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Central bank communication with non-experts: a road to nowhere?

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Abstract

Central banks have intensified their communication with non-experts – an endeavour which some have argued is bound to fail. This paper studies English and German Twitter traffic about the ECB to understand whether its communication is received by non-experts and how it affects their views. It shows that Twitter traffic is responsive to ECB communication, also for non-experts. For several ECB communication events, Twitter constitutes primarily a channel to relay information: tweets become more factual and the views expressed more moderate and homogeneous. Other communication events, such as former President Draghi's "Whatever it takes" statement, trigger persistent traffic and a divergence in views. Also, ECB-related tweets are more likely to get retweeted or liked if they express stronger or more subjective views. Thus, Twitter also serves as a platform for controversial discussions. The findings suggest that central banks manage to reach non-experts, i.e. their communication is not a road to nowhere.

JEL Codes: E52, E58.

Keywords: monetary policy, central bank communication, social media, non-experts

Non-technical summary

Over recent years, central banks have considerably stepped up their communication efforts with non-experts. Doing so raises a number of challenges. The expert audience that central banks have traditionally communicated with is easy to reach – experts have a professional interest to follow central bank communication. By definition, they also have detailed knowledge and understanding of central banking, making it easy for central banks to convey their messages. And they react instantaneously, for instance in financial markets, and in ways that are straightforward to monitor, such that it is possible to understand whether and how a certain message was received. In contrast, non-experts know less about central banks, might not be easily reached, and will not necessarily respond as fast and visibly to central bank messages. Given these challenges, it is understandable why Blinder (2018) predicts that "central banks will keep trying to communicate with the general public, as they should. But for the most part, they will fail."

A necessary condition to communicate with non-experts is that the central bank communication reaches the intended recipients. The literature on this central question is surprisingly scant. In this paper, we follow a novel avenue to observe the reaction of non-experts to central bank communication: we study how non-experts talk about the ECB in social media, by analysing tweets posted on Twitter. We study tweets about the ECB for the years 2012 to 2018 in two languages, English and German. We chose English because of its status as a lingua franca, because it is the most common language spoken in financial markets and in the economics and finance community more generally, and because it is the language within which the ECB mostly communicates. At the same time, it is not the first language of most euro area citizens. Accordingly, we also study tweets in German, the largest language in the euro area. Doing so is of interest also because of the controversial public debate about the ECB's monetary policy in Germany.

By assuming that non-experts write tweets about a variety of issues, and only occasionally tweet about the ECB or its policies, we are able to provide a meaningful way of differentiating experts from non-experts. Non-experts, while being much more numerous, contribute only little to the ECB-related Twitter traffic. They express stronger opinions, are more subjective in their views, and represent a larger variety of views than the experts in the sample.

In general, ECB-related Twitter traffic is responsive to ECB communication events. For most events, this effect is contained to the same day, and it is characterised by an increased number of Twitter accounts being active, with decreased subjectivity and lower strength of opinions and a relatively more homogeneous set of expressed views. This pattern suggests that tweets on these days mainly relay information about the ECB.

In contrast, other ECB communication events also lead to increased Twitter traffic and higher participation of Twitter accounts, but they show a more persistent response over several days and see a divergence of views that get expressed. This can be seen in particular among tweets in German, and is the case for the ECB press conference and most prominently for former President Draghi's "Whatever it takes statement". These patterns suggest that Twitter also serves as a platform to controversially discuss the ECB's policies.

We also find that non-experts are less responsive to ECB communication events than experts. They discuss the ECB press conference with less lead time and their response coefficients are generally smaller and estimated at lower levels of statistical significance. This holds predominantly for those events where Twitter serves as a vehicle for information transmission. For these, tweets by non-experts tend to become more factual – the subjectivity of the tweets not only becomes less pronounced, it also becomes less dispersed. Also, there is a tendency towards more moderate views being expressed on Twitter. In contrast, “Whatever it takes”, our prime example of a communication event where Twitter served as a platform for controversial discussions, constitutes an important exception, as it has led to very similar reactions of experts and non-experts alike.

Twitter’s role as a platform for controversial discussions also becomes apparent when we analyse which tweets are more likely to get retweeted or liked. The likelihood to get retweeted or liked is higher for tweets that formulate their opinion in relatively strong and relatively more subjective language.

These findings have important implications for central banks. First, they suggest that central banks’ efforts to monitor the related social media traffic should be relatively granular and try to differentiate between expert and non-expert users, and furthermore between Twitter activity that serves primarily the purpose of information transmission and the more controversial discussions on Twitter. Second, monitoring the latter is particularly important, because the retweet and like analysis suggests that strong views and more subjective contributions are reposted more often, and hence are more influential in the discussion. At the same time, our results go against the views that central bank communication with non-experts is bound to fail because it does not reach the intended recipients. The ECB manages to reach out to non-experts, even if to a lesser degree than it reaches the traditional expert audience. And central bank communication has the potential to make discussions in social media somewhat more factual and moderate.

1. Introduction

Central banks have travelled a long journey when it comes to their communication practices (Issing 2019). From a tradition of being highly secretive, they started revealing more and more about their reaction function, their actions, their assessment of the current and future states of the economy, and even their expected future path of policy. Much of this increased communication has been with experts, and in particular with financial markets. The developments have been so wide-ranging that a discussion started on possible limits to transparency – how much more, it was asked, could central banks possibly communicate without going too far, e.g. by stifling the discussion in the committee, or by communicating more than the recipients could possibly digest (Cukierman 2009; Issing 2014)? To stay in the metaphor of the central bank journey, this discussion asks how far down the same road central banks would want to travel.

In the meantime, central banks have embarked on another journey, travelling a new road that had previously been largely unexplored. This new road leads to a different audience, namely to non-experts. Communicating with this audience has gained in importance following the global financial crisis, the subsequent use of unconventional monetary policy tools and the broadening of central bank mandates. New mandates and new tools require more explanation (also to the expert audiences); furthermore, these changes made monetary policy the focus of an intensifying and highly controversial public debate (Blinder et al. 2017). In addition, central banks saw an erosion of citizens' trust in them and their policies, which for the case of the European Central Bank (ECB) has only sluggishly recovered in the meantime (Bergbauer et al. 2020). More communication with non-experts was therefore in order; indeed, in her confirmatory parliamentary hearing in September 2019, incoming ECB President Lagarde stated that she will make the ECB's communication with the general public one of the priorities of her presidency.[1]

Reaching out to non-experts raises a number of challenges – up to the point that Blinder (2018) predicts that "central banks will keep trying to communicate with the general public, as they should. But for the most part, they will fail." Experts are easy to reach – they have a professional interest to follow central bank communication. By definition, they also have detailed knowledge and understanding of central banking, making it easy for central banks to convey their messages. And they react instantaneously, for instance in financial markets, and in ways that are straightforward to monitor, such that it is possible to understand whether and how a certain message was received. In contrast, non-experts know less about central banks, might not be in reach, and will not necessarily respond as fast and visibly to central bank messages. In light of this, Haldane et al. (2020) call for "explanation, engagement and education", or what they call the "3 E's of central bank communication with the public".

A necessary condition to explain and educate is that the central bank gets through to the non-experts. The literature on this central question is surprisingly scant. Ter Ellen et al. (2021) show that central bank communication requires an intermediator, as it reaches consumers primarily via news media. Their evidence for Norway suggests that the central bank can affect consumer confidence via this channel, which is in line with the findings

[1] "The ECB needs to be understood by the markets that transmit its policy, but it also needs to be understood by the people whom it ultimately serves. People need to know that it is their central bank, and it is making policy with their interests at heart. One of the priorities of my Presidency, if confirmed, will be to reinforce that bridge with the public.", see https://www.europarl.europa.eu/cmsdata/186560/Opening%20Statement%20by%20Christine%20Lagarde%20to%20the%20ECON%20Committee-original.pdf

of Lewis et al. (2019) that monetary policy surprises have instantaneous effects on consumer confidence in the United States. In contrast, the results of a survey among US consumers by Lamla and Vinogradov (2019) cast doubt on the ability of central banks to get through to consumers: while relatively more survey respondents report to have heard news about the Federal Reserve following policy announcements, people's beliefs are effectively unchanged. Lamla and Vinogradov (2021) replicate these results for the UK, and furthermore that awareness of the Bank of England following policy announcements increases relatively more among Twitter users.

In this paper, we follow a novel avenue to observe the reaction of non-experts to central bank communication: we study how non-experts talk about the ECB in social media, by analysing tweets posted on Twitter. This approach has several advantages: it is entirely based on real-life data (in contrast to lab or survey experiments which impose that the central bank signals are received) which are available at high frequency (therefore allowing us to make causal statements in line with the assumptions underlying the event studies literature) and on a continuous basis (therefore not restricting us to specific communication events). Furthermore, it represents many individuals (more than could possibly be invited to listening events, into a laboratory, or to surveys), and it allows us to trace differences and interactions between non-experts and experts, as we observe both of them on Twitter.

We study tweets about the ECB for the years 2012 to 2018 in two languages, English and German. We chose English because of its status as a lingua franca, because it is the most common language spoken in financial markets and in the economics and finance community more generally, and because it is the language within which the ECB mostly communicates. At the same time, it is the official language in only two – and relatively small – euro area countries (Ireland and Malta), meaning that it might be more difficult to capture non-expert citizens through this approach. Accordingly, we also study tweets in German, the largest language in the euro area (spoken as first language by 20%, and as second language by another 16% of EU citizens).[2] Studying tweets in German is particularly interesting because the public debate about the ECB's monetary policy has become particularly heated. As noted by Schnabel (2020), "the conversation is dominated by various narratives, such as the 'expropriation' of German savers through 'punishment rates', the 'flood of money' that will inevitably lead to massive inflation, and the creation of 'zombie firms' as a result of expansionary monetary policy."

Our key findings are as follows. First, by assuming that non-experts write tweets about a variety of issues, and only occasionally tweet about the ECB or its policies, we are able to provide a meaningful way of differentiating experts from non-experts. For instance, the group that we label non-experts is considerably more likely to tweet during weekends, which is in line with the idea that their Twitter activity is not based on professional motives. Non-experts, while being much more numerous, contribute only little to the ECB-related Twitter traffic. They express stronger opinions, are more subjective in their views, and represent a much larger variety of views than the experts in the sample.

Second, our analysis identifies a dual role that Twitter plays - a channel for information transmission on the one hand and a platform for controversial and subjective discussions on the other hand. In general, ECB-related Twitter traffic is responsive to ECB communication events. For most events, this effect is contained to the same day, and it is characterised by an increased number of Twitter accounts being active, with decreased subjectivity and opinionatedness (i.e., stronger language, displaying more favourable

[2] Source: https://www.deutschland.de/en/topic/culture/the-german-language-surprising-facts-and-figures.

and/or unfavourable sentiment) and a relatively more homogeneous set of expressed views. This pattern suggests that tweets on these days mainly relay information about the ECB.

In contrast, other ECB communication events also lead to increased Twitter traffic and higher participation of Twitter accounts, but they show a more persistent response over several days and see a divergence of views that get expressed. This can be seen in particular among tweets in German, and is the case for the ECB press conference and most prominently for former President Draghi's "Whatever it takes statement". These patterns suggest that Twitter also serves as a platform to controversially discuss the ECB's policies.

Third, non-experts are less responsive to ECB communication events than experts. They discuss the ECB press conference with less lead time and their response coefficients are generally smaller and estimated at lower levels of statistical significance. This holds predominantly for those events where Twitter serves as a vehicle for information transmission. For these, tweets by non-experts tend to become more factual – the subjectivity of the tweets not only becomes less pronounced, it also becomes less dispersed. Also, there is a tendency towards more moderate views being expressed on Twitter. In contrast, "Whatever it takes", our prime example of a communication event where Twitter served as a platform for controversial discussions, constitutes an important exception, as it has led to very similar reactions of experts and non-experts alike.

Fourth, Twitter's dual role as information transmission channel and a platform for controversial discussions also becomes apparent when we analyse which tweets are more likely to get retweeted or liked. Retweets and likes seem to be more prominent in the latter case: we find that the likelihood to get retweeted or liked is higher for tweets that formulate their opinion in relatively strong and relatively more subjective language.

Finally, we find that Twitter users differentiate between the ECB president as a person on the one hand and the institution or its policies on the other hand, with the discourse around the person having become much more heterogeneous following the "Whatever it takes" remarks.

These findings have important implications for central banks. First, they suggest that central banks' efforts to monitor the related social media traffic should be relatively granular and try to differentiate between expert and non-expert users, and furthermore between Twitter activity that serves primarily the purpose of information transmission and the more controversial discussions on Twitter. Second, monitoring the latter is particularly important, because the retweet and like analysis suggests that strong views and more subjective contributions are reposted more often, and hence are more influential in the discussion. At the same time, our results go against the views that central bank communication with non-experts is bound to fail because it does not reach the intended recipients. The ECB manages to reach out to non-experts, even if to a lesser degree than it reaches the traditional expert audience. And central bank communication has the potential to make discussions in social media somewhat more factual and moderate.

The remainder of this paper is organized as follows. Section 2 discusses the related literature and explains where our paper contributes. Section 3 describes the data that is underlying our analysis. Section 4 develops our approach to differentiating experts from non-experts. Section 5 studies which tweets are more likely to get liked or retweeted, and Section 6 investigates the determinants of Twitter behaviour by experts and non-experts. Section 7 concludes.

