and Pre respectively. The full models 9 and 10 do not present any significant results. Only for the separate models 4 and 6, are Con and Unc found to have significant positive effects on SX7E returns, which is statistically significant on the 10% level. However, FG is an important tool for policymakers in times where conventional policy tools are less effective (e.g., Woodford, 2012). In addition, Wiederholt (2016) suggests that once monetary policy reaches the effective lower bound, central bank communication and therefore FG plays an increasingly important role in mitigating the risks of deflationary trends. This raises the question whether the effects of linguistic characteristics on stock returns may differ in respect to a changing macroeconomic environment. Therefore, a subsample analysis separating our sample into three specific time periods is conducted: The i) Pre-Crisis sample covers the time period from January 2002 until December 2007 followed by the ii) Crisis sample from January 2008 until June 2013, which covers the takeover of Bear Stearns in May 2008 and the bankruptcy of Lehman Brothers in September 2008, two of the major events at the beginning of the Global Financial Crisis. Finally, the iii) Quantitative Easing (QE) sample from July 2013 until June 2019 covers the period starting with the ECB press conference at which former ECB President Mario Draghi first used formal FG on the future path of key ECB interest rates by stating that policy rates were expected to remain at present or lower levels for an extended period, leading the ECB to focus on unconventional monetary policy tools for the rest of the sample period.[19]

[19] Please note that we recognize that the definitions of such subsamples are inevitably imperfect. Thus, in additional robustness analyses, we modified the subsamples and were able to conclude that our main results remain unchanged.

The findings indicate that the effects of positive tone in the introductory statement are mainly driven by the Crisis period. In line with Coenen et al. (2017) it is argued that economic agents might not fully understand the decision taken by central banks in times of high uncertainty. Thus, if market participants do not fully grasp the reasoning behind monetary policy decisions, it could be the positivity or negativity conveyed through policy makers' choice of words that impact investor sentiment and consequently, move markets. Again, the coefficients of $Tone$ indicate stronger effects for the SX7E index.

Table 2 shows that the variables Unc and Pre have no significant effects on stock returns for the subsample analysis. Interestingly, we find a positive relationship between constraining sentiment (Con) and the returns in the QE period that is significant on the 5% and 1% level for the STOXX50 and SX7E index, respectively. Consistent with prior findings, market reactions are stronger for the SX7E index compared to the STOXX50 index.

In general, stronger constraining sentiment indicates that policy makers state to be constrained in their scope of action. However, central bankers may also use constraining language to express policy commitment, as the most logical way for central bankers to achieve credible commitment is by publicly stating the commitment within public press conferences. To provide additional support for this claim, n-gram analysis is conducted in order to point out words that drive the constraining sentiment. Unreported results show that 50% of constraining word-matches within the QE-Period subsample are *mandate*, *commitment*, and *committed*, while in 90% of all cases, the word *commitment* is preceded by the word *unanimous*. This result is particularly interesting as it highlights the group-based nature of the decision-making process of the ECB Governing Council (e.g., Blinder 2007). ECB policymakers are obviously concerned with enhancing the credibility of their commitment by the consensus around policy decisions. At the same time, rising tensions between the official communication of the Governing Council and dissenting voices of individual members of the Governing Council in the press are observed. Thus, we think future research on central bank communication should examine the medium- and long-term implications of policy including, but not limited to, heterogenous beliefs of ECB council members with regards to the overall effectiveness of monetary policy.

Overall, these results suggest that market participants appreciate communicating a strong commitment in times of the zero lower bound as it reduces uncertainties about the future path of the ECB's monetary policy decisions. Furthermore, these findings are also consistent with Woodford (2012) and Filardo and Hofmann (2014) who argue that effective FG requires a credible commitment of central banks to shape market expectations.

Table 1: Baseline regression of intraday returns on ECB communication – Full Sample

Asset	(1) STOXX50	(2) SX7E	(3) STOXX50	(4) SX7E	(5) STOXX50	(6) SX7E	(7) STOXX50	(8) SX7E	(9) STOXX50	(10) SX7E
Tone	0.012 **	0.022 **							0.013 **	0.015 **
	(0.006)	(0.01)							(0.007)	(0.008)
Con			0.067	0.121 *					0.079	0.128
			(0.042)	(0.063)					(0.057)	(0.098)
Unc					0.014	0.027 *			0.022	0.029
					(0.015)	(0.019)			(0.020)	(0.032)
Pre							0.004	-0.043	0.022	-0.026
							(0.029)	(0.047)	(0.036)	(0.059)
FOG	0.039	0.066	0.064	0.111 *	0.052	0.088	0.058	0.099	0.014	0.022
	(0.052)	(0.068)	(0.049)	(0.065)	(0.053)	(0.069)	(0.051)	(0.068)	(0.061)	(0.077)
Timing	0.001	0.006	-0.000	0.003	0.001	0.006	0.001	0.006	-0.003	-0.003
	(0.02)	(0.026)	(0.02)	(0.026)	(0.02)	(0.026)	(0.02)	(0.025)	(0.020)	(0.025)
ForGui	-0.030 ***	-0.048 ***	-0.026 *	-0.041 **	-0.028 **	-0.045 **	-0.029 **	-0.045 **	-0.024 *	-0.038 **
	(0.014)	(0.019)	(0.015)	(0.019)	(0.014)	(0.018)	(0.014)	(0.019)	(0.014)	(0.019)
QuantE	0.017	0.109	0.021	0.116	0.019	0.111	0.018	0.112	0.018	0.114
	(0.045)	(0.079)	(0.045)	(0.08)	(0.045)	(0.081)	(0.046)	(0.081)	(0.046)	(0.080)
LagRet	-0.138	-0.088	-0.130	-0.081	-0.135	-0.084	-0.134	-0.0856	-0.155	-0.126
	(0.119)	(0.144)	(0.116)	(0.142)	(0.118)	(0.148)	(0.119)	(0.147)	(0.121)	(0.140)
RateCh	-0.218 *	-0.362 *	-0.239 *	-0.400 ***	-0.240 *	-0.401 **	-0.234 *	-0.396 **	-0.166	-0.265
	(0.126)	(0.184)	(0.122)	(0.182)	(0.123)	(0.186)	(0.125)	(0.187)	(0.120)	(0.175)
UncovMP	0.116	0.711	0.113	0.703 *	0.132	0.748 *	0.076	0.737	-0.007	0.508
	(0.350)	(0.450)	(0.324)	(0.3996)	(0.329)	(0.408)	(0.339)	(0.468)	(0.327)	(0.441)
IJC	-0.086 *	-0.071	-0.089 *	-0.076	-0.088 *	-0.074	-0.091 *	-0.083	-0.069	-0.045
	(0.048)	(0.075)	(0.048)	(0.077)	(0.049)	(0.076)	(0.048)	(0.076)	(0.047)	(0.070)
Crisisdum	-	-	-	-	-	-	-	-	0.004	-0.140
									(0.113)	(0.156)
QEdum	-	-	-	-	-	-	-	-	0.215	0.367 *
									(0.143)	(0.205)
Obs	184	184	184	184	184	184	184	184	184	184
Adj. R^2	0.036	0.066	0.037	0.070	0.030	0.059	0.026	0.060	0.041	0.087
F	2.468	2.737	2.416	3.206	2.210	3.077	2.038	2.470	2.034	3.017
P	0.011	0.005	0.013	0.001	0.024	0.002	0.038	0.011	0.018	0.000