2. Related Literature

Our paper relates to two, so far largely unconnected, strands of literature. The first deals with social media in financial market and central bank-related contexts.[3] Korhonen and Newby (2019) report that almost all central banks in Europe have institutional Twitter accounts, but that their activity is rather heterogeneous. Based on tweets sent from these institutional Twitter accounts, the paper documents how the importance of communication about financial stability has increased over time, in line with the enlarged mandates of several central banks in Europe. That central banks have become active Twitter users is also confirmed by Conti-Brown and Feinstein (2020) for the Federal Reserve, which seems more engaged on Twitter than other independent U.S. agencies.

A number of papers use Twitter to identify market sentiment or to understand what topics are on the mind of financial market participants. Masciandaro et al. (2020) study tweets just before and after the announcement of monetary policy decisions; by calculating similarity of their content, they retrieve a monetary policy surprise measure, and then test how this affects financial markets. Meinusch and Tillmann (2017) and Stiefel and Vivès (2019) exploit tweets to identify beliefs about monetary policy (in the former case about the timing of the exit from the Fed's quantitative easing, in the latter case about the likelihood of an ECB intervention following former ECB president Draghi's 2012 "Whatever it takes" statement), and show that these beliefs are mirrored in financial market developments. Similarly, Lüdering and Tillmann (2020) find that the discussion on Twitter around the "taper tantrum" episode in 2013 contains relevant information for market pricing. Furthermore, Azar and Lo (2016) provide evidence that the content of tweets referencing the Federal Reserve around FOMC meetings can be used to predict future returns, even after controlling for common asset pricing factors.

A third set of tweets is analysed by Bianchi et al. (2019), Camous and Matveev (2021) and Tillmann (2020). These papers show that tweets by former U.S. president Trump about the Federal Reserve and its monetary policy led to a reduction in interest rates, suggesting that market participants priced in future rate cuts in response to Trump's statements. They also seem to have affected long-term inflation expectations and confidence of consumers (Binder 2021).

To summarise, this literature has provided compelling evidence that the Twitter activity of central banks, financial market participants (or experts for that matter) and politicians contains useful information to study various aspects related to central banking. What is missing, to the best of our knowledge, is an analysis of Twitter activity by non-experts. This is where the current paper comes in.

The second strand of literature to which this paper contributes is the recent but rapidly increasing research on central bank communication with non-experts. A bit more than a decade ago, in their survey of the pre-crisis literature on central bank communication, Blinder et al. (2008) stated: "Virtually all the research to date has focused on central bank communication with the financial markets. It may be time to pay some attention to communication with the general public." This picture is changing rapidly, along several dimensions.

[3] Twitter activity is studied in many other fields, too; reviewing this literature is beyond the scope of the current paper. Still, it is worth highlighting studies of information diffusion in social media, as this has a bearing on the application in the current paper. For instance, Gorodnichenko et al. (2018) report that diffusion of information related to the 2016 Brexit referendum and the 2016 U.S. presidential elections is largely complete within one to two hours and shows signs of an "echo chamber", with stronger interactions across agents with similar beliefs.

Many recent contributions – many of which conducted by central banks, or with involvement of central bank researchers – resort to surveys and lab experiments to test how non-experts understand and respond to central bank communication. For instance, the Bank of England augmented its Inflation Report with new layers of content aimed explicitly at speaking to a less-specialist audience, and then conducted controlled experiments to assess the impact of this change (Haldane and McMahon 2017). In order to understand the determinants of trust, the ECB has been experimenting with changing the order of questions in its knowledge and attitudes survey among the general public (Angino and Secola 2019), and the Bank of Canada has embarked on lab experiments to test the causal effects of central bank communication on economic expectations and their underlying mechanisms (Kryvtsov and Petersen 2021). Randomised control trials (RCTs) have also been increasingly used by researchers outside central banks. Coibion et al. (2019), for instance, study how different forms of communication influence inflation expectations, and D'Acunto et al. (2021) investigate whether diversity in the committee helps reaching out to different population groups.

A clear message that emerges from these studies is that simple and relatable messages are more powerful in affecting beliefs or behaviours of non-experts (Bholat et al. 2019; Coibion et al. 2019; Kryvtsov and Petersen 2021). This evidence is consistent with models in which agents have constrained capacity to collect and process information (Coibion et al. 2020). This is an important message for central banks – after all, their communications are usually far from being a simple read: for instance, it requires around 13-15 years of formal education to understand the monetary policy statements of the ECB (Coenen et al. 2017).

Focus groups, lab experiments and RCTs in surveys have in common that they all guarantee that the recipient receives the central bank signal – the participants get confronted with a message (or deliberately do not receive this message, to generate a control group), and then can react to it (or not). This is an advantage of these approaches, as it allows for a causal interpretation. At the same time, this is arguably also their largest downside – in real life, no one can guarantee that non-experts are within reach of the central bank's communication channels and do therefore receive the central bank signal. As a matter of fact, households tend to have little knowledge about central banks, and show little interest in keeping up to date with monetary policy issues (van der Cruijsen et al. 2015). A rather sobering finding, reported by Kumar et al. (2015), suggests that even in New Zealand, the pioneer of inflation targeting, business managers' inflation expectations were not anchored around the Reserve Bank of New Zealand's inflation target, implying that they have not received (or believed) the most fundamental communication by their central bank. Also in the United States, the Fed's announcement of a 2% inflation target was not getting through to all non-experts: Binder (2017) shows that inflation expectations of relatively more informed consumers got anchored more than those of relatively less informed consumers. Furthermore, Coibion et al. (2020) report that neither households' nor firms' expectations respond much to monetary policy announcements in low-inflation environments. Information channels also matter: Conrad et al. (2021) show that consumers of traditional media have lower and more accurate inflation perceptions, whereas households which inform themselves about monetary policy via social media display greater uncertainty regarding future inflation.

All of this implies that central bank communication with non-experts can substantially improve their knowledge and possibly also affect their expectations and behaviour – if the signals get through to them. This is where the current paper comes in – it studies to what extent the ECB manages to reach out to non-experts, which communication channels are most promising in this regard, and whether and how the tone of the corresponding social media discussion can be affected by the ECB.

3. Data

In this section, we describe the data we use for our empirical analysis.

Tweets

Our sample of tweets covers the time period from 2012 to 2018. We start in 2012 because usage of Twitter in Europe has been growing rapidly until then and has stabilised since. It could well be that different types of users were represented less in the earlier years, such that changes over time could reflect changes in sample composition. Starting in 2012 allows us to minimise this issue, while still giving us a reasonable sample size to work with. We end the sample in December 2018 to ensure that our analysis is not affected by the changeover of the ECB presidency from Mario Draghi to Christine Lagarde in 2019. While a changeover in the leadership could generally make a difference, the fact that – in contrast to Mario Draghi – Christine Lagarde has a Twitter account and uses it actively is likely to imply a structural break in our data series.

We filter and scrape tweets via Twitter's Advanced Search using the Python library "GetOldTweets" (Henrique 2016).[4] We collect tweets in English - as identified by Twitter's language filter - that contain "ecb", "european central bank" or "draghi" in the text, hashtag or username and were posted between 2012 and 2018. For the sample of tweets in German, we set the Twitter Advanced Search language filter to German and search for tweets containing "ecb", "ezb", "europäische zentralbank" or "draghi" in the text, hashtag or username. All searches are insensitive to capitalisation and special letters such as the umlaut. This results in over 4.7 million English tweets and almost 120,000 German tweets. Note that our dataset covers original tweets (this also entails tweets where the majority of content is copied from another tweet, but often a comment or remark is added) and replies[5], but not retweets or quote retweets. In addition, we identify the number of times each of our tweets gets retweeted.

We clean our samples in several steps to ensure that the final samples are not contaminated by tweets that are unrelated to the European Central Bank. To do this, we start by looking at random subsamples of tweets and manually identify those that are unrelated. This gives us a broad idea of what types of other tweets our data collection method extracted. With these unrelated tweets, we establish certain words or phrases that distinguish them from observations that are indeed talking about central banking (for instance, the term "cricket" helps distinguishing tweets about the English Cricket Board from those about the European Central Bank, both of which are often abbreviated as ECB). Furthermore, we implement a visual check using word clouds. Word clouds visualise the most frequent words of a given text sample. In our case, we create two types of clouds, one based on our cleaned sample and the other on dropped observations. The

[4] The data collection is not done in real time, but ex post. This implies that it retrieves all tweets that were publicly available online at the time of data collection, but does not discover tweets that got deleted in the meantime. This method of collecting tweets for scientific analysis has been used, inter alia, by Lan et al. (2019) who focus on the locations of users and show that twitter data can serve as an alternative to census population data, by Tavazoee et al. (2017) who look at popularity of candidates of the US election 2016 in social media or by Song and Miled (2017) who use tweets to monitor flu vaccine rates.

[5] Whenever we refer to tweets in our sample, this also includes replies.

former cloud helps us check whether the majority of words is related to central banking, and it helps us identify other unrelated and frequent topics (such as cricket). The latter type of word cloud enables us to check whether we do not indeed exclude central banking-related tweets, and by displaying words that appear frequently in the unrelated set of tweets it helps us singling out further key words for our cleaning procedure (e.g. the names of cricket players). Examples of such word clouds are found in Figure A1 in the Appendix. During all steps of the cleaning procedure, we regularly repeat these steps until we are satisfied with the content of the final sample.

Through this procedure, we drop all tweets that contain the identified text in their body or hashtags. To list only the most relevant cases, this removes tweets related to the English Cricket Board, as we filter out all tweets that contain certain names of cricket players, and terms like “cricket”, “skipper”, “sport”, “coach”, “batsman” or “ecb.co.uk”. We further remove tweets about the Extra Care Buck by the American drugstore chain CVS, a Samsung charger called “ECB-DU4EWE”, a camera case called “ECB-1 EVA”, a part of SharePoint (a Microsoft’s document management tool) called Edit Control Block and others.

Next, we check whether tweets that got downloaded because the usernames contain one of our key terms (i.e. usernames that contain “draghi”,[6] “ecb”, or – in the German sample – “ezb”) are in fact related to the ECB. Here, we also exclude users that are clearly connected to the English Cricket Board. This leaves us with a list of around 300 users to disregard. Since it is common Twitter practice to mention users in tweets (preceded by a “@”), we further remove the tweets that contain the identified unrelated usernames in their text. This leaves us with 3.8 million English tweets and 116,000 German tweets.

We double-check for the language of tweets using the Python library “langdetect”[7] (Danilak 2015) because despite the language filter of the Twitter Advanced Search, numerous tweets in other languages were returned. For the sample of tweets classified as English by Twitter, we only keep those that “langdetect” also identifies as English. For the sample of tweets classified as German by Twitter, we allow detected languages to be either German or English due to the common usage of English terms even when the tweet is primarily in German language. This results in dropping around 200,000 English tweets and around 6,000 German tweets.

As we are interested in understanding different types of Twitter users and their behaviour, we drop all tweets by users who have tweeted less than 100 times in their entire Twitter history. This leads to a loss of 24,000 English tweets written by ~17,000 user accounts (5.6% of all accounts in sample) and less than 1,000 German tweets by 520 accounts (3% of all accounts in sample), which has no impact on the time series properties of the variables that we will study subsequently.

Overall, our data collection leaves us with more than 3.5 million original tweets, which generated more than 2 million retweets, not including quote retweets[8] (see Table 1). The sample of tweets in German is considerably smaller; there are only around 110,000 original tweets, which were retweeted around 50,000 times. There are even thirteen days without any ECB-related tweet in German at all.

[6] Note that this is an Italian surname and thus not unlikely to occur in a username. In addition, it means “dragons” in Italian.

[7] The langdetect library is a direct port of Google’s language-detection library, which generates language profiles from Wikipedia abstracts and claims to have 99% precision in language detection.

[8] Since quote retweets have only been introduced in 2015, we do not provide an overview of quote retweets for our sample.

The top panel of Figure 1 tracks the evolution of tweets over time, and shows, first, that Twitter activity across the English and German subsample is highly correlated and, second, that Twitter activity peaks around major ECB decisions.[9] The first peak corresponds to former President Draghi's "Whatever it takes" statement (which we will analyse in more detail later), in July 2012. Also 2014 and 2015 show an elevated level of Twitter activity. This can be explained by the comprehensive monetary policy easing strategy starting in June 2014.[10] This provides a first indication that ECB actions are an important determinant of ECB-related Twitter activity.

Table 1 and Figure 1 here

Recall that we chose the starting date for our sample to ensure that we are not picking up an upward trend in Twitter activity that is due to an increasing adoption of Twitter as social medium.[11] It is evident from the top panel of Figure 1 that this has clearly been achieved – if anything, we see a declining trend over time, which we ascribe to a reduction in the intensity of the debate surrounding the ECB and its policies, not to a decline in overall Twitter activity. Another way to test whether the patterns for the Twitter data mirror a changing adoption of Twitter, or instead reflect varying interest in ECB matters is to compare Twitter volume with other measures of interest in the ECB. The middle panel of Figure 1 plots the time series of searches for ECB-related terms on Google, and the lower panel of Figure 1 reports the number of ECB-related articles in English-speaking newspapers. The three sources yield similar trends, suggesting that our collected tweets reflect well the general interest in ECB-related matters.

Content of tweets

Besides the volume of tweets and retweets, we are interested in the content that is tweeted. We use Natural Language Processing (NLP), which is generally based on unsupervised machine learning, to systematically analyse the text of our tweets and focus particularly on sentiment analysis. There are several different methods on which statistical sentiment analysis can be based (and many are currently being developed and improved). We follow a dictionary approach, which is, as the name suggests, based on word lexica and among the most common methods to this date.[12] A sentiment lexicon is a list of words with attached pre-defined sentiment values. Since we use the python library TextBlob (Loria 2014) for the English sample and its German extension (Killer 2015) for the German sample, our English lexicon is based on Princeton University's WordNet[13]

[9] For a detailed review, see Hartmann and Smets (2018).

[10] Various easing steps were implemented, first with negative interest rates and credit-easing measures via targeted long-term refinancing operations, then complemented by an asset-backed securities purchase programme and a third covered bond purchase programme in September 2014. In January 2015, an expanded asset purchase programme (APP) was introduced, which started the public sector purchase programme (PSPP), consisting of the purchase of bonds issued by euro-area governments, agencies and European institutions. Furthermore, in March 2016, the ECB decided to lower rates even further and to expand its APP considerably. The notable drop in Twitter activity in August 2015 likely arises because of the absence of an ECB press conference in this month, together with the regular low activity in August.

[11] At the very beginning of our sample, the number of active Twitter users was still on the rise, but it has stabilised shortly thereafter, see https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/.

[12] Shortcomings of this dictionary approach could be missing or misinterpreted words in the lexicon (e.g. "negative interest rate" returns a negative favourability value and a positive subjectivity score), unidentified sarcasm in text, missed identification of words due to spelling mistakes, and it has arguably scope to improve its performance on complex text or slang.

[13] https://wordnet.princeton.edu/

and our German lexicon on the German equivalent GermaNet[14]. Sentiment measures do not only measure the tone of a text, they can also indicate other dimensions of sentiment such as subjectivity or strength of emotion (i.e. opinionatedness) and many more.

In our analysis, we calculate three types of sentiment for each tweet: favourableness (i.e. tone of tweet), absolute favourableness (or sentiment strength) and subjectivity. To get a rough idea of the words available in the lexicon and how these contribute to sentiment in their raw form, a list of example adjectives that return very high or low values for favourability and subjectivity can be found in Table A1 in the Annex.

Favourableness ranges from -1 to 1, where a higher value reflects a more positive sentiment. For instance, the words “awful” or “dreadful” are given a favourableness value of -1, the words “exceptional” or “marvelous” yield a value of +1. Words in the intermediate range are, for instance, “challenging” (0.5) or “inconvenient” (-0.6).

The absolute value of favourableness identifies sentiment strength. It ranges from 0 to 1, where values closer to 1 reflect stronger sentiment. “Awful” or “dreadful” as well as “exceptional” or “marvelous” express strong views, with the absolute value of favourableness being +1. Words such as “consistent” or “basic” are neutral in terms of favourability, and hence low in terms of sentiment strength, with (absolute) favourableness of 0.

Subjectivity also ranges from 0 to 1, where higher values indicate less factual (more subjective) statements. “Nasty” or “terrible” yield high subjectivity values of 1, whereas the words “actual” or “contemporary” are given the lowest subjectivity value of 0.

With the algorithm used, certain words, as well as their combinations and co-occurrence with other words, will result in different sentiment values. Generally, if multiple words carrying sentiment occur in one text passage, their average value of favourability and subjectivity is returned. However, if “not” occurs before a word, its favourability value is multiplied by –0.5, while its subjectivity score remains the same. For example, the word “good” returns a polarity of 0.7 and a subjectivity of 0.6, which indicates that it is a pretty positive word and it is somewhat subjective. The combination “not good” halves the returned polarity and reverses its sign to -0.35, while its subjectivity is unaffected at 0.6. In contrast, the combination “very good” increases the sentiment to almost the maximum (0.9), but also increases the value of subjectivity to 0.8.

Table 2 here

From the sentiment measures for each individual tweet, we obtain means, medians and standard deviations of all tweets in a given day.[15] Table 2 reports summary statistics, and shows that some tweets reach the minimum and maximum favourableness and subjectivity values possible, however most tweets show no or very low, positive favourableness. This is reflected in an average favourableness of only 0.04. It is also noteworthy that positive values for favourableness are considerably more frequent than negative values. Absolute favourableness averages at 0.11, and subjectivity has the

[14] http://www.sfs.uni-tuebingen.de/GermaNet/. It is important to keep in mind that the measures of sentiment cannot be directly compared across languages, on the one hand because the method is dictionary-based and the libraries do not use the same (translated) dictionaries, on the other hand because at the time of analysis, the authors of the German library recommended further refinement of the sentiment measures.

[15] To define the date line and for other time-relevant calculations, we consistently use Central European (Summer) Time (CET or CEST), as this is the time in Frankfurt, Germany, the location of the ECB’s headquarter.

highest mean of 0.24. Few tweets are completely objective (i.e. with a subjectivity value of zero). The German sample shows the same patterns, but with fewer tweets having non-zero values for (absolute) favourableness and subjectivity.

Associated twitter accounts

For each user who is associated with at least one tweet about the ECB in our sample, we further use common web-scraping techniques to obtain more information on the account. We collect the date of account creation, the number of followers, and the number of overall tweets ("statuses") that have been issued by the specific account since its creation.

As mentioned before, we restrict our sample to include only users who tweeted more than 100 times in their entire Twitter history. The ECB-related tweets in English originate from 287,648 accounts; those in German were written by 16,336 users.[16] Figure 2 reveals that most of the traffic stems from relatively few accounts: the yellow line in the figure shows the Lorenz curve of ECB-related Twitter activity, and reveals that the top 5% of accounts generate 75% of tweets in the English sample, and 62% in the German sample. The distance from the equality line (in blue) shows how unequal this distribution is. What is more, the top 5% Twitter accounts are responsible for 93% of tweets that get "liked", and for 97% of retweets in the English sample, and for 89% of retweets and likes in the German sample. This suggests that there is a small number of Twitter accounts that account for most of the traffic, and an even smaller number that constitutes the most influential opinion-makers - a standard feature of social media.

Looking at Figure 3, it is evident that both in the German and English-speaking sample, the bulk of accounts has only very few followers (slightly more than 100 for the account at the 25th percentile), whereas some accounts have a very large number of followers (the 95th percentile records more than 10,000 followers).

Figures 2 and 3 here

Given the extremely unequal distribution, it is fair to use aggregate Twitter activity as representative for the expert population, be it media, financial market participants or economists and finance professionals. These agents are clearly overrepresented when looking at overall numbers. This is what has been done by the previous literature, which has also shown that Twitter activity correlates well with financial market developments. At the same time, as we will argue below, it is possible to isolate experts from non-experts, such that a more differentiated analysis is feasible – in other words, by only looking at aggregate numbers, interesting information contained in the overall Twitter activity is disregarded.

ECB communication events

We capture the following communication events by the ECB, which we source from the ECB's website:

[16] Note that users who tweet in German and English would be counted in both groups.

- Announcements of monetary policy decisions along with the accompanying press conference (monthly until 2014, eight times a year since 2015; 68 observations in the sample);
- Publication of the Economic Bulletin, which provides an overview of the economic and monetary information that forms the basis for the Governing Council's policy decisions (released two weeks after each monetary policy meeting; 68 observations in the sample);
- The publication of the accounts of the monetary policy meetings (published since 2015, usually 4 weeks after the monetary policy meetings; 31 observations in the sample);
- Tweets originating from the ECB’s institutional Twitter account, on days without any other ECB communication events (1,062 observations, roughly equally distributed across the various years);
- Speeches by the ECB president (131 observations);
- Speeches by all other Executive Board members (519 observations);
- Former ECB president Draghi’s “Whatever it takes” statement on 26 July 2012.

4. Differentiating Experts From Non-Experts

This section describes how we separate experts from non-experts, and how the two groups differ in their Twitter activity and their views about the ECB. In doing so, it is important to be aware that Twitter users are not representative of the entire population. A recent study for the United States (Wojcik and Hughes 2019) has shown that Twitter users are younger, more likely to identify as Democrats, more highly educated and have higher incomes than U.S. adults overall. At the same time, there are no particular differences with regard to gender or ethnicity. Our collection of tweets about the ECB is even less likely to be representative of the entire population – we only observe users who tweet about the ECB (and do so publicly), we do not observe those who have never done so. Hence, when we aim to distinguish experts from non-experts, it needs to be kept in mind that the latter group cannot and should not be generalised to the entire population.

Differentiating experts from non-experts is not a straightforward endeavour. Institutional twitter accounts in our sample could be one option to identify experts, as many of these are run by professionals in the economic or financial sphere, or by media. However, identification along these lines might be too noisy – on the one hand, there are potentially many experts that do not have institutional accounts; on the other hand, there might be institutional twitter accounts that typically deal with other issues, i.e. are not experts in central banking or monetary policy matters. This means that we need to define experts and non-experts based on their behaviour. We will rely on two main criteria in this regard.

First, we assume that experts are “regulars”, meaning that they comment on ECB policies repeatedly. The obvious point in time when we would expect experts to voice their opinion is on days when the monetary policy decisions are announced and commented upon in a press conference by the ECB president and vice-president. Until 2014, these were taking place monthly; since 2015, their frequency has changed to a six-week cycle. Our benchmark definition assumes that experts comment on ECB decisions at least every second press conference. We do not require that they issue a tweet for every single press conference in order to allow for the possibility that not every press conference is equally newsworthy, or that our experts are taking time off – especially those that are not writing from institutional accounts.

A second criterion that we use in our identification is ECB centricity of the various accounts. In particular, we assume that non-experts write tweets about a variety of issues, and only occasionally tweet about the ECB or its policies.[17] While we consider low ECB centricity to be a good criterion to identify non-experts, we do not include ECB centricity in our benchmark definition of experts, for the following reason: Twitter accounts from journals or other media outlets tend to release statements about a large range of issues, and do therefore have a low level of ECB centricity. Still, we would assume that tweets about the ECB issued from these accounts are written by experts.

Based on these considerations, we adopt the following benchmark (*bm*) definitions for experts and non-experts:

$$expert_i^{bm} = \begin{cases} 1 \; if \; PC\_activity_i \geq 0.5 \\ 0 \; else \end{cases} \tag{1}$$

$$nonexpert_i^{bm} = \begin{cases} 1 \; if \; PC\_activity_i < 0.5 \; \& \; centricity_i < P25(centricity) \\ 0 \; else \end{cases}, \tag{2}$$

where i denotes the account and $PC\_activity_i$ is the share of press conferences for which we observe an ECB-related tweet on the same day. $centricity_i$ is the share of ECB-related tweets in the total number of tweets originating from the account,[18] and $P25(centricity)$ denotes the 25th percentile of ECB centricity across all accounts in our sample.

It is important to note that these definitions split the sample of accounts into three parts – experts and non-experts, but also a third group which sits in between (i.e. those who did not release tweets on at least every second press conference day, but do have a relatively higher ECB centricity than our non-experts). Effectively, this means that we discard a (potentially large) number of observations. While this implies that we are losing potentially valuable information, it might help us better differentiating the two groups, therefore providing cleaner evidence on their respective behaviour.

To test for robustness of our results with regard to these definitions, we redefine our expert and non-expert groups in various ways: for experts, a less narrow definition characterises anyone as expert who comments on at least every third press conference ($expert_i^{0.33}$), a more narrow definition requires experts to comment on at least three out of four press conferences ($expert_i^{0.75}$), and another alternative defines experts according to the benchmark definition (a tweet around at least every second press conference), but furthermore requires a high level of ECB centricity, by only including accounts which are at least at the 75th percentile of ECB centricity across all accounts in our sample ($expert_i^{ECB-centric}$).

In a similar vein, robustness for non-experts is tested using two variants, one being more restrictive, the other being less restrictive. The less restrictive definition removes the ECB centricity criterion, and as such only requires that an account does not follow the press

[17] Recall that we only include Twitter accounts that have issued at least 100 tweets. This is important here, as otherwise there could be some accounts with a very small number of tweets, leading to extreme values of ECB centricity.

[18] We observe the total number of tweets originating from a given account since the creation of the account, and the number of ECB-related tweets since 2012. For accounts created before 2012, we do therefore approximate the total number of tweets since 2012 by subtracting the average number of tweets per year times the number of years the account had existed prior to 2012.

conference regularly ($nonexpert_i^{excl.centricity}$; note that this definition comprises all accounts that are not classified as experts in the benchmark definition of experts). The more restrictive definition requires in addition that non-experts have few followers, defined as being below the 25th percentile of accounts according to the number of followers ($nonexpert_i^{few\ followers}$). The idea here is to make sure we capture non-experts from the general public, rather than for instance politicians or experts in other fields who have many followers and occasionally make remarks about the ECB.

Table 3 provides an overview of various characteristics of our groups, each time according to the benchmark definition (an overview including the robustness definitions is provided in Appendix Table A2).

Table 3 here

Out of our 287,648 accounts, roughly 25% are classified as non-experts, and around 0.5% are experts. These numbers show that our classification is rather conservative: we discard nearly 75% of accounts, only to increase the likelihood that we appropriately classify the accounts into groups.[19] The ratios in our German sample are similar, with 24% of accounts classified as non-experts and 0.1% as experts.[20]

Given their different activity, these account types contribute in very different ways to the overall Twitter volume. While representing around 25% of the account sample, our non-experts issued only around 4% of all ECB-related tweets (namely 150,540 out of 3,610,722), whereas the 0.5% of experts contributed 874,465 tweets, i.e. nearly 25%. In the German sample, 6% of tweets were issued by non-experts and 9% by experts.