The table presents results of the baseline regression model, which involves time series data and is estimated using OLS with White robust standard errors. Model 1 to 8 regress intraday returns of the EuroStoxx 50 and SX7E on each dimension of the text mining variables separately as well as on monetary surprise factors and control variables. Table A.1 (Appendix) outlines definitions of the variables. ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

As the next step of the analysis of central bank communication, we divide the introductory statement into two segments containing information about (i) the monetary analysis and (ii) the economic analysis.[20] Consequently, each text-mining variable for both segments is calculated separately.

[20] In Section 3, we propose an approach to separate the sections based on the HTML-code of the transcript.

Table 2: Regression of intraday returns on ECB communication – Subsample

	FULL SAMPLE		PRE-CRISIS		CRISIS		QE-PERIOD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asset	STOXX50	SX7E	STOXX50	SX7E	STOXX50	SX7E	STOXX50	SX7E
$Tone$	0.013 **	0.015 **	-0.006	-0.008	0.0296 **	0.0356 **	0.014	0.044 *
	(0.007)	(0.008)	(0.014)	(0.012)	(0.014)	(0.018)	(0.016)	(0.022)
Con	0.079	0.128	0.0174	0.015	0.054	0.185	0.181 **	0.258 ***
	(0.057)	(0.098)	(0.053)	(0.048)	(0.104)	(0.220)	(0.092)	(0.093)
Unc	0.022	0.029	-0.023	0.001	-0.008	-0.067	-0.013	0.031
	(0.020)	(0.032)	(0.021)	(0.021)	(0.045)	(0.085)	(0.070)	(0.090)
Pre	0.022	-0.026	-0.022	-0.020	0.014	-0.090	0.050	-0.037
	(0.036)	(0.059)	(0.048)	(0.047)	(0.075)	(0.151)	(0.078)	(0.135)
FOG	0.014	0.022	0.149 **	0.132 **	0.099	0.259	-0.156	-0.248 *
	(0.061)	(0.077)	(0.050)	(0.045)	(0.128)	(0.220)	(0.139)	(0.173)
$Timing$	-0.003	-0.003	-0.034	-0.024	0.023	0.033	-0.239 **	-0.323 **
	(0.020)	(0.025)	(0.027)	(0.025)	(0.022)	(0.031)	(0.106)	(0.143)
$ForGui$	-0.024 *	-0.038 **	0.011	-0.001	-0.011	-0.008	-0.198 **	-0.268 **
	(0.014)	(0.019)	(0.020)	(0.021)	(0.018)	(0.029)	(0.094)	(0.116)
$QuantE$	0.018	0.114	-0.038	-0.042	0.133 **	0.289 **	-0.045	0.066
	(0.046)	(0.080)	(0.048)	(0.046)	(0.065)	(0.141)	(0.051)	(0.076)
$LagRet$	-0.155	-0.126	-0.178	-0.244 *	0.001	-0.008	-0.147	-0.218
	(0.121)	(0.140)	(0.128)	(0.137)	(0.156)	(0.212)	(0.247)	(0.171)
$RateCh$	-0.166	-0.265 **	-0.410 **	-0.406 **	-0.044	-0.232	0.229	0.376
	(0.120)	(0.175)	(0.145)	(0.153)	(0.194)	(0.363)	(0.410)	(0.596)
$UncovMP$	-0.007	0.508					-0.334	0.192
	(0.327)	(0.441)					(0.295)	(0.470)
IJC	-0.069	-0.045	-0.123 *	-0.130 **	-0.014	-0.037	-0.183	-0.054
	(0.047)	(0.070)	(0.064)	(0.058)	(0.082)	(0.137)	(0.140)	(0.167)
$Crisisdum$	0.004	-0.140	-	-	-	-	-	-
	(0.113)	(0.156)						
$QEdum$	0.215	0.367 *	-	-	-	-	-	-
	(0.143)	(0.205)						
Obs	184	184	66	66	64	64	54	54
Adj. R^2	0.041	0.087	0.171	0.209	0.129	0.144	0.263	0.200
F	2.034	3.017	3.126	3.206	2.422	2.393	2.913	3.571
P	0.018	0.000	0.003	0.002	0.007	0.008	0.005	0.001

The table presents results of the regression model for our subsample analysis, which involves time series data and is estimated using OLS with White robust standard errors. Model 1 to 8 regress intraday returns of the EuroStoxx 50 and SX7E on text mining variables, monetary surprise factors and control variables for the Full Sample-, Pre-Crisis- (1/2002-12/2007), Crisis- (1/2008-6/2013) and QE-period (7/2013-6/2019). Table A.1 (Appendix) outlines definitions of the variables. ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 3 presents the results of a regression model, where we regress intraday returns calculated within the press conference window for the STOXX50 (model 1) and SX7E (model 2) on the text-mining variables for each segment. For the purpose of brevity, the results for the monetary surprise factors and the other control variables are not reported. However, qualitatively the results remain the same compared to the subsample analysis.[21]

Table 3: Regression of intraday returns on ECB communication – Monetary and Economic analysis

	FULL SAMPLE		PRE-CRISIS		CRISIS		QE-PERIOD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asset	STOXX50	SX7E	STOXX50	SX7E	STOXX50	SX7E	STOXX50	SX7E
Mon_Tone	0.005	-0.003	0.023 ***	0.023 **	-0.004	-0.017	-0.008	-0.020
	(0.008)	(0.012)	(0.009)	(0.01)	(0.012)	(0.019)	(0.021)	(0.03)
Mon_Con	0.053	0.062	0.015	0.017	0.030	0.073	0.125 ***	0.091 **
	(0.034)	(0.059)	(0.034)	(0.031)	(0.060)	(0.147)	(0.036)	(0.043)
Mon_Unc	-0.017 **	-0.004	-0.004	0.003	-0.045 **	-0.085 **	-0.034	0.050
	(0.008)	(0.014)	(0.014)	(0.012)	(0.022)	(0.039)	(0.047)	(0.067)
Mon_Pre	-0.000	-0.019	0.016	0.018	-0.050	-0.211	0.058	0.058
	(0.02)	(0.034)	(0.021)	(0.021)	(0.068)	(0.149)	(0.055)	(0.078)
Eco_Tone	0.016 **	0.038 **	-0.009	-0.010	0.031 *	0.062 *	0.030	0.048
	(0.007)	(0.015)	(0.011)	(0.01)	(0.018)	(0.035)	(0.024)	(0.038)
Eco_Con	0.035	0.049	0.016	0.007	0.013	0.058	0.129	0.352
	(0.032)	(0.051)	(0.038)	(0.037)	(0.057)	(0.108)	(0.199)	(0.310)
Eco_Unc	0.048 ***	0.048 *	0.012	0.021	0.071 **	0.077 *	0.082 **	0.065 *
	(0.015)	(0.025)	(0.016)	(0.016)	(0.031)	(0.045)	(0.036)	(0.033)
Eco_Pre	0.044 *	0.061	-0.009	-0.008	0.060	0.108	0.031	-0.005
	(0.023)	(0.038)	(0.042)	(0.040)	(0.042)	(0.080)	(0.048)	(0.071)
Obs	184	184	66	66	64	64	54	54
Adj. R^2	0.101	0.104	0.196	0.250	0.287	0.272	0.284	0.181
F	2.882	2.648	2.856	2.797	2.012	2.623	5.078	3.775
P	0.000	0.001	0.002	0.003	0.032	0.005	0.000	0.000

The table presents results of the regression model for our subsample analysis, which involves time series data and is estimated using OLS with White robust standard errors. Model 1 to 8 regress intraday returns of the EuroStoxx 50 and SX7E on text mining variables for monetary and economic analysis, monetary surprise factors and control variables for the Full Sample-, Pre-Crisis- (1/2002-12/2007), Crisis- (1/2008-6/2013) and QE-period (7/2013-6/2019). Table A.1 (Appendix) outlines definitions of the variables. ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

The results show that the monetary analysis segment primarily accounts for the statistically significant positive effect of constraining language (Mon_Con) on stock returns during the QE-Period. Consistent with Berger, de Haan and Sturm (2011) who

[21] Unreported results on the other regression variables are available upon request.

find that the monetary analysis was not an important determinant of the ECB's actions in its early years, we find no significant relationship of this language dimension prior to the QE sample. Moreover, consistent with the assumption that the commitment driven Odyssean FG exclusively relates to the ECB's path of monetary policy, no significant results for the constraining score of the economic analysis are found. The positive commitment effect is also sizable in economic terms as one standard deviation increase (decrease) in Mon_Con translates into an annualized return of 4.6 percent for the STOXX 50 and 6.6 percent for the SX7E both distinctly higher than the average annualized return of both indices over the QE-period.

It is also found that uncertain language in the monetary analysis (Mon_Unc) has a significantly negative effect on stock returns in times of crisis. This result indicates that vague statements of central bankers on how they seek to address imminent financial risks within their monetary policy strategy seem to amplify market uncertainty and therefore reduce stock returns. In contrast, using vague language and addressing economic and financial risks in their economic outlook (Eco_Unc) has a significantly positive influence on the stock returns in the Crisis- and the QE-period.

To understand these results, it is necessary to consider the primary objectives of the monetary analysis and economic analysis segments. Within the monetary analysis, the ECB Presidents reflect on their *current* course of monetary policy. Consequently, stating commitment (Mon_Con) will reduce uncertainty about the future path of monetary policy fostering expectations of further policy accommodation in the Crisis- and QE-Period. However, if central bankers only vaguely explain their monetary policy strategy in the monetary policy segment (Mon_Unc), the future path of monetary policy is rather nebulous, thus leading to negative market reactions. This evidence is broadly in line with the theoretical model of Pastor and Veronesi (2013) predicting that political uncertainty commands a risk premium.

In the economic analysis, central bankers use economic projections to forecast the macroeconomic environment as part of their Delphic FG.[22] Projecting economic and financial risks going forward can influence stock returns in two different ways. Firstly, in line with evidence provided by Jarocinski and Karadi (2018), these projections can induce information shocks that may decrease stock returns. Secondly, market participants might

[22] Unreported results show that the economic analysis section contains significantly more forward-looking statements compared to the monetary policy section.

interpret central bank communication addressing potential economic and financial risks, which may weaken the macroeconomic environment as a signal of expansive monetary policy decisions. Our results indicate that the second effect of Delphic FG seems to dominate based on language used in the economic analysis. To the best of our knowledge, this paper is first to provide empirical evidence on the effects central bank language within Delphic FG. Finally, Eco_Tone has a significantly positive effect on both STOXX50- and the SX7E-returns, whereas Mon_Tone is only significant for the Pre-Crisis period.

6 Additional Analysis

Since the literature on ECB communication generally suggests that the introductory statement is the most important part of the press conferences, the Q&A sessions have been of very little interest in prior research. However, not only does the Q&A Session account for a significant part of the conference (up 51% of the total transcripts), but we also believe that, due to the prewritten nature of the introductory statement, the answers of ECB Presidents are much less standardized.[23] Therefore, journalists may well succeed in having ECB Presidents disclose further information relevant to capital markets in their answers.

Thus, the baseline regression is re-run by us using only answers given during the Q&A session. The results presented in Panel A of Table 4 show that the coefficients of $Tone$ are only significant on the 10% level for the Crisis- and the QE-period, whereas all other text mining variables remain insignificant. This indicates that the language used in the Q&A sessions is of less importance for capital markets compared to the introductory statements.

A possible explanation for this might be that journalists frequently ask central bankers for their opinion on current or even past economic and political events. Nevertheless, since financial markets are inherently forward-looking, any ex-post rationalizations of past events do not influence market expectations today. Therefore, it is argued that analysing statements that address a future point in time can be of great importance especially for the answers given by the ECB Presidents during the Q&A sessions.

[23] In fact, in Section 4 of this paper, we show that the similarity between the introductory statements over time is on average about twice as high compared to the answers given by ECB Presidents over time for the whole sample period. For an analysis how similarity in central bank press release the capital market reactions, see Ehrmann and Talmi (2017).

For further analysis, we intend to focus on statements offering clarifications on the future path of monetary policy. Galardo and Guerrieri (2017) were the first to analyse the effects of forward-looking statements in central bank communication. They rely on the fact that English can be classified as a "strong future-time reference" language as it requires auxiliary and modal verbs to mark the timing of future events. Therefore, they identify forward-looking statements by simply counting the occurrences of auxiliary and modal verbs such as *will* or *might*. However, this method can be subject to severe biases as it fails to identify forward-looking sentences that do not contain auxiliary or modal verbs.[24] For example, it leaves out the specifics of ECB communication since the ECB often provides FG through their economic and monetary outlook. For instance, the sentence "the outlook for real GDP growth has been revised down for 2019 and 2020" would not be considered forward-looking even though it contains important information about the future.