Table 3 shows that non-experts are considerably more likely to tweet during weekends – 18% of their tweets are published on Saturdays and Sundays, compared to 7% for the experts. This pattern is very similar for the accounts in German, with 20% weekend-activity for non-experts and 8% for experts. This is in line with the notion that non-experts' Twitter activity is not based on professional motives and therefore makes us rather confident that our differentiation of experts and non-experts has worked well.

There is no difference with regard to the number of followers that experts and non-experts have (both in the English and the German sample). This suggests that non-experts might be equally influential in shaping the public discourse about the ECB as experts; understanding their behaviour is therefore of interest to the central bank.

The statistics with regard to ECB centricity are an artefact of the way we separated our groups – by definition, ECB centricity is considerably smaller for the non-experts than for the experts.

The next three statistics look at the subjectivity that gets expressed in the tweets originating from the various account types. As explained in Section 4, subjectivity is measured on a scale from 0 to 1 and denotes to what extent the text represents factual information (in which case the measure is closer to 0) or expresses subjective opinions (in which case the measure is closer to 1). Mean subjectivity is significantly higher for non-

[19] Note that we do not discard any account in our sample if we use the alternative classification of non-experts according to $nonexpert_i^{excl.centricity}$, plus the benchmark definition of experts.

[20] In all cases, the ECB's own Twitter account is classified as an expert account. ECB tweets amount to around 0.3% of all ECB-related tweets on average.

experts, which is in line with the idea that experts provide, on average, more factual information. At the same time, looking at the within-account standard deviation of subjectivity, subjectivity is significantly more dispersed for the experts than for the non-experts. While these patterns are evident for the English and the German tweets, statistical significance is (expectedly) less pronounced in the smaller German sample (recall also that the level of subjectivity should not be compared across languages). This implies that experts issue a mixture of more factual and more subjective tweets, whereas there is less such variation in the Twitter behaviour of non-experts. Another interesting feature is that, the distribution of subjectivity across accounts has a much higher standard deviation for non-experts than for experts, suggesting that the range of views expressed by non-experts is much larger.

Looking at favourableness, very similar results are obtained. Favourableness measures the strength of opinions that get expressed in tweets, on a scale from -1 (very negative) to +1 (very positive). Non-experts are on average somewhat more positive,[21] and (as with subjectivity) they show less variation over time for a given account than experts, but there is much more variation across accounts than for experts. In addition, the strength of emotions that get expressed (measured via absolute favourableness i.e. opinionatedness) is higher for non-experts.

The picture that emerges therefore is that non-experts express stronger opinions, are more subjective in their views, and represent a much larger variety of views than the experts in the sample. All these findings are intuitive and make us comfortable that the differentiation of accounts has indeed succeeded in singling out experts and non-experts.[22]

5. Determinants of Retweets and Likes

We start our analysis by investigating which tweets get liked and retweeted. Our original download of ECB-related tweets identified 3.6 million tweets in English, which further led to up to 2.1 million retweets; for the sample of tweets in German, these numbers stand at 100,000 vs. 50,000 (see Table 1). This suggests that a lot of Twitter traffic is simply a repeat of opinions that have been expressed earlier, by others. But which tweets do get retweeted, and are therefore relatively more influential? Of the 3.6 million original tweets in English, less than 500,000 got retweeted at least once. On average, a retweeted tweet gets shared around 4.5 times, but this number masks substantial heterogeneity: while the median stands at 2, the 99th percentile is 43, and the maximum is 4,868. These patterns are comparable in the German sample – of the 100,000 tweets, less than 15,000 got retweeted at least once; on average, conditional on being retweeted, a tweet gets shared 3.5 times, while the median amounts to 1, the 99th percentile to 21, and the maximum is 4,775.

Similarly, most tweets don't get liked, and there is massive heterogeneity among those that are being liked: overall, there are around 418,000 liked tweets in the English sample; conditional on receiving at least one like, a tweet gets on average 3.8 likes, but the median is 1, the 99th percentile 35, and the maximum 20,622. In the German sample,

[21] For both groups in the English sample, the average level of favourableness is significantly larger than zero at standard levels of statistical significance. In the German sample, this is only the case for non-experts.

[22] The four most pronounced differences (in subjectivity, absolute favourableness, the standard deviation of average favourableness and weekend activity) are remarkably robust to changing the definitions of experts and non-experts (see Table A2).

13,612 tweets received at least one like, with a conditional mean of 4.5, a median of 1, a 99th percentile of 27, and a maximum of 14,347.

While these numbers look very similar for retweets and likes, the two don't overlap much – in the English sample, around 222,000 tweets got retweeted but were not liked, and around 176,000 tweets are liked but were not retweeted; also in the German sample, the overlap is similar, with around half of the retweeted tweets being liked, and around half of the liked tweets being retweeted. This suggests that likes and retweets are different concepts. We will therefore study them separately, but will also try to understand how they interact.

We are particularly interested in how the semantic content of the original tweet affects the likelihood of being retweeted or liked. In particular, we are interested in whether more factual or more subjective tweets are more likely to be retweeted and liked, whether there is a "negativity bias", implying that negative views are more likely to be liked or retweeted, and to what extent it matters how strong the views are that get expressed. These hypotheses go back to the work by Mullainathan and Shleifer (2005), which shows that newspapers are likely to slant stories toward the views of their readers, and that they slant toward extreme positions in the presence of heterogeneous views. Berger et al. (2013) have found supportive evidence for this hypothesis for the newspaper reporting about the ECB, so the question here is whether similar findings apply to social media. Also, Naveed et al. (2011) report that negative tweets are more likely to be retweeted, so we are interested in understanding whether this general pattern also applies to central bank-related content in Twitter.

Furthermore, we test whether tweets from experts and from non-experts differ in any way, using the benchmark definitions for these two account types. We use three types of regression equations. The first one explains whether or not a tweet gets retweeted, or liked, based on probit models:

$$R_i = \begin{cases} 1 & if \quad Y_i^* > 0 \\ 0 & otherwise \end{cases} \tag{3}$$

$$Y_i^* = \alpha_{dow} + \alpha_{moy} + \alpha_{hol} + \alpha_t t + \alpha_{t^2} t^2 + \beta_p p_i + \beta_l l_i + \beta_n D_i^n + \beta_f |f_i| + \beta_s s_i + \beta_{ne} D_i^{n-exp} + \beta_e D_i^{exp} + \varepsilon_i, \tag{4}$$

where R_i denotes the dependent variable, α_{dow} controls for day of the week effects, α_{moy} for month of the year effects (capturing seasonality), α_{hol} is a dummy variable for holidays,[23] and t and t^2 are a linear and quadratic time trend, respectively. p_i is the percentile at which the account is located in the distribution of followers across all accounts – the more followers a certain account has, the more likely it is that a tweet gets read, liked and retweeted. l_i denotes the length of the tweet, as measured by the number of characters.

[23] These cover New Year's Day (January 01), Good Friday, Saturday before Easter, Easter Sunday, Easter Monday, Labour Day (May 01), Robert Schumann Day (May 09), Ascension Day, Whit Monday, Corpus Christi, Day of German Unity (October 03), All Saints' Day (November 01), Christmas (December 24, 25 and 26) and New Year's Eve (December 31).

The variables of interest are D_i^n, a dummy for tweets with negative favourability, $|f_i|$, the absolute value of the tweet's favourableness, s_i, its subjectivity, and two dummy variables D_i^{n-exp} and D_i^{exp}, which indicate whether a tweet was originally written by a non-expert or an expert.

The second regression equation looks at how often a tweet gets retweeted or liked (N_i), conditional on being retweeted or liked at least once. For this analysis, we explain the log of the number of retweets or likes, and employ standard ordinary least squares. The explanatory variables are identical to those in the probit regression, therefore leading to the equivalent specification as in equation (5), with $\ln(N_i)$ as dependent variable.

The third set of tests estimates a multinomial logit model, and identifies the determinants whether a tweet gets i) retweeted but not liked, ii) liked but not retweeted, or iii) liked and retweeted (relative to tweets that get neither liked nor retweeted). Once again, the explanatory variables are as described above, implying a specification equivalent to equation (5).

As we have very many observations (more than 3.6 mio for the English tweets, and more than 100,000 for German tweets), we would expect very low standard errors in our estimations. To ensure that statistical significance is not merely resulting from the large number of observations, we randomly pick 36,000 observations, i.e. slightly less than one percent of the English tweets and slightly below one third of the German tweets.

For each of these regressions, we calculate robust standard errors. Table 4 reports the corresponding results and Table A3 in the appendix contains the results for the full sample, which are broadly comparable). For the multinomial logit and the probit models, the table reports marginal effects.

Table 4 here

For both languages, we consistently find that tweets from accounts with more followers have a considerably higher likelihood of getting retweeted or liked, and even conditional on being retweeted or liked, they are retweeted or liked much more often. The same also holds true for tweets with more characters. In addition, there is considerable seasonality (not shown in the table for brevity), both over the year and over the weekdays, as well as evidence for holiday effects and time trends. Neither of these findings is very surprising.

The origin of a tweet also matters. English tweets from experts are more likely to be retweeted and liked than those from the bulk of the accounts, whereas tweets from our identified non-experts are less likely to be retweeted and liked.

Regarding the semantic content of the tweets, patterns among German tweets are mostly not statistically significant, but a number of interesting results are obtained for the tweets in English. First, there is some little evidence of a negativity bias. Tweets with a negative sentiment are more likely to be retweeted, but they are not more likely to be liked. However, the effect is small: the likelihood of being retweeted increases by 1 percentage point.[24] Furthermore, conditional on being retweeted or liked, negative tweets don't travel farther – they are retweeted or liked less often.

[24] Including account fixed effects, the results become generally smaller and less significant, suggesting that the likelihood of a retweet or like does not increase if a tweet is relatively more negative, opinionated or subjective than the

Second, strong views are much more likely to generate retweets and likes in the English sample, both unconditionally and for likes also conditionally. These effects are not only statistically significant, they are also economically large. If absolute favourableness increases from 0 to 1 (i.e. from the lowest possible to the largest possible value), the likelihood that a tweet gets retweeted (liked) increases by 2 (5.4) percentage points. While this might seem a small number, it is important that the unconditional probability of being retweeted or liked is around 10%, so these increases are sizable.

Third, the likelihood of being retweeted or liked is also increasing in the subjectivity of the tweet, once more with important magnitudes: Tweets with a subjectivity of 1 are 1.5 percentage points more likely to be retweeted and 2.1 percentage points more likely to be liked than tweets with a subjectivity of 0.

These results are therefore well aligned with the earlier evidence by Berger et al. (2013) regarding newspaper reporting about the ECB, and suggest that the discussion about the ECB on Twitter is disproportionately influenced by views that are expressed in strong language, and by relatively subjective tweets – patterns that the ECB should be aware of, as such views are likely to shape the tone of the public discourse.

6. Determinants of Twitter Behaviour

Hypotheses and specification of the econometric model

To study determinants of Twitter behaviour, we resort to aggregated data, at a daily frequency (including Saturdays and Sundays), yielding 2,537 observations. The reason for using aggregated data is that we are not only interested in the content of tweets, but also at the amount of Twitter traffic, the number of accounts that participate in the discussion and the heterogeneity of the views that get expressed on a given day, i.e. variables that are most conveniently analysed at an aggregated level.

We will analyse the following questions. First, to what extent does twitter traffic respond to ECB communication? We use the log number of tweets posted each day as our measure of twitter traffic, and would expect an increase in traffic, both for experts and non-experts, if the ECB's communication manages to reach out to non-experts.[25] Second, we study to what extent more Twitter users participate in the discussion – increased traffic could result from the same number of users tweeting more, or from more users participating, or both. We do so by means of the Herfindahl-Hirschman indicator (which provides a measure of concentration – the larger the indicator, the larger the "market share" of the participating accounts on a given day).[26] Presumably, if the ECB's communication manages to reach out to non-experts, we should see an increase in participation.

typical tweet from the account; rather, it is tweets from accounts that tend to write negative, opinionated or subjective tweets that get retweeted or liked more.

[25] We ignore retweets in the analysis in this section, given that the time series properties of tweets and retweets are highly correlated – of course, the more tweets, the more material that can be retweeted. The correlation coefficient of daily tweets and retweets is 0.77 in the English sample (0.67 in the German sample). Once different time trends are controlled for (the share of retweets has been increasing over time), the correlation increases substantially: a regression that explains log retweets with a linear and quadratic time trend and log tweets yields a regression coefficient for log tweets of 1.04 in the English sample, of 0.85 in the German sample.

[26] $Herfindahl - Hirschman\ indicator_t = \sum_{i=1,t}^{N_t} s_{i,t}^2$, where $s_{i,t}$ is the "market share" of a tweeting user i in the "tweet market" on day t ($s_{i,t} = \frac{\sum tweets_{i,t}}{\sum tweets_t}$), and N_t is the number of users on day t.

Subsequently, we go beyond the number of tweets and users and analyse whether the content of tweets changes. We study their subjectivity, favourableness and absolute favourableness, each time looking at the average for a given day and the standard deviation across tweets. The daily averages allow assessing whether the discussion on Twitter becomes more or less factual, more or less favourable and is expressed in more or less strong language. Studying the standard deviation of these variables across tweets adds to the picture by telling us whether the views become more similar or more divergent. These tests will allow differentiating whether Twitter is mainly a channel for information transmission or hosts controversial discussions. If tweets are predominantly about relaying information, they should be rather factual, written in relatively neutral language, and be so in a homogeneous fashion across tweets. In contrast, a controversial discussion implies heterogeneous views across tweets, and is likely characterised by less factual tweets expressed in stronger language. The diagram below summarises the direction of responses we expect in line with this hypothesis, indicating whether Twitter functions as either an information transmitting platform or as a platform hosting controversial discussions.