Therefore, a novel rule-based text mining approach to identify forward-looking statements in ECB press conferences is proposed. Firstly, each sentence is tested for whether it contains "will", "going to", "outlook" or "projection". The auxiliary verbs "will" and "going to" are used to express future tense, whereas the words "outlook" and "projection" are often used in ECB press conferences to provide forward-looking information about the ECB's monetary and economic analysis.[25] Secondly, in order to identify date-related text NER is applied using the *spaCy* module provided in *Python*. Date-related text usually consists of dates or years such as "1st January 2019" and "2019" but also phrases that are somehow related to a particular point in time such as "last year" or "this week". For each Named Entity labelled as "DATE", regular expressions are used to test whether it contains a four-digit year. If it contains a year that is greater than the year of the press conference under review, the sentence is labelled as a forward-looking statement.[26] In order to account for future-related expressions that do not include four-digit years, all Named Entities labelled as "DATE" of all press conferences are collected and expressions that relate to a future point in time are manually identified.

[24] In addition, some words in the list can also appear in past tense sentences.
[25] For instance, see the introductory statement of the ECB on 25 July 2019: "Accordingly, if the medium-term inflation *outlook* continues to fall short of our aim, the Governing Council is determined to act, in line with its commitment to symmetry in the inflation aim."
[26] For instance, see the introductory statement of the ECB on 25 July 2019: "First of all the introduction of the easing bias through the introduction of the word "lower", and at least through the first half of *2020* and in any case, for as long as necessary to ensure the continued sustained convergence of inflation to our aim over the medium term".

In total, a glossary of 86 future-related expressions is identified that does not contain four-digit years such as "next year" or "the end of this year". Therefore, a sentence is also labelled as a forward-looking statement if it contains one of these future-related expressions. However, for the purpose of this study, this methodology might be subject to bias as it identifies a significant number of sentences that are negligible for investors. For instance, the sentence "we will now report on the outcome of today's meeting" is in some manner future-related but should have no impact on market expectations. To mitigate methodical biases and reduce noise in textual analysis, we focus on sentiment-bearing forward-looking statements of the ECB Presidents.

Figure 3 shows the length and the number of forward-looking statements with either positive, negative, uncertain, or constraining sentiment for the introductory statements and the answers given in the Q&A-session.[27] The graphs clearly show that the answers are significantly longer than the introductory statement. In comparison, the introductory statements contain more forward-looking statements even though it is on average much shorter. Consistent with Coenen et al. (2017), it is found that the introductory statements of the ECB have on average become more forward-looking. However, this finding is only limited to the introductory statement. While the length of the answers increases, the number of future-related statements decreases, starting in the time of the financial crises. This may indicate that the ECB became more aware of the impact of their communication, tending to communicate forward-looking information in a more controlled manner by, for instance, using the introductory statement instead of the Q&A session.

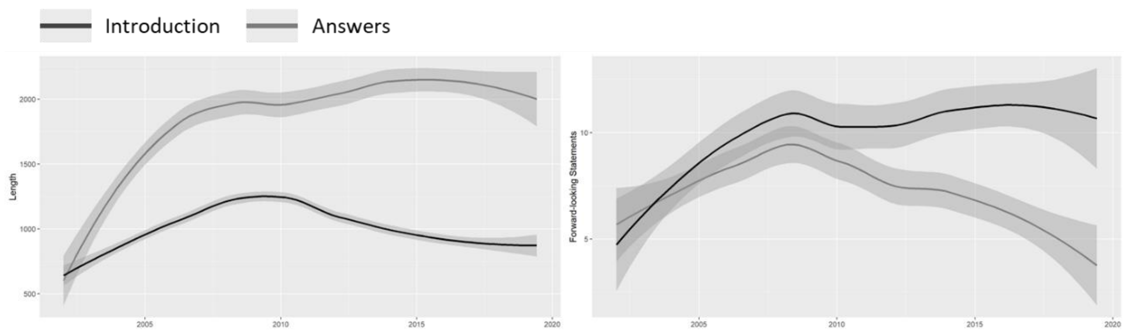


Table 4 Panel B shows the regression results using answers with forward-looking sentiment. Each sentiment dimension is calculated as the average sentiment score of the forward-looking statements for tone, constraining and uncertain sentiment. In line with expectations, focusing on forward-looking information mitigates noise arising from

[27] *Length* is defined as the total word count after stop word removal.

irrelevant information within the Q&A session. Forward looking statements that bear positive (negative) sentiment ($Tone\_F$) are associated with increasing (decreasing) intraday stock returns during times of financial crises. This finding corroborates the results of our subsample analysis. If market participants do not fully understand current policy actions, the positivity or negativity in central bankers' language might affect investor sentiment and market expectations in times of high uncertainty. Finally, consistent with the subsample analysis, the uncertainty sentiment Unc_F is found to be associated with increasing intraday returns during the pre-crisis period and the constraining sentiment to be also associated with increasing intraday returns during the QE-period.[28]

As an additional robustness test, the event window is extended to account for possible influences of the announcement effects arising from the policy decisions released prior to the press conferences. Therefore, we re-estimate our regression models using intraday returns in the monetary event window including stock price movements during the press release window from the EA-MPD provided by Altavilla et al. (2019).[29] Table 5 presents the results for the regression of intraday stock returns on text-mining variables for the monetary and economic analysis section. The significantly positive effects of constraining sentiment (Mon_Con) in the QE period suggest robustness for our results that central bank language supports the conduct of Odyssean FG. In addition, the results are generally consistent with the results regarding the role of central bank language in ECB' Delphic FG. In addition, the time frames are also adjusted by us for our subsample analyses. Unreported results are qualitatively the same. Finally, following Schmeling and Wagner (2019), a measure for similarity (Sim) is also included in our baseline regression to control for an additional dimension of language. Consistent with the findings of Schmeling and Wagner (2019), Sim is not significant for any analysis while the other results are consistent with prior findings.

[28] Estimating the regression models for the introductory statements focusing on expressions with forward looking sentiment confirm our prior findings. The unreported results are available upon request.

[29] The monetary event window is defined as change in the median quote from the window 13:25-13:35 before the press release to the median quote in the window 15:40-15:50 after the press conference.

Table 4: Regression of intraday returns on ECB communication – Forward-looking Statements

	FULL SAMPLE		PRE-CRISIS		CRISIS		QE-PERIOD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asset	STOXX50	SX7E	STOXX50	SX7E	STOXX50	SX7E	STOXX50	SX7E
Panel A: Answers of Q&A Session								
$Tone$	0.006	0.017	-0.007	-0.007	0.038 *	0.064 *	0.045	0.087 **
	(0.013)	(0.018)	(0.018)	(0.019)	(0.021)	(0.036)	(0.035)	(0.042)
Con	-0.021	-0.085	-0.069 *	-0.060	-0.097	-0.315	0.068	-0.010
	(0.047)	(0.083)	(0.040)	(0.041)	(0.143)	(0.311)	(0.098)	(0.150)
Unc	0.013	0.028	-0.001	0.002	-0.063	-0.140	0.072	0.069
	(0.018)	(0.026)	(0.017)	(0.017)	(0.068)	(0.140)	(0.051)	(0.086)
Obs	184	184	66	66	64	64	54	54
Adj. R^2	0.015	0.053	0.139	0.166	0.154	0.172	0.223	0.152
F	1.817	2.168	3.103	3.609	2.467	2.573	2.297	2.094
P	0.046	0.015	0.003	0.000	0.015	0.012	0.024	0.039
Panel B: Answers of Q&A Session (Forward-looking)								
$Tone\_F$	0.001	0.005	-0.002	-0.001	0.012 **	0.026 **	0.002	0.007
	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.011)	(0.007)	(0.012)
Con_F	-0.001	-0.003	-0.005	-0.003	-0.005	-0.010	0.014 **	0.0133
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.008)	(0.007)	(0.011)
Unc_F	0.009 *	0.013 **	0.013 ***	0.013 ***	-0.000	0.004	-0.014	-0.014
	(0.005)	(0.006)	(0.005)	(0.004)	(0.009)	(0.011)	(0.009)	(0.015)
Obs	184	184	66	66	64	64	54	54
Adj. R^2	0.020	0.054	0.254	0.284	0.164	0.196	0.325	0.190
F	1.881	2.553	3.427	5.107	1.942	2.021	3.247	2.804
P	0.040	0.004	0.001	0.000	0.053	0.045	0.002	0.007

The table presents results of the regression models for our analysis of answers given in Q&A sessions (Panel A) as well as forward looking statements in answers given in Q&A sessions (Panel B). Both models involve time series data and are estimated using OLS with White robust standard errors. Model 1 to 8 in each panel regress intraday returns of the EuroStoxx 50 and SX7E on text mining variables, monetary surprise factors and control variables for the Full Sample-, Pre-Crisis- (1/2002-12/2007), Crisis- (1/2008-6/2013) and QE-period (7/2013-6/2019). Table A.1 (Appendix) outlines definitions of the variables. ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5: Baseline regression of intraday returns on ECB communication – Monetary Event Window

	FULL SAMPLE				PRE-CRISIS				CRISIS				QE-PERIOD			
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Asset	STOXX50		SX7E		STOXX50		SX7E		STOXX50		SX7E		STOXX50		SX7E	
Mon_Tone	0.020	**	0.019		0.042	***	0.036	***	0.008		0.008		0.023		0.055	
	(0.009)		(0.017)		(0.013)		(0.013)		(0.014)		(0.027)		(0.023)		(0.038)	
Mon_Con	0.047		0.092		-0.014		-0.010		0.024		0.096		0.100	***	0.150	***
	(0.037)		(0.066)		(0.047)		(0.044)		(0.075)		(0.175)		(0.031)		(0.053)	
Mon_Unc	-0.016		0.003		0.018		0.027	*	-0.076	***	-0.127	**	0.012		0.031	
	(0.011)		(0.019)		(0.015)		(0.014)		(0.024)		(0.047)		(0.046)		(0.070)	
Mon_Pre	0.023		0.034		0.035		0.032		-0.082		-0.251		0.115	**	0.185	**
	(0.022)		(0.045)		(0.032)		(0.029)		(0.078)		(0.160)		(0.045)		(0.095)	
Eco_Tone	0.011	*	0.037	**	-0.003		-0.007		0.021	*	0.045		0.007		0.051	
	(0.006)		(0.016)		(0.013)		(0.012)		(0.012)		(0.040)		(0.029)		(0.047)	
Eco_Con	0.033		0.069		0.016		0.005		0.045		0.142		0.116		0.131	
	(0.041)		(0.065)		(0.053)		(0.048)		(0.070)		(0.138)		(0.211)		(0.273)	
Eco_Unc	0.033	**	0.029		-0.007		0.014		0.056	**	0.038		0.105	**	0.062	
	(0.014)		(0.032)		(0.024)		(0.024)		(0.028)		(0.068)		(0.041)		(0.063)	
Eco_Pre	0.042	*	0.068		0.009		0.003		0.041		0.075		0.006		0.017	
	(0.024)		(0.044)		(0.054)		(0.047)		(0.039)		(0.091)		(0.047)		(0.081)	
Obs	184		184		66		66		64		64		54		54	
Adj. R^2	0.112		0.108		0.201		0.245		0.254		0.289		0.429		0.337	
F	2.822		2.757		2.538		3.350		2.016		2.125		7.033		4.970	
P	0.000		0.001		0.006		0.000		0.030		0.021		0.000		0.000	

The table presents results of the regression model, which involves time series data from the monetary event window (from 13:25 to 15:50) and is estimated using OLS with White robust standard errors. Model 1 to 8 regress intraday returns of the EuroStoxx 50 and SX7E on text mining variables for monetary and economic analysis, monetary surprise factors and control variables for the Full Sample-, Pre-Crisis- (1/2002-12/2007), Crisis- (1/2008-6/2013) and QE-period (7/2013-6/2019). Table A.1 (Appendix) outlines definitions of the variables. ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

7 Conclusion

The objective of this paper is to examine how the language used by central bank officials within their conduct of FG influences stock returns. We aim to provide a linguistic analysis on the effectiveness of ECB' FG based on textual analysis of ECB press conferences.

Therefore, this paper contributes to the existing literature on FG in numerous manners. Firstly, to the best of our knowledge, this paper is the first to provide empirical evidence on how central banks use language in their pursuit of Odyssean FG and Delphic FG. With specific reference to Odyssean FG, it is demonstrated that ECB officials use constraining sentiment to state policy commitment. In line with Woodford (2012) and Filardo and Hofmann (2014), it is found that the use of constraining words and stating commitment has a significant positive effect on intraday stock returns of the STOXX50 and the SX7E in times of unconventional monetary policy. Secondly, consistent with Delphic FG, it is demonstrated that the language used by ECB officials in their economic outlook has a significant effect on intraday returns of the STOXX50 and the SX7E. We find that uncertainty sentiment has a significant positive effect on intraday returns prior to the global financial crisis. Hence, market participants interpret uncertain language and the risk-related choice of words by ECB officials as a signal of upcoming policy accommodation leading to positive stock market reactions. Thirdly, we find that the overall tone of ECB press conferences also has a significant positive effect on intraday stock returns during times of economic uncertainty. Fourthly, by focusing on forward-looking statements within answers by ECB officials during Q&A sessions in ECB press conferences this paper is the first to show that answers significantly influence intraday returns. Additional analyses suggest the robustness of our findings. Moreover, this paper also contributes to the literature of text mining in the field of finance. In this regard, we propose a new and easy-to-adapt approach to gauge the sentiment of financial texts by combining common word lists (Bodnaruk et al., 2015; LM, 2011) and the VADER-heuristics used to assess sentiment intensity provided by Hutto and Gilbert (2014). Furthermore, a novel approach to identify forward-looking statements in ECB press conferences is proposed.