	Number of tweets	Number of accounts participating	Persistent response	Subjectivity	Favourableness	Absolute favourableness	Standard deviation of subjectivity	Standard deviation of favourableness	Standard deviation of abs. favourableness
Information transmission	↑	↑	No	↓	?	↓	↓	↓	↓
Controversial discussions	↑	↑	Yes	↑	?	↑	↑	↑	↑

Notes: The diagram provides an overview of the expected response patterns of Twitter traffic if Twitter serves as a platform for transmitting information (first row) and hosting controversial discussions (second row). The dependent variables are reported in the column headers, and the expected response pattern is summarised qualitatively. ↑ denotes a positive response, ↓ a negative response, ↔ an inconclusive (insignificant) response.

In order to exploit the granularity of our data, we run all regressions first for all accounts, and subsequently separately for each identified user group.

This approach entails an underlying identification assumption, which we share with the event study literature, namely that on days of ECB communications, these are the dominant drivers of Twitter traffic about the ECB. While we can of course not preclude that there are other relevant pieces of news or tweets that affect the discussion about the ECB, we consider it as unlikely that this would be systematically the case. In addition, the ECB communication events are largely predetermined, making reverse causality unlikely. Accordingly, we interpret our regression coefficients as causal.

We employ identical regression equations for all dependent variables, of the form

$$x_t = \alpha_{dow} + \alpha_{moy} + \alpha_{hol} + \alpha_t t + \alpha_{t^2} t^2 + \beta_{c,l}^{e} C_{t,l}^{e} + \varepsilon_t, \tag{5}$$

where the variables of interest are $C_{t,l}^{e}$, which cover the various ECB communication events e (see the list of events covered in Section 3), possibly with different leads and lags l.

The equations are estimated using ordinary least-squares regressions, with robust standard errors. For each type of communication event, we allow lags. In addition, we also allow leads for the ECB press conference. The press conferences are pre-announced well ahead of time. In line with a substantial literature on financial market effects prior to the announcement of monetary policy decisions,[27] we also find that Twitter activity intensifies already several days ahead of the press conferences, therefore warranting the

[27] See, e.g., Lucca and Moench (2015).

presence of lead terms in the regression equation. To get at a parsimonious model specification, we delete leads and lags that are not significant in the first specification where we explain the daily number of tweets originating from all accounts. To ensure comparability, we keep this lead and lag structure across all other specifications.

The first result to note, therefore, relates to the number of leads and lags that are required to model the number of tweets originating from all accounts. With two exceptions, the various ECB communication events affect Twitter volume only on the same day. The exceptions are the ECB press conference and the "Whatever it takes" statement. For the press conference, it is necessary to include 5 leads and 4 lags, meaning that the press conference is reflected in the English sample of tweets already the preceding weekend, and for a total of 10 days.[28] For the German sample, the time span is considerably shorter – one lead day and two lags are sufficient to capture the dynamics around press conferences. The "Whatever it takes" statement requires 15 lags, in both languages. Given the usually short attention spans on social media, this is a highly persistent effect, which is why we will treat this as a separate event (rather than subsuming this statement into the category of speeches by the ECB president).

We will now report the empirical results, for the overall activity on Twitter (where we look at the number of tweets and user concentration) and the content of tweets (which contains the analysis on subjectivity and (absolute) favourableness. We will first focus on the results in the English sample, then compare those with the tweets in German, before we report results of several robustness tests and finally will test whether tweets differentiate between the ECB as an institution and its president.

Twitter traffic and user concentration

Table 5 reports the coefficient estimates for the log number of tweets and the user concentration measure. For brevity, estimates for leads and lags of the press conference and "Whatever it takes" are omitted, and the overall sum of coefficients across all lags and leads is reported. The omitted coefficients are provided in Appendix Table A4.

Starting with the results for Twitter volume originating from all accounts, it is apparent that there is a reaction to all events on the same day. The press conference and "Whatever it takes" stand out in terms of magnitude, not only because they affect Twitter volume over several days, but also because of the strength of the effect on the same day: In the English sample, Twitter volume increases by a factor of 2 to 3 (in contrast to all other events, where volume increases by a factor of 0.2 to 0.6). The responsiveness to speeches by the ECB president is around 60% higher than to speeches by the other Executive Board members, in line with earlier findings that these are more important for gauging the future path of monetary policy (e.g., Bennani et al., 2020).

Table 5 here

Looking at the overall response to the press conference and "Whatever it takes" demonstrates how powerful these communication events are. For the ECB press conference, the overall number aggregates 10 coefficients, meaning that on average over

[28] The estimated coefficients are increasing over time in the uprun to the press conference, and then decline subsequently, suggesting that the effect is not triggered by other communications such as speeches which breach the ECB's quiet period (Gnan and Rieder 2021).

each of these days, Twitter volume about the ECB is 60% higher than on normal days.[29] "Whatever it takes" has been even more influential – the aggregated coefficient is close to 25, implying that, on average, Twitter activity about the ECB was more than 150% higher than normal, for 16 consecutive days.

Turning to the concentration measure (reported in the right panel of Table 5), we find that most events reduce concentration, which clarifies that the increased Twitter traffic is not triggered by the "usual suspects" sending out a higher number of tweets, but instead come about at least partially because more people are part of the discussion. To get a sense of the economic magnitude, it is helpful to know that the mean concentration measure for the overall English sample is 0.0052, with a standard deviation of 0.0058. This suggests, first of all, that Twitter activity about the ECB is not highly concentrated (in competition economics, an index below 0.01 is typically seen to characterise a highly competitive industry). Second, the drop in concentration on the ECB press conference days amounts to 0.7 standard deviations, i.e. is considerable. Also the discussion surrounding "Whatever it takes" can be characterised as one where very many Twitter accounts contributed. Compared to a standard day, concentration was on average two thirds of a standard deviation lower, for 16 consecutive days. This pattern can also be identified in Figure 4, which shows the Lorenz curves for Twitter activity on event days and days without ECB communications. It shows very clearly how large the impact of the "Whatever it takes" statement had been on the discussion – the Lorenz curve is much flatter, suggesting that many more people participated in the debate.

Figure 4 here

Comparing non-experts with experts yields a number of interesting insights. First, as shown in Appendix Table A4, non-experts are not talking about upcoming press conferences more than one day ahead – it is the experts who are driving the results for the overall sample, as they show strong response coefficients up to 5 days ahead. Second, non-experts are not responsive to most of the more specialised communication events, such as the Economic Bulletin, or speeches by other Executive Board members than the ECB president. Third, where they are responsive, the magnitude of the response is typically much smaller than for the experts (for instance, the overall response to the press conference is only half as strong as for the experts). The smaller responsiveness of non-experts is also reflected by the substantially smaller R^2 of the regression models – while they explain around 70% of the variation in the English expert sample, they explain roughly half of this in the non-expert sample.

The striking exception to this difference in responsiveness is "Whatever it takes" – here, the response coefficients of experts and non-experts are very similar in magnitude. Also, we find that Twitter traffic intensified for the same number of days for experts and non-experts alike. This suggests that "Whatever it takes" had a long-lasting effect on both groups.

These findings imply that the ECB's communication manages to reach out to experts and non-experts. They also provide us with a first indication that there might be different

[29] A more detailed analysis of ECB-related Twitter traffic around ECB press conference days (not shown here for brevity) shows that the main determinant for the amount of traffic (as well as many aspects of its content) is whether or not there has been a policy change. Measures of monetary policy surprises as typically used in the analysis of financial market reactions to the press conference, in contrast, do not show up significantly.

types of ECB-related tweets. On the one hand, we find events that lead to increased traffic by more accounts only on the same day, with non-experts responding less than experts. On the other hand, some events lead to persistent Twitter traffic by experts and non-experts alike. These patterns are compatible with a more prominent information transmission role in the first case (with all relevant information being transmitted within the day, and primarily among experts), and with Twitter being used as a platform for more controversial discussions (which are not resolved within one day and attract more participation by non-experts). To get a clearer picture of this dual role, we will now look at the content of tweets, covering their subjectivity, their favourableness and their absolute level of favourableness (which yields a measure of the opinionatedness).

The content of tweets

Table 6 contains the results for subjectivity, both for the daily average (left panel) and the daily standard deviation across tweets (right panel). There are several interesting findings. First, compared to the results reported in Table 5, the number of coefficients that are estimated to be statistically significant is much smaller, meaning that subjectivity is not nearly as responsive to ECB communication events as Twitter volume. This can probably be explained by the fact that there is a tendency toward zero for most sentiment measures (also induced by short text), suggesting that detecting a response in sentiment is inherently difficult. Still, starting from the overall English sample, there are a number of events where subjectivity is affected, namely for the press conference, the Economic Bulletin, the accounts and the speeches by the president. In all cases, subjectivity declines, meaning that the tweets become more factual. This implies that ECB communication events lead to a more factual discussion about the ECB on Twitter. This finding does not only arise because of a compositional effect (whereby the discussion on Twitter becomes more factual because more Twitter users join the discussion, and these tend to write more factual tweets) but also because the views expressed by given Twitter users become more factual.[30]

Tables 6-8 here

Interestingly, this is particularly the case for the group of non-experts, which do not only show a lower level of subjectivity, but furthermore also have a lower standard deviation, meaning that the distribution of subjectivity becomes narrower around a lower mean. For instance, in response to the press conference, the standard deviation declines by around a third, and in response to “Whatever it takes” by about half of a standard deviation (which is 0.09).

Table 7 reports the results for favourableness. Recall that favourableness measures the opinions that get expressed in tweets, on a scale from -1 (very negative) to +1 (very

[30] We test this using the underlying microdata, by studying the effect of communication events on subjectivity in a regression with and without account fixed effects (results not reported for brevity). The analysis without the fixed effects replicates the time series analysis reported in the paper and shows the overall effect on the discussion, whereas the analysis with the fixed effects controls for the average views of given Twitter accounts and reports the variation of these views on communication days. We find that for the overall sample and for experts, the coefficients typically have the same sign and remain statistically significant. In contrast, for non-experts the coefficient estimates become statistically insignificant in the fixed effect model, which implies that the finding for non-experts is mainly driven by a compositional effect, whereas the finding for the overall sample and the expert sample cannot be explained by a compositional effect alone.

positive). We find little evidence that the ECB communication events affect mean favourableness. This was to be expected, because it is unlikely that all events for a certain type (e.g., all speeches) affect public opinion in one direction. The results with regard to the standard deviation of favourableness are potentially more interesting – they tell us to what extent the spectrum of opinions has become wider or narrower after communication events. Looking at the right panel of Table 7, we find that the views expressed in English tweets narrows considerably, for most of the event types, and for experts and non-experts alike.

The last set of results, reported in Table 8, studies absolute favourableness, i.e. the strength of opinions that get expressed. Starting from the overall set of tweets written in English, it is apparent that most ECB communication events lead to a moderation of views, as both the average absolute favourableness and its standard deviation get reduced significantly in response to most types of events. This is particularly true for the non-experts, where average favourableness drops by more than half a standard deviation on the day of the press conference, and by around a third on the day of the "Whatever it takes" statement. Recall that, as discussed in Section 4, non-experts tend to be stronger in opinion on average. These findings do therefore suggest that ECB communication might be helpful in containing the strength of views expressed by non-experts.

Any difference for tweets in German?

So far, we have focused on English tweets. It could well be that we find different patterns for those written in German, given the heated public debate about the ECB's monetary policy in the aftermath of the global financial crisis. Tillmann and Walter (2020) show that the tone of monetary policy-related communication by the German Bundesbank is persistently more negative than the tone of the ECB's communications. This divergence of opinions is also reflected in the public discourse. Schnabel (2020) noted: "it is surprising that the ECB has for years faced such fierce public criticism in Germany. The media and politicians never tire of pointing out the supposed perils and deficiencies of today's monetary policy". In line with this, Hayo and Neuenkirch (2020) document that more intense newspaper reading leads to lower trust in the ECB among German households. Against this background, we might expect to see a more controversial and possibly a more negative and more subjective discussion on the ECB in the German-speaking Twitter community.

Overall, the patterns documented for the tweets in English are also found in the German sample: we find i) same-day reactions to many communication events, for experts and for non-experts; ii) particularly strong and more persistent reactions following the press conference and "Whatever it takes"; iii) non-experts to be generally less responsive than experts, and not to discuss the more specialised communication events; iv) in response to ECB communications more Twitter users to join the discussion; v) tweets to become more factual after ECB communication; and vi) most ECB communication events to lead to a moderation of views.

At the same time, there are substantial differences. We will focus on the discussion of "Whatever it takes", where these differences are most pronounced. "Whatever it takes" has clearly been the single most influential communication event in the German-speaking Twitter community, even more so than for tweets in English. The same-day as well as the overall increase in the number of German tweets is more than 1.5 times the increase in the English sample. A large number of Twitter users contributed to the discussion, leading to a much larger reduction in the concentration measure than in the English sample. What is remarkable is the contribution of the non-experts to the discussion.

While in the English sample, it was the experts who increased their traffic by more than the non-experts, in the German sample, the responsiveness of the non-experts is considerably larger than the one of the experts (the estimated coefficients are 26 and 17, respectively). Also the concentration measure declines by more for the non-experts than for the experts. This suggests that "Whatever it takes" had a particularly strong effect on non-experts in the German-speaking community.