Table A.1: Variable Definition

i) Baseline Analysis

Tone	Heuristic-adjusted sentiment score for positive and negative sentiment in financial texts based on the word lists proposed in LM (2011).
Con	Heuristic-adjusted sentiment score for constraining sentiment in financial texts based on the word lists proposed in Bodnaruk et al. (2015).
Unc	Heuristic-adjusted sentiment score for uncertainty sentiment in financial texts based on the word lists proposed in LM (2011).
Pre	Precision score, capturing the fraction of precise content in text.
Mon_Tone	Heuristic-adjusted sentiment score for positive and negative sentiment in the monetary analysis section of the introductory statement based on the word lists proposed in LM (2011).
Mon_Con	Heuristic-adjusted sentiment score for constraining sentiment in the monetary analysis section of the introductory statement based on the word lists proposed Bodnaruk et al. (2015).
Mon_Unc	Heuristic-adjusted sentiment score for uncertainty sentiment in the monetary analysis section of the introductory statement based on the word lists proposed in LM (2011).
Mon_Pre	Precision score, capturing the fraction of precise content in the monetary analysis section of the introductory statement.
Eco_Tone	Heuristic-adjusted sentiment score for positive and negative sentiment in the economic analysis section of the introductory statement based on the word lists proposed in LM (2011).
Eco_Con	Heuristic-adjusted sentiment score for constraining sentiment in the economic analysis section of the introductory statement based on the word lists proposed Bodnaruk et al. (2015).
Eco_Unc	Heuristic-adjusted sentiment score for uncertainty sentiment in the economic analysis section of the introductory statement based on the word lists proposed in LM (2011).
Eco_Pre	Precision score, capturing the fraction of precise content in the economic analysis section of the introductory statement.

ii) Additional Analysis

Tone_F	Heuristic-adjusted sentiment score for positive and negative sentiment in in forward-looking statements.
Con_F	Heuristic-adjusted sentiment score for constraining sentiment in in forward-looking statements.
Unc_F	Heuristic-adjusted sentiment score for uncertainty sentiment in in forward-looking statements.

Control Variables

Target	Latent factor variable capturing monetary policy surprises about interest rate decisions. See Altavilla et al. (2019) for more details.
Timing	Latent factor variable capturing monetary policy surprises about the near future. See Altavilla et al. (2019) for more details.
ForGui	Latent factor variable capturing changes in market expectations about the future path of policy rates that are unrelated to the current policy surprise. See Altavilla et al. (2019) for more details.
QuantE	Latent factor variable capturing OIS-rates movement at the long-term end of the yield curve. See Altavilla et al. (2019) for more details.
LagRet	Lagged cumulative stock market returns from previous press conference to the day of the current press conference
UncovMP	Dummy variable that equals 1 if the event is associated with an unconventional monetary decision and 0 otherwise.
IJC	Initial Jobless Claims issued on a weekly basis during the press conference window.
FOG	Gunning-Fog index, capturing the readability of texts. The score estimates the years of formal education a person needs to understand the text on the first reading.
Sim	Similarity in language of two following press conferences, calculated as the distance between two Euclidean vectors.
Crisisdum	Crisisdum is a dummy variable set to unity for the Crisis-Period from January 2008 to June 2013 and zero for the rest of the sample period.
QEdum	QEdum is a dummy variable set to unity for the Crisis-Period from July 2013 to June 2019 and zero for the rest of the sample period.

References

Adrian, T., Liang, N. (2018). Monetary Policy, Financial Conditions, and Financial Stability. *International Journal of Central Banking*, 14, 73–132. https://www.ijcb.org/journal/ijcb18q0a3.htm.

Altavilla C., Brugnolini, L., Gürkaynak, R. S., Motto, R., Ragusa, G. (2019). Measuring euro area monetary policy. *Journal of Monetary Economics*, 108, 162–179. https://doi.org/10.1016/j.jmoneco.2019.08.016

Andrade, P., Ferroni, F. (2018). Delphic and Odyssean Monetary Policy Shocks: Evidence from the Euro Area. FRB of Chicago Working Paper No. WP-2018-12. http://dx.doi.org/doi.org/10.21033/wp-2018-12.

Bekaert, G., Hoerova, M., Lo Duca, M. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, 60, 771–788. https://doi.org/10.1016/j.jmoneco.2013.06.003.

Bernanke, B. S. (2004). The Logic of Monetary Policy. *FRB Speech*. https://www.federalreserve.gov/boarddocs/speeches/2004/20041202/default.htm.

Bernanke, B. S., Kuttner, K. N. (2005). What Explains the Stock Market's Reaction to Federal Reserve Policy?. *The Journal of Finance*, 60, 1221–1257. https://doi.org/10.1111/j.1540-6261.2005.00760.x.

Berger, H., de Haan, J., Sturm, J.-E. (2011). Does money matter in the ECB strategy? New evidence based on ECB communication. *International Journal of Finance and Economics*, 16, 16–31. https://doi.org/10.1002/ijfe.412.

Bholat, D., Hansen, S., Santos, P., Schonhardt-Bailey, C. (2015). Text mining for central banks: handbook. *Centre for Central Banking Studies*, 33, 1-19. http://eprints.lse.ac.uk/62548/.

Binder, C. (2017). Fed speak on main street: Central bank communication and household expectations. *Journal of Macroeconomics*, 52, 238–251. https://doi.org/10.1016/j.jmacro.2017.05.003.

Blinder, A., Ehrmann, M., Fratzscher, M., de Haan, J., Jansen, D.-J. (2008). Central Bank Communication and Monetary Policy: A Survey of Theory and Evidence. *Journal of Economic Literature*, 46, 910–945. https://doi.org/10.1257/jel.46.4.910.

Blinder, A., Ehrmann, M., de Haan, J., Jansen, D.-J. (2017). Necessity as the mother of invention: monetary policy after the crisis. *Economic Policy*, 32, 707–755. https://doi.org/10.1093/epolic/eix013.