Turning to the content of the tweets, "Whatever it takes" consistently raised the standard deviation of subjectivity, for experts and non-experts alike, both instantaneously on the day of the statement and over the entire span of the discussion. The effects are large – on the day of the statement, the standard deviation of experts' subjectivity increased by 2 standard deviations, the one of non-experts by one standard deviation. Also the tone of the tweets is affected; German tweets overall, and those by non-experts in particular, seem to be relatively more negative. And the spectrum of views widens up; both the standard deviation of favourableness and the standard deviation of absolute favourableness increase substantially, meaning that the strength of opinions expressed got considerably more varied.

These findings suggest that "Whatever it takes" has not only led to a long-lasting and intense discussion by German-speaking non-experts, it has also been highly controversial and was overall met with a certain degree of negativity. This episode provides us with a clean example of how Twitter constitutes a platform for controversial discussions about the ECB's policies. To take a stark contrast, let us compare these findings to those for the reaction of tweets in English, written by experts in response to the ECB's monetary policy accounts in the below diagram:

	Number of tweets	Number of accounts participating	Persistent response	Subjectivity	Favourableness	Absolute favourableness	Standard deviation of subjectivity	Standard deviation of favourableness	Standard deviation of abs. favourableness
Response to ECB accounts, English tweets by experts	↑	↑	No	↓	↔	↓	↓	↓	↓
Response to "Whatever it takes", German tweets by non-experts	↑	↑	Yes	↔	↓	↔	↑	↑	↑

Notes: The diagram provides an overview of the response patterns of Twitter traffic, using two contrasting examples that illustrate the information flow and the discussion platform functions of Twitter. The first row reports the patterns found for tweets in English by experts to the ECB's monetary policy accounts, the second row the patterns found for tweets in German by non-experts to "Whatever it takes". The dependent variables are reported in the column headers, and the response pattern is summarised qualitatively. ↑ denotes a positive response, ↓ a negative response, ↔ an insignificant response. Colours displayed indicate which findings support the hypothesis as shown in the diagram at the beginning of this section (green), which ones go against it (red) and which ones are neutral (black).

In both cases Twitter traffic increases and more accounts participate in it. The reaction to the accounts is contained within the same day, the one to "Whatever it takes" continues over a long timespan. For the accounts, we find that subjectivity and absolute favourableness decline; for "Whatever it takes", they are not affected, but favourableness declines. Finally, for the accounts, the views expressed *converge*, whereas for "Whatever it takes", they *diverge* (for subjectivity, favourableness and absolute favourableness alike). Nearly all symbols in the diagram are plotted in green, meaning that they conform to the expected results outlined in the earlier diagram. While being extreme, these two communication events nicely illustrate how Twitter traffic serves information transmission on the one hand and hosts controversial discussions about the ECB on the other hand.

Robustness

Appendix Tables A5-A12 provide the estimated coefficients for the different ways of classifying non-experts and experts, for all dependent variables. Overall, results are remarkably robust. It is important to note that some of the groups are rather small – this is in particular the case for the most restricted definition of non-experts in the sample of German tweets. It comprises 327 accounts, from which only few tweets are posted, such that there are only 273 observations at the daily aggregate level. This needs to be kept in mind when studying the results.

With regard to Twitter volume, the four main findings (i) non-experts are not responsive to some, more specialised, types of ECB communication; ii) if they respond, the coefficients are smaller in magnitude; iii) the smaller responsiveness is also reflected in a lower R^2; iv) the exception to this is the “Whatever it takes” statement, which led to a similar response by non-experts and experts) all go through, independent of the exact way of defining experts and non-experts.

Coming to subjectivity, most results are also confirmed. However, some results change when we define non-experts according to the third set of criteria (i.e., restricting to accounts with few followers). For this group, mean subjectivity is not responsive to the press conference, whereas it increases in response to “Whatever it takes”. For both events, the standard deviation of subjectivity increases. All other results go through: the standard deviation of subjectivity increases for the experts following the press conference, and in the German sample, the standard deviation of subjectivity increases in response to “Whatever it takes”, both on the same day and over the duration of the Twitter discussion, both for experts and non-experts.

For favourableness, the main results were a decrease in its standard deviation for the tweets in English, for experts and non-experts alike, and an increase for the tweets in German, in particular for “Whatever it takes”. The latter finding is robustly repeated across our various definitions. Also the former is broadly robust, once more with the exception of non-experts that have few followers, where the sign of the coefficients changes: for this group, the standard deviation of favourableness is increasing in response to the press conference and “Whatever it takes”, whereas it is decreasing for the other non-expert groups.

Also for the last set of results, studying absolute favourableness, results are broadly robust, with the partial exception of English-speaking non-experts with few followers, where the standard deviation increases in response to the press conference and “Whatever it takes”.

To summarise, the robustness tests broadly confirm the earlier picture, but suggest that the group of non-experts with few followers in the English-speaking group behaves differently from other non-experts – the views expressed by this group become more varied in all dimensions, i.e. in their subjectivity, in the opinions, and in the strength of the opinions. Note that this group does not look any different per se in terms of the underlying characteristics (see Table A4).

Views about the person of the ECB president versus the ECB overall

Do Twitter users differentiate between the ECB president and the ECB overall? To get at this question, we will now analyse the views expressed in relation to Mario Draghi, and compare these to the views expressed in the tweets overall.

To recover a sentiment measure that is indicative of the tone toward Mario Draghi, we want to extract only terms that actually refer to him. We focus on adjectives because they carry the relevant sentiment. To create our "Draghi Sentiment" measure, we follow these steps: First, we discard any tweets that do not contain the key term "draghi". In the second step, we identify the adjectives that are specifically targeted toward Mario Draghi. Our approach is rooted in Part-of-speech (POS) tagging, i.e. the analysis of sentence structure. By parsing our text and tagging each word, we predict a word's class, its relationship to other words and its role in a sentence. Figure 5 is an example of what the final information extracted from a sentence after POS tagging looks like. To apply POS tagging, we use the model provided by the spaCy library (Explosion AI 2017). This library further allows us to retrieve connected word groups. This enables us to identify describing adjectives that occur before "draghi" in a sentence (e.g. "famous draghi"). However, describing adjectives may also occur after our key term (e.g. "draghi is famous"). To identify these, we again draw from the information returned by POS tagging, allowing us to identify adjectives and nouns. By default, we define our key term "draghi" to always be labelled a noun. We connect all adjectives to the most recent noun in a sentence, which allows us to identify multiple describing adjectives in a sentence (e.g. "draghi is famous and well-known"). In the third and final step, we estimate the sentiment by applying the dictionary approach described above to the adjectives (with their negation whenever applicable) which, according to our identification, refer to Mario Draghi.[31]

Figure 5 and Table 9 here

Table 9 reports the results, for Draghi-related content in the left panel, and (for ease of comparison) for the benchmark results discussed up to now in the right panel. We focus on the two types of events that are most associated with the person of the president, namely his speeches and the particular speech during which he made his "whatever it takes" remarks. The very bottom of the table contains the mean and standard deviation of the various variables that we study. The mean sentiment, favourableness and absolute favourableness are very similar for Draghi and the tweets overall, but they are considerably more volatile for Draghi.

Starting with the results for speeches by Draghi, the results are consistent for the benchmark results and the sentiment related to Draghi directly. For tweets from all accounts, the sign of the estimated coefficients is identical and their statistical significance is similar. The differences in the magnitude of the estimated coefficients suggests that sentiment about Draghi is more responsive to his speeches than sentiment about the ECB overall. This increased responsiveness is in line with the fact that the sentiment expressed about Draghi is generally more volatile; as a matter of fact, the coefficients are broadly comparable when put in relation to the standard deviation of the dependent variables.

One difference that results, however, relates to the responses of the non-experts. While the subjectivity and the favourableness of their views about the ECB becomes less dispersed after speeches by Draghi, the dispersion of their views about the ECB president himself increases in response to these communication events.

Bigger differences are observed for the "Whatever it takes" statement. Subjectivity of the views about the ECB is barely affected, but the views about Draghi become more

[31] We only apply this process to the tweets in English.

subjective – and more dispersed, which is not the case for the subjectivity of the views about the ECB. In addition, the views expressed about the ECB president become stronger in opinion, which is not the case for the views expressed about the ECB overall. It is also apparent that the discourse about the person of the ECB president becomes considerably more dispersed – the cross-sectional standard deviation of all three variables increases after the "Whatever it takes" statement, rather uniformly across all types of Twitter accounts. In contrast, the dispersion of the views expressed about the ECB overall is less affected; if anything, it declines.

These findings suggest that Twitter users do differentiate between the ECB president as a person on the one hand and the institution or its policies on the other hand, with the discourse around the person having become much more heterogeneous following the "Whatever it takes" remarks. Furthermore, these remarks were special, because no such pattern is detected for the other speeches by the ECB president.

7. Conclusions

Following the global financial crisis, the subsequent use of unconventional monetary policy tools and the broadening of central bank mandates, many central banks have put more emphasis on communication with non-expert audiences. This endeavour raises several new challenges, since compared to the traditional counterparts, non-experts are less knowledgeable about central banking matters and might not even be reached by central bank communication (Haldane et al. 2020). Accordingly, some commentators predicted that central banks' attempts to communicate with the general public are bound to fail (Blinder 2018).

Against this background, this paper has tried to shed light on the question whether central banks can reach out to non-experts. The analysis uses ECB-related Twitter traffic as a testing device, which implies that it is not a study of the general public at large, but of a particular subset of non-experts. Still, the paper shows that it is possible to identify non-expert Twitter accounts, allowing us to study and compare the determinants of Twitter traffic by experts and non-experts. Compared to surveys or lab experiments (the main avenue pursued in existing research, where it is ensured that participants get exposed to central bank communication), this approach is entirely based on real-life data which are available at high frequency and on a continuous basis. It therefore allows us to test to what extent non-experts are responsive to central bank communication, and how their views evolve around such communication events.

Twitter traffic by experts and non-experts is responsive to the ECB's communication, in two ways. First, there are communication events (typically the relatively more technical ones) where Twitter mainly serves as an information transmission channel. For these types of events, Twitter traffic returns to normal within one day, non-experts are less involved than experts, and the views expressed tend to converge. Second, in sharp contrast to these events, there are other occasions where Twitter serves as a platform for controversial discussions, which last several days, draw in many non-experts, and are characterised by a divergence of views. This has particularly been the case for former President Draghi's "Whatever it takes" statement and the ensuing discussion among German-speaking Twitter accounts.

A lot of the ECB-related Twitter traffic stems from retweets of earlier tweets, implying that some opinions get shared widely, and are therefore more influential in shaping non-experts' views about the ECB. The analysis in this paper shows that this is particularly the case for tweets posted by accounts with many followers, implying that there are relatively few individuals who are instrumental in shaping the debate. In addition, tweets are more likely to get retweeted or liked if they express strong views about the ECB and if they are less factual.

These findings have important implications for central banks. First, they suggest that central bank communication manages to reach out to non-experts, even if to a lesser degree than it reaches the traditional expert audience. Second, the retweet and like analysis suggests that strong views and more subjective contributions are likely to be read more often. At the same time, central bank communication has the potential to make discussions in social media somewhat more factual and moderate. All in all, communication with non-experts is therefore not a road to nowhere. Whether it ultimately succeeds in fostering trust, making central banks accountable, or influencing agents' inflation expectations and behaviour remains an open issue, however.

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Table 1: Number of ECB-related tweets and retweets

Year	English		German	
	Tweets	Retweets	Tweets	Retweets
2012	763,667	167,242	23,063	3,375
2013	471,206	149,320	12,140	2,542
2014	625,313	278,859	16,471	5,053
2015	731,745	600,296	19,454	9,465
2016	445,482	335,137	18,008	9,069
2017	323,540	270,475	12,456	6,798
2018	249,769	307,069	8,339	15,237
Total	3,610,722	2,108,398	109,931	51,539

Notes: The table shows the number of ECB-related tweets and retweets, by year. Tweets in English are reported in the left panel, tweets in German in the right panel.

Table 2: Descriptive statistics of tweet content

English

	Mean	Std	Min	25%	50%	75%	Max
Subjectivity	0.24	0.28	0.00	0.00	0.13	0.45	1.00
Favourableness	0.04	0.20	-1.00	0.00	0.00	0.10	1.00
Absolute favourableness	0.11	0.18	0.00	0.00	0.00	0.16	1.00

German

	Mean	Std	Min	25%	50%	75%	Max
Subjectivity	0.04	0.15	0.00	0.00	0.00	0.00	1.00
Favourableness	0.01	0.10	-1.00	0.00	0.00	0.00	1.00
Absolute favourableness	0.02	0.09	0.00	0.00	0.00	0.00	1.00

Notes: The table shows the descriptive statistics of the subjectivity, favourableness and absolute favourableness of the granular sample of English (top) and German (bottom) tweets.

Table 3: Summary statistics for different account types

	Non-experts		Experts
Panel A: English			
Number of accounts	69,031		1,282
Average weekend activity	0.1835	***	0.0716
Average percentile followers	68		68
Average percentile ECB centricity	12	***	84
Average subjectivity	0.2746	***	0.2434
Average standard deviation of subjectivity	0.2153	***	0.2579
Standard deviation of average subjectivity	0.2756	***	0.0954
Average favourableness	0.0544	**	0.0418
Average standard deviation of favourableness	0.1526	***	0.1714
Standard deviation of average favourableness	0.2247	***	0.0627
Average absolute favourableness	0.1389	***	0.0994
Average standard deviation of absolute favourableness	0.1306	***	0.1491
Standard deviation of average absolute favourableness	0.1922	***	0.0564
Panel B: German			
Number of accounts	3,921		23
Average weekend activity	0.2024	*	0.0755
Average percentile followers	65		63
Average percentile ECB centricity	12	***	84
Average subjectivity	0.1305	**	0.0309
Average standard deviation of subjectivity	0.1172		0.1278
Standard deviation of average subjectivity	0.2592	***	0.0459
Average favourableness	0.0472		0.0013
Average standard deviation of favourableness	0.0735		0.0661
Standard deviation of average favourableness	0.1811	***	0.0209
Average absolute favourableness	0.0734	*	0.0156
Average standard deviation of absolute favourableness	0.0717		0.0645
Standard deviation of average absolute favourableness	0.1727	***	0.0279

Notes: The table shows summary statistics for the different account types, defined according to the benchmark definitions, in the English sample (Panel A) and the German sample (Panel B). ***/**/* denote statistical significance at the 1%/5%/10% level, between non-experts and experts. Statistical significance is based on mean comparison tests, with the exception of standard deviation of average subjectivity and favourableness, where statistical significance is calculated using Levene's (1960) robust test statistic for the equality of variances.

Table 4: Determinants of Retweets and Likes, random sample

	English							German						
	Probit	OLS	Probit	OLS	Multinomial Logit			Probit	OLS	Probit	OLS	Multinomial Logit		
	Retweet		Like		Retweet	Like	R & L	Retweet		Like		Retweet	Like	R & L
Negative sentiment	0.010**	-0.066*	0.001	-0.058*	0.007*	-0.001	0.002	-0.001	0.353***	-0.007	0.164	-0.004	-0.005	0.001
	(0.005)	(0.037)	(0.004)	(0.035)	(0.004)	(0.003)	(0.003)	(0.013)	(0.131)	(0.012)	(0.125)	(0.010)	(0.008)	(0.010)
Abs(favourableness)	0.022*	0.064	0.054***	0.269***	0.003	0.029***	0.021**	-0.033	-0.544**	0.059*	-0.286	-0.008	0.053***	-0.015
	(0.012)	(0.095)	(0.011)	(0.079)	(0.010)	(0.008)	(0.009)	(0.036)	(0.231)	(0.032)	(0.218)	(0.030)	(0.020)	(0.028)
Subjectivity	0.015*	0.051	0.021***	-0.001	0.004	0.012**	0.010*	0.008	0.212*	0.011	0.082	-0.004	0.007	0.011
	(0.008)	(0.060)	(0.007)	(0.053)	(0.006)	(0.005)	(0.006)	(0.021)	(0.127)	(0.019)	(0.135)	(0.017)	(0.013)	(0.015)
Percentile Followers	0.005***	0.014***	0.003***	0.010***	0.002***	0.000***	0.004***	0.004***	0.011***	0.003***	0.010***	0.002***	0.000***	0.003***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-expert	-0.051***	-0.055	-0.038***	0.139*	-0.026***	-0.013**	-0.025***	-0.057***	0.065	-0.021***	0.138**	-0.041***	-0.002	-0.017***
	(0.009)	(0.081)	(0.008)	(0.081)	(0.007)	(0.006)	(0.007)	(0.007)	(0.056)	(0.006)	(0.056)	(0.006)	(0.005)	(0.005)
Expert	0.033***	0.313***	0.004	0.200***	0.014***	-0.021***	0.017***	-0.146***	-0.554***	-0.144***	-0.518***	-0.037***	-0.034***	-0.120***
	(0.003)	(0.031)	(0.003)	(0.032)	(0.002)	(0.003)	(0.002)	(0.007)	(0.034)	(0.007)	(0.036)	(0.005)	(0.005)	(0.008)
No. of Characters	0.000***	0.001***	0.000***	0.001***	0.000*	-0.000	0.000***	0.000***	0.001***	0.000***	0.001***	0.000***	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	36,000	4,557	36,000	4,095		36,000		36,000	4,835	36,000	4,450		36,000	
R-squared		0.145		0.140					0.123		0.127			

Notes: The table shows coefficient estimates for the determinants of Retweets and Likes. The left panel reports results for English sample, the right panel for the German sample. Results for probit and multinomial logit models are marginal effects. The OLS models explain the log of the number of Retweets and Likes and are thus conditional on a tweet being retweeted or liked, respectively. The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table 5: Explaining Twitter traffic and concentration of users

	Log number of tweets						Concentration index					
	English			German			English			German		
	All	Non-experts	Experts	All	Non-experts	Experts	All	Non-experts	Experts	All	Non-experts	Experts
Panel A: Contemporaneous response												
Press Conference	2.475***	2.059***	2.847***	2.475***	1.194***	2.735***	-0.004***	-0.037***	-0.022***	-0.113***	-0.388***	-0.536***
	(0.075)	(0.109)	(0.076)	(0.120)	(0.163)	(0.150)	(0.001)	(0.003)	(0.003)	(0.014)	(0.047)	(0.041)
Whatever it takes	2.020***	1.883***	1.740***	3.239***	1.590***	2.413***	-0.002***	-0.016***	-0.012***	-0.098***	-0.441***	-0.416***
	(0.073)	(0.094)	(0.080)	(0.126)	(0.154)	(0.158)	(0.000)	(0.003)	(0.003)	(0.016)	(0.058)	(0.052)
Economic Bulletin	0.233***	0.142	0.362***	-0.149	-0.185	-0.209	-0.001	-0.006*	-0.006**	0.006	0.063	0.010
	(0.083)	(0.102)	(0.084)	(0.124)	(0.166)	(0.165)	(0.001)	(0.003)	(0.003)	(0.019)	(0.071)	(0.057)
Accounts	0.608***	0.324***	0.986***	0.062	0.054	-0.103	-0.002***	-0.016***	-0.016***	-0.022	-0.069	0.009
	(0.076)	(0.097)	(0.091)	(0.131)	(0.196)	(0.185)	(0.000)	(0.003)	(0.003)	(0.021)	(0.077)	(0.067)
Speeches by others	0.270***	0.080	0.450***	0.164**	0.050	0.129	-0.001***	-0.004**	-0.014***	-0.029**	-0.037	-0.054
	(0.042)	(0.052)	(0.047)	(0.071)	(0.081)	(0.091)	(0.001)	(0.002)	(0.003)	(0.012)	(0.033)	(0.033)
Speeches by president	0.434***	0.385***	0.499***	0.914***	0.453***	1.223***	-0.001***	-0.012***	-0.001	-0.047***	-0.150***	-0.307***
	(0.051)	(0.067)	(0.055)	(0.088)	(0.115)	(0.107)	(0.000)	(0.002)	(0.001)	(0.008)	(0.040)	(0.030)
Tweet	0.191***	0.157***	0.274***	0.115*	0.053	0.169**	-0.001**	-0.006**	-0.012***	-0.021*	-0.051*	-0.076**
	(0.041)	(0.048)	(0.046)	(0.067)	(0.071)	(0.084)	(0.001)	(0.002)	(0.003)	(0.012)	(0.030)	(0.031)
Panel B: Overall response												
Press Conference	**5.965**	**4.169**	**7.494**	**4.587**	**2.144**	**4.624**	**-0.020**	**-0.125**	**-0.205**	**-0.303**	**-0.755**	**-1.044**
Std. error	0.271	0.325	0.303	0.247	0.316	0.315	0.002	0.013	0.021	0.030	0.107	0.104
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Whatever it takes	**24.800**	**20.901**	**22.446**	**43.029**	**26.200**	**17.056**	**-0.059**	**-0.433**	**-0.527**	**-2.741**	**-6.984**	**-4.759**
Std. error	0.748	0.739	0.833	1.180	1.338	1.186	0.007	0.038	0.059	0.186	0.485	0.416
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	2,537	2,537	2,537	2,531	1,551	1,284	2,537	2,537	2,537	2,531	1,551	1,284
R-squared	0.630	0.365	0.717	0.375	0.219	0.434	0.257	0.241	0.395	0.180	0.165	0.256
Mean(dependent var)	6.742	3.606	5.135	3.028	0.874	1.205	0.005	0.043	0.037	0.132	0.589	0.581
Stdev(dependent var)	0.899	0.823	1.168	1.130	0.934	1.143	0.006	0.035	0.061	0.160	0.358	0.344

Notes: The table shows coefficient estimates for the effect of ECB communication events on log number of tweets and the user concentration index, based on equation (5). The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for "Whatever it takes" (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table 6: Explaining subjectivity

	Average subjectivity						Standard deviation of subjectivity					
	English			German			English			German		
	All	Non-experts	Experts	All	Non-experts	Experts	All	Non-experts	Experts	All	Non-experts	Experts
Panel A: Contemporaneous response												
Press Conference	-0.011**	-0.029***	0.012**	-0.006	-0.038	0.040***	-0.012***	-0.015***	0.001	0.030***	0.062***	0.130***
	(0.005)	(0.009)	(0.006)	(0.007)	(0.030)	(0.009)	(0.003)	(0.006)	(0.004)	(0.010)	(0.019)	(0.014)
Whatever it takes	-0.005	-0.045***	0.010	-0.005	0.020	0.093***	-0.006**	-0.005	0.003	0.028**	0.134***	0.170***
	(0.006)	(0.012)	(0.008)	(0.007)	(0.031)	(0.011)	(0.003)	(0.007)	(0.005)	(0.013)	(0.019)	(0.013)
Economic Bulletin	-0.010*	-0.010	-0.003	0.017	-0.010	0.057***	-0.010***	-0.013*	-0.009**	0.016	-0.006	0.040**
	(0.006)	(0.012)	(0.007)	(0.010)	(0.041)	(0.019)	(0.003)	(0.008)	(0.004)	(0.014)	(0.019)	(0.018)
Accounts	-0.029***	-0.026*	-0.018**	0.000	-0.059**	0.109**	-0.013***	-0.005	-0.009*	0.011	-0.004	0.027
	(0.006)	(0.016)	(0.008)	(0.009)	(0.029)	(0.055)	(0.004)	(0.010)	(0.005)	(0.019)	(0.023)	(0.026)
Speeches by others	0.001	0.004	0.007	0.007	0.001	0.021**	-0.001	0.004	0.003	0.008	-0.000	0.021***
	(0.004)	(0.006)	(0.005)	(0.008)	(0.017)	(0.011)	(0.002)	(0.004)	(0.003)	(0.008)	(0.010)	(0.008)
Speeches by president	-0.008**	-0.024***	-0.003	-0.013***	-0.019	-0.013	-0.005**	-0.012**	-0.003	0.010	0.022	0.037***
	(0.004)	(0.008)	(0.005)	(0.005)	(0.017)	(0.011)	(0.002)	(0.005)	(0.003)	(0.008)	(0.014)	(0.012)
Tweet	-0.004	0.005	-0.004	0.000	0.011	0.012	-0.002	0.003	-0.002	0.003	-0.003	0.020***
	(0.003)	(0.006)	(0.005)	(0.006)	(0.016)	(0.008)	(0.002)	(0.003)	(0.003)	(0.007)	(0.009)	(0.007)
Panel B: Overall response												
Press Conference	**-0.064**	**-0.098**	0.010	-0.014	-0.028	**0.086**	**-0.025**	**-0.040**	**0.046**	**0.053**	**0.140**	**0.189**
Std. error	0.023	0.040	0.033	0.020	0.058	0.039	0.013	0.023	0.021	0.025	0.038	0.033
p-value	0.006	0.014	0.754	0.467	0.633	0.026	0.052	0.087	0.026	0.033	0.000	0.000
Whatever it takes	-0.010	-0.087	**0.362**	**-0.348**	-0.292	-0.006	**-0.171**	-0.061	0.011	**0.598**	**1.298**	**0.576**
Std. error	0.053	0.090	0.073	0.086	0.272	0.143	0.029	0.050	0.048	0.112	0.138	0.091
p-value	0.858	0.331	0.000	0.000	0.282	0.968	0.000	0.225	0.822	0.000	0.000	0.000
Observations	2,537	2,537	2,537	2,531	1,551	1,284	2,537	2,537	2,537	2,531	1,551	1,284
R-squared	0.170	0.075	0.084	0.033	0.035	0.096	0.069	0.029	0.096	0.045	0.072	0.162
Mean(dependent var)	0.253	0.267	0.223	0.043	0.082	0.025	0.282	0.286	0.265	0.107	0.052	0.030
Stdev(dependent var)	0.050	0.087	0.069	0.072	0.178	0.095	0.027	0.049	0.044	0.102	0.109	0.084

Notes: The table shows coefficient estimates for the effect of ECB communication events on the average and standard deviation of subjectivity, based on equation (5). The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for "Whatever it takes" (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table 7: Explaining favourableness