Bodnaruk, A., Loughran, T., McDonald, B. (2015). Using 10-K Text to gauge financial constraints. *Journal of Financial and Quantitative Analysis*, 50, 623-646. https://doi.org/10.1017/S0022109015000411.

Borio, C., Zhu, H. (2012). Capital regulation, risk-taking and monetary policy: A missing link in the transmission mechanism?. *Journal of Financial Stability*, 8, 236–251. https://doi.org/10.1016/j.jfs.2011.12.003.

Brand, C., Buncic, D., Turunen, J. (2010). The impact of ECB monetary policy decisions and communication on the yield curve. *Journal of the European Economic Association*, 8, 1266–1298. https://www.jstor.org/stable/40961559.

Campbell, J. R., Evans, C. L., Fisher, J., Justiniano, A. (2012). Macroeconomic effects of Federal Reserve forward guidance. *Brookings Papers on Economic Activity*, 2012. https://EconPapers.repec.org/RePEc:bin:bpeajo:v:43:y:2012:i:2012-01:p:1-80.

Campbell, J. R., Fisher, J. D., Justiniano, A., Melosi, L. (2017). Forward guidance and macroeconomic outcomes since the financial crisis. *NBER Macroeconomics Annual*, 31, 283–357. https://doi.org/10.1086/690242.

Campbell, J. R., Sunderam, A., Viceira, L. M. (2017). Inflation bets or deflation hedges? The changing risk of nominal bonds. *Critical Finance Review*, 6 http://cfr.ivo-welch.info/published/campbell-sunderam-viceira.pdf.

Coenen, G., Ehrmann, M., Gaballo, G., Hoffmann, P., Nakov, A., Nardelli, S., Persson, E., Strasser, G. (2017). Communication of monetary policy in unconventional times. *European Central Bank*, Working Paper, No. 2080. https://ssrn.com/abstract=3043098.

Conrad, C., Lamla, M. J. (2010). The High-Frequency Response of the EUR-USD Exchange Rate to ECB Communication. *Journal of Money, Credit and Banking*, 42, 1391–1417. https://doi.org/10.1111/j.1538-4616.2010.00346.x.

Cragg, J. G., Donald, S. G. (1997). Inferring the rank of a matrix. *Journal of Econometrics*, 76, 223-250. https://doi.org/10.1016/0304-4076(95)01790-9

Dougal, C., Engelberg, J., Garcia, D., Parsons, C. (2011). Journalists and the Stock Market. Review of Financial Studies, 25, 639–679. https://doi.org/10.1093/rfs/hhr133.

Drechsler, I., Savov, A., Schnabl, P. (2018). A Model of Monetary Policy and Risk Premia. *The Journal of Finance*, 73, 317–373. https://doi.org/10.1111/jofi.12539.

Eggertsson, G. B., Woodford, M. (2003). The zero bound on interest rates and optimal monetary policy. *Brookings Papers on Economic Activity*, 139-211. https://www.jstor.org/stable/1209148.

Ehrmann, M., Fratzscher, M. (2004). Taking Stock: Monetary Policy Transmission to Equity Markets. *Journal of Money, Credit and Banking*, 36, 719–737. https://www.jstor.org/stable/3839039.

Ehrmann, M., Gaballo, G., Hoffmann, P., Strasser, G. (2019). Can more public information raise uncertainty? The international evidence on forward guidance. *European Central Bank*, Working Paper, No. 2263. https://ssrn.com/abstract=3372933.

Ehrmann, M., Talmi, J. (2019). Starting from a blank page? Semantic similarity in central bank communication and market volatility. *Journal of Monetary Economics*, In Press, Corrected Proof. https://doi.org/10.1016/j.jmoneco.2019.01.028.

Filardo, A., Hofmann, B. (2014). Forward Guidance at the Zero Lower Bound. *BIS Quarterly Review*, March 2014. https://ssrn.com/abstract=2457107.

Gagnon, J., Raskin, M., Remache, J., Sack, B. P. (2010). Large-Scale Asset Purchases by the Federal Reserve: Did They Work?. *FRB of NY Staff Report*, 441, 1–41. http://dx.doi.org/10.2139/ssrn.1576596.

Galardo, M., Guerrieri, C. (2017). The effects of central bank´s verbal guidance: evidence from the ECB. Banca d'Italia Working Papers, No. 1129. http://dx.doi.org/10.2139/ssrn.3040650.

Gerlach, S. (2007). Interest Rate Setting by the ECB, 1999-2006: Words and Deeds. *International Journal of Central Banking*, 3, 1–46. https://www.ijcb.org/journal/ijcb07q3a1.htm.

Gertler, M., Karadi, P. (2015). Monetary Policy Surprises, Credit Costs, and Economic Activity. *American Economic Journal: Macroeconomics*, 7, 44–76. https://doi.org/10.1257/mac.20130329.

de Guindos, L. (2019). Communication, expectations and monetary policy. Speech at the Annual Congress of the European Economic Association, Manchester, 27 August 2019. https://www.bis.org/review/r190827a.htm (visited on 03.02.2020).

Gürkaynak, R. S., Sack, B., Swanson, E. (2005a). Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. *International Journal of Central Banking*, 1, 55–93. https://www.ijcb.org/journal/ijcb05q2a2.htm.

Gürkaynak, R. S., Sack, B., Swanson, E. (2005b). The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models. *American Economic Review*, 95, 425–436. https://doi.org/10.1257/0002828053828446.

Hansen, S., McMahon, M., Prat, A. (2018). Transparency and deliberation within the FOMC: A computational linguistics approach. The Quarterly Journal of Economics, 133, 801-871. https://doi.org/10.1093/qje/qjx045.

Hanson, S. G., Lucca, D. O., Wright, J. H. (2018). The Excess Sensitivity of Long-Term Rates: A Tale of Two Frequencies. *FRB of NY Staff Report*, 810, 1–21. https://ssrn.com/abstract=2943920.

Hanson, S. G., Stein, J. C. (2015). Monetary policy and long-term real rates. *Journal of Financial Economics*, 115, 429–448. https://doi.org/10.1016/j.jfineco.2014.11.001.

Hillert, A., Jacobs, H., Müller, S. (2014). Media makes momentum. *The Review of Financial Studies*, 27, 3467–3501. https://doi.org/10.1093/rfs/hhu061.

Hope, O.-K., Hu, D., Lu, H. (2016). The Benefits of Specific Risk-Factor Disclosures. *Review of Accounting Studies*, 21, 1005–1045. https://link.springer.com/article/10.1007/s11142-016-9371-1.

Hutto, C. J., Gilbert, E. (2014). VADER: A parsimonious rule-based model for sentiment analysis of social media text. Proceedings of the 8th International Conference on Weblogs and Social Media, ICWSM 2014, Conference Paper.

Ippolito, F., Ozdagli, A. K., Perez-Orive, A. (2018). The transmission of monetary policy through bank lending: The floating rate channel. *Journal of Monetary Economics*, 95, 49–71. https://doi.org/10.1016/j.jmoneco.2018.02.001.

Jansen, D. J., de Haan, J. (2007). The Importance of Being Vigilant: Has ECB Communication Influenced Euro Area Inflation Expectations? CESifo Working Paper No. 2134. https://ssrn.com/abstract=1027576

Jarocinski, M., Karadi, P. (2018). Deconstructing Monetary Policy Surprises: The Role of Information Shocks. *ECB Working Paper*, No.2133, https://ssrn.com/abstract=3131573.

Jegadeesh, N., Wu, D. (2017). Deciphering Fedspeak: The Information Content of FOMC Meetings. Working Paper. http://dx.doi.org/10.2139/ssrn.2939937.

Jiménez, G., Ongena, S., Peydro, J.-L., Saurina, J. (2014): Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking?. *Econometrica*, 82, 463–505. https://doi.org/10.3982/ECTA10104

Kane, A., Rogers, J., Sun, B. (2018). Communications Breakdown: The Transmission of Different Types of ECB Policy Announcements. http://box5181.temp.domains/~ndrewkan/wp-content/uploads/2017/12/kane_rogers_sun.pdf

Kim C., Wang K., Zhang L. (2019) Readability of 10-K Reports and Stock Price Crash Risk. Contemporary Accounting Research, 36, 1184–1216. https://doi.org/10.1111/1911-3846.12452.

Krishnamurthy, A., Vissing-Jorgensen, A. (2015). The impact of Treasury supply on financial sector lending and stability. *Journal of Financial Economics*, 118, 571–600. https://doi.org/10.1016/j.jfineco.2015.08.012.

Krugman, P. R., Dominquez, K. M., Rogoff, K. (1998). It's Baaack: Japan's Slump and the Return of the Liquidity Trap. *Brookings Papers on Economic Activity*, 1998, 137–206. https://www.jstor.org/stable/2534694.

Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. *Journal of Monetary Economics*, 47, 523–544. https://doi.org/10.1016/S0304-3932(01)00055-1.

Kuttner, K. N. (2018). Outside the Box: Unconventional Monetary Policy in the Great Recession and Beyond. *Journal of Economic Perspectives*, 32, 121–146. https://doi.org/10.1257/jep.32.4.121.

Leombroni, M., Vedolin, A., Venter, G., Whelan, P. (2018). Central Bank Communication and the Yield Curve. Working Paper. http://dx.doi.org/10.2139/ssrn.2873091.

Li, F. (2008). Annual report readability, current earnings, and earnings persistence. Journal of Accounting and Economics, 45, 221–247. https://doi.org/10.1016/j.jacceco.2008.02.003.

Loughran, T., McDonald, B. (2011). When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *The Journal of Finance*, 66, 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x.

Loughran, T., McDonald, B. (2016). Textual Analysis in Accounting and Finance: A Survey. Journal of Accounting Research, 54, 1187–1230. https://onlinelibrary.wiley.com/doi/epdf/10.1111/1475-679X.12123.

Morris, S., Shin, H. S. (2014). Risk-taking channel of monetary policy: A global game approach. Unpublished Working Paper. https://www.aeaweb.org/conference/2015/retrieve.php?pdfid=368.

Musard-Gies, M. (2006). Do European Central Bank´s Statements Steer Interest Rates In The Euro Zone? *The Manchester School*, 74, 116–139. https://doi.org/10.1111/j.1467-9957.2006.00520.x.

Nakamura, E., Steinsson, J. (2018). High-Frequency Identification of Monetary Non-Neutrality: The Information Effect. *The Quarterly Journal of Economics*, 133, 1283–1330. https://doi.org/10.1093/qje/qjy004.

Pastor, L., Veronesi, P. (2013). Political Uncertainty and Risk Premia. *Journal of Financial Economics*, 110, 520-545. https://doi.org/10.1016/j.jfineco.2013.08.007

Picault, M., Renault, T. (2017). Words are not all created equal: A new measure of ECB communication. *Journal of International Money and Finance*, 79, 136–156. https://doi.org/10.1016/j.jimonfin.2017.09.005.

Rigobon, R., Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics*, 51, 1553–1575. https://doi.org/10.1016/j.jmoneco.2004.02.004.

Romer, C. D., Romer, D. H. (1989). Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz. *NBER Macroeconomics Annual*, 4, 121–170. https://doi.org/10.1086/654103.

Romer, C. D., Romer, D. H. (2004). A New Measure of Monetary Shocks: Derivation and Implications. *American Economic Review*, 94, 1055–1084. https://doi.org/10.1257/0002828042002651.

Rosa, C., Verga, G. (2007). On the consistency and effectiveness of central bank communication: Evidence from the ECB. *European Journal of Political Economy*, 23, 146–175. https://doi.org/10.1016/j.ejpoleco.2006.09.016.

Schmeling, M., Wagner, C. (2019). Does Central Bank Tone Move Asset Prices? Working Paper. http://dx.doi.org/10.2139/ssrn.2629978.

Swanson, E. T. (2017). Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets. *The National Bureau of Economic Research,* Working Paper No. 23311. https://doi.org/10.3386/w23311.

Tetlock, P. C. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market, *The Journal of Finance*, 60, 1139–1168. https://doi.org/10.1111/j.1540-6261.2007.01232.x.

Tsai, F., Lu H., Hung, M. (2016). The impact of news articles and corporate disclosure on credit risk valuation. *Journal of Banking & Finance*. 68, 100–116. https://doi.org/10.1016/j.jbankfin.2016.03.018

Wiederholt, M. (2016). Empirical properties of inflation expectations and the zero lower bound. Working Paper, Goethe University.

Woodford, M. (2001). Monetary Policy in the Information Economy. *The National Bureau of Economic Research,* Working Paper No. 23311. https://doi.org/10.3386/w8674.

Woodford, M. (2005). Central bank communication and policy effectiveness. *The National Bureau of Economic Research*, Working Paper No. 11898. http://www.nber.org/papers/w11898.

Woodford, M. (2012). Methods of Policy Accommodation at the Interest-Rate Lower Bound. Working Paper. https://academiccommons.columbia.edu/doi/10.7916/D8Z899CJ.

Wright, J. H. (2012). What does Monetary Policy do to Long-term Interest Rates at the Zero Lower Bound? *The Economic Journal*, 122, F447–F466. https://doi.org/10.1111/j.1468-0297.2012.02556