	Average favourableness						Standard deviation of favourableness					
	English			German			English			German		
	All	Non-experts	Experts	All	Non-experts	Experts	All	Non-experts	Experts	All	Non-experts	Experts
Panel A: Contemporaneous response												
Press Conference	-0.003	-0.014*	0.004	-0.007*	-0.037**	-0.003	-0.032***	-0.031***	-0.010**	0.012	0.015	0.065***
	(0.004)	(0.008)	(0.004)	(0.004)	(0.018)	(0.006)	(0.004)	(0.007)	(0.004)	(0.007)	(0.015)	(0.009)
Whatever it takes	0.019***	0.015	0.022***	-0.003	0.003	0.013*	-0.008*	-0.027***	0.010*	-0.010	0.036**	0.051***
	(0.005)	(0.009)	(0.005)	(0.005)	(0.020)	(0.007)	(0.004)	(0.009)	(0.005)	(0.009)	(0.015)	(0.008)
Economic Bulletin	0.005	0.005	0.007*	0.012	0.023	0.024	-0.009**	0.001	-0.004	0.015	-0.006	0.027***
	(0.004)	(0.009)	(0.004)	(0.008)	(0.026)	(0.016)	(0.005)	(0.010)	(0.005)	(0.012)	(0.017)	(0.010)
Accounts	0.005	-0.006	0.005	-0.004	-0.015	-0.080*	-0.020***	-0.011	-0.017***	-0.002	-0.031**	0.009
	(0.005)	(0.012)	(0.005)	(0.005)	(0.018)	(0.043)	(0.005)	(0.009)	(0.005)	(0.013)	(0.012)	(0.015)
Speeches by others	0.002	-0.001	0.002	-0.003	-0.012	-0.007	-0.004	0.005	0.000	0.004	-0.001	0.010**
	(0.003)	(0.005)	(0.003)	(0.005)	(0.011)	(0.008)	(0.003)	(0.005)	(0.003)	(0.006)	(0.008)	(0.005)
Speeches by president	0.004	0.003	0.006**	-0.008***	-0.000	-0.007	-0.011***	-0.015**	-0.007**	0.003	0.018	0.027***
	(0.003)	(0.006)	(0.003)	(0.003)	(0.012)	(0.008)	(0.003)	(0.006)	(0.003)	(0.006)	(0.011)	(0.007)
Tweet	-0.000	-0.003	0.001	-0.007*	-0.005	-0.003	-0.003	0.010**	-0.003	-0.000	-0.004	0.011***
	(0.003)	(0.005)	(0.003)	(0.003)	(0.009)	(0.006)	(0.003)	(0.005)	(0.003)	(0.005)	(0.006)	(0.004)
Panel B: Overall response												
Press Conference	-0.007	-0.033	**0.039**	0.011	-0.035	0.012	**-0.123**	**-0.075**	0.001	0.021	0.051	**0.102**
Std. error	0.019	0.031	0.022	0.012	0.038	0.026	0.018	0.032	0.022	0.018	0.027	0.021
p-value	0.724	0.291	0.070	0.347	0.348	0.648	0.000	0.020	0.948	0.224	0.063	0.000
Whatever it takes	-0.045	-0.087	0.000	**-0.324**	**-0.569**	0.071	-0.042	-0.118	**0.186**	**0.368**	**0.929**	**0.424**
Std. error	0.038	0.067	0.046	0.054	0.160	0.099	0.039	0.074	0.049	0.078	0.093	0.047
p-value	0.239	0.192	0.996	0.000	0.000	0.477	0.282	0.108	0.000	0.000	0.000	0.000
Observations	2,537	2,537	2,537	2,531	1,551	1,284	2,537	2,537	2,537	2,531	1,551	1,284
R-squared	0.078	0.033	0.042	0.024	0.021	0.072	0.150	0.046	0.083	0.034	0.057	0.162
Mean(dependent var)	0.049	0.054	0.037	0.008	0.021	-0.001	0.211	0.224	0.172	0.062	0.031	0.016
Stdev(dependent var)	0.037	0.065	0.044	0.045	0.116	0.062	0.038	0.068	0.046	0.073	0.079	0.049

Notes: The table shows coefficient estimates for the effect of ECB communication events on the average and standard deviation of favourableness, based on equation (5). The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for "Whatever it takes" (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table 8: Explaining absolute favourableness

	Average absolute favourableness						Standard deviation of absolute favourableness					
	English			German			English			German		
	All	Non-experts	Experts	All	Non-experts	Experts	All	Non-experts	Experts	All	Non-experts	Experts
Panel A: Contemporaneous response												
Press Conference	-0.023***	-0.035***	-0.008**	-0.007*	-0.025	0.017***	-0.026***	-0.024***	-0.009**	0.011	0.020	0.064***
	(0.004)	(0.007)	(0.003)	(0.004)	(0.018)	(0.006)	(0.003)	(0.006)	(0.004)	(0.007)	(0.014)	(0.008)
Whatever it takes	-0.003	-0.021***	0.009**	-0.010**	0.007	0.028***	-0.003	-0.015**	0.011**	-0.010	0.031**	0.044***
	(0.004)	(0.008)	(0.004)	(0.005)	(0.019)	(0.007)	(0.004)	(0.007)	(0.004)	(0.009)	(0.014)	(0.008)
Economic Bulletin	-0.005	-0.000	-0.000	0.013*	0.009	0.046***	-0.008**	-0.000	-0.005	0.014	-0.000	0.027***
	(0.004)	(0.008)	(0.004)	(0.008)	(0.026)	(0.013)	(0.004)	(0.008)	(0.004)	(0.012)	(0.016)	(0.010)
Accounts	-0.017***	-0.016*	-0.014***	-0.004	-0.036*	0.075*	-0.012**	-0.007	-0.012***	-0.001	-0.026**	0.009
	(0.004)	(0.009)	(0.004)	(0.005)	(0.018)	(0.042)	(0.005)	(0.008)	(0.004)	(0.013)	(0.011)	(0.015)
Speeches by others	-0.004*	0.001	-0.001	0.002	-0.001	0.014*	-0.003	0.003	0.000	0.003	-0.002	0.010**
	(0.002)	(0.005)	(0.003)	(0.004)	(0.011)	(0.008)	(0.002)	(0.004)	(0.003)	(0.005)	(0.007)	(0.005)
Speeches by president	-0.006***	-0.012**	-0.003	-0.008***	-0.011	-0.009	-0.008***	-0.008	-0.006**	0.003	0.021*	0.027***
	(0.002)	(0.005)	(0.002)	(0.003)	(0.011)	(0.008)	(0.002)	(0.005)	(0.003)	(0.006)	(0.011)	(0.007)
Tweet	-0.003	0.005	-0.004	-0.002	0.003	0.005	-0.002	0.006*	-0.003	-0.001	-0.004	0.011***
	(0.002)	(0.004)	(0.002)	(0.003)	(0.009)	(0.006)	(0.002)	(0.004)	(0.003)	(0.005)	(0.006)	(0.004)
Panel B: Overall response												
Press Conference	**-0.084**	**-0.092**	-0.015	-0.008	-0.032	0.053	**-0.100**	-0.043	0.001	0.022	**0.057**	**0.098**
Std. error	0.016	0.027	0.019	0.012	0.036	0.025	0.015	0.026	0.019	0.017	0.026	0.020
p-value	0.000	0.001	0.427	0.507	0.372	0.035	0.000	0.101	0.968	0.208	0.030	0.000
Whatever it takes	0.027	**-0.173**	**0.219**	**-0.223**	-0.033	-0.014	**-0.084**	-0.089	0.063	**0.377**	**0.877**	**0.419**
Std. error	0.034	0.063	0.039	0.054	0.156	0.098	0.032	0.058	0.042	0.076	0.090	0.046
p-value	0.436	0.006	0.000	0.000	0.832	0.886	0.010	0.121	0.133	0.000	0.000	0.000
Observations	2,537	2,537	2,537	2,531	1,551	1,284	2,537	2,537	2,537	2,531	1,551	1,284
R-squared	0.143	0.060	0.063	0.031	0.028	0.097	0.145	0.036	0.073	0.034	0.059	0.164
Mean(dependent var)	0.118	0.136	0.094	0.023	0.044	0.014	0.183	0.193	0.152	0.061	0.030	0.015
Stdev(dependent var)	0.033	0.058	0.038	0.044	0.113	0.061	0.032	0.054	0.039	0.071	0.075	0.048

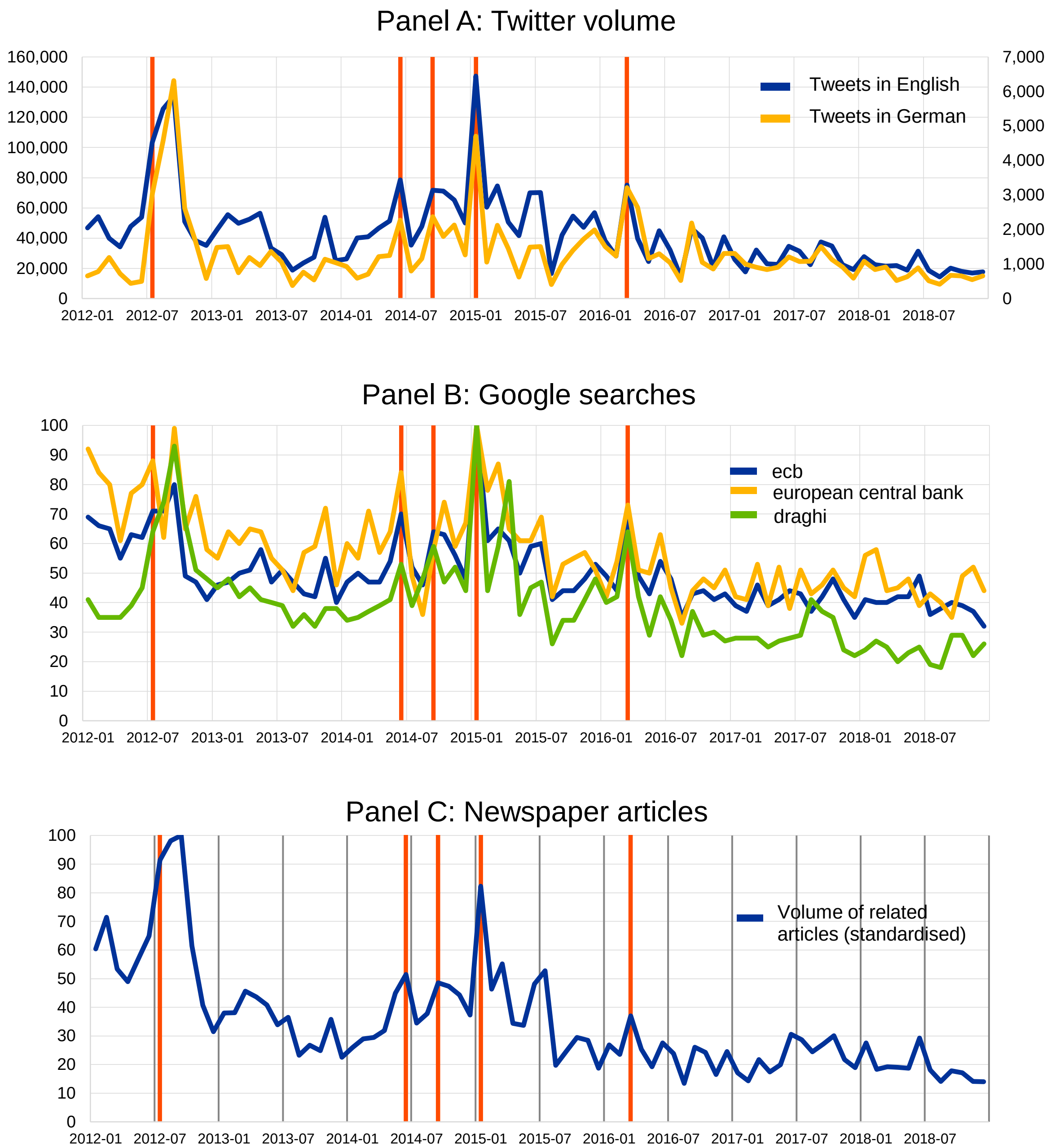
Notes: The table shows coefficient estimates for the effect of ECB communication events on the average and standard deviation of absolute favourableness, based on equation (5). The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for "Whatever it takes" (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table 9: Views about the ECB president vs views about the ECB

	Draghi						Benchmark					
	Subjectivity		Favourableness		Abs. favourableness		Subjectivity		Favourableness		Abs. favourableness	
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Panel A: Whatever it takes (contemporaneous effect)												
All	0.050***	0.018***	0.029***	0.010	0.019***	0.005	-0.005	-0.006**	0.019***	-0.008*	-0.003	-0.003
	(0.011)	(0.006)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)
Non-experts	0.036	0.093***	0.006	0.067***	0.007	0.062***	-0.045***	-0.005	0.015	-0.027***	-0.021***	-0.015**
	(0.028)	(0.018)	(0.023)	(0.016)	(0.019)	(0.014)	(0.012)	(0.007)	(0.009)	(0.009)	(0.008)	(0.007)
Experts	0.056***	0.049***	0.045***	0.032***	0.018*	0.028***	0.010	0.003	0.022***	0.010*	0.009**	0.011**
	(0.015)	(0.011)	(0.012)	(0.010)	(0.010)	(0.009)	(0.008)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Panel A: Speeches by Draghi (contemporaneous effect)												
All	-0.022***	-0.013***	0.006	-0.027***	-0.023***	-0.019***	-0.008**	-0.005**	0.004	-0.011***	-0.006***	-0.008***
	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Non-experts	-0.029*	0.058***	0.022*	0.049***	-0.015	0.046***	-0.024***	-0.012**	0.003	-0.015**	-0.012**	-0.008
	(0.016)	(0.011)	(0.013)	(0.010)	(0.011)	(0.009)	(0.008)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Experts	-0.014	0.014**	0.002	-0.003	-0.022***	-0.001	-0.003	-0.003	0.006**	-0.007**	-0.003	-0.006**
	(0.009)	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Mean(dependent var - All)	0.259	0.292	0.054	0.223	0.138	0.197	0.253	0.282	0.049	0.211	0.118	0.183
Stdev(dependent var - All)	0.125	0.079	0.101	0.088	0.087	0.071	0.050	0.027	0.037	0.038	0.033	0.032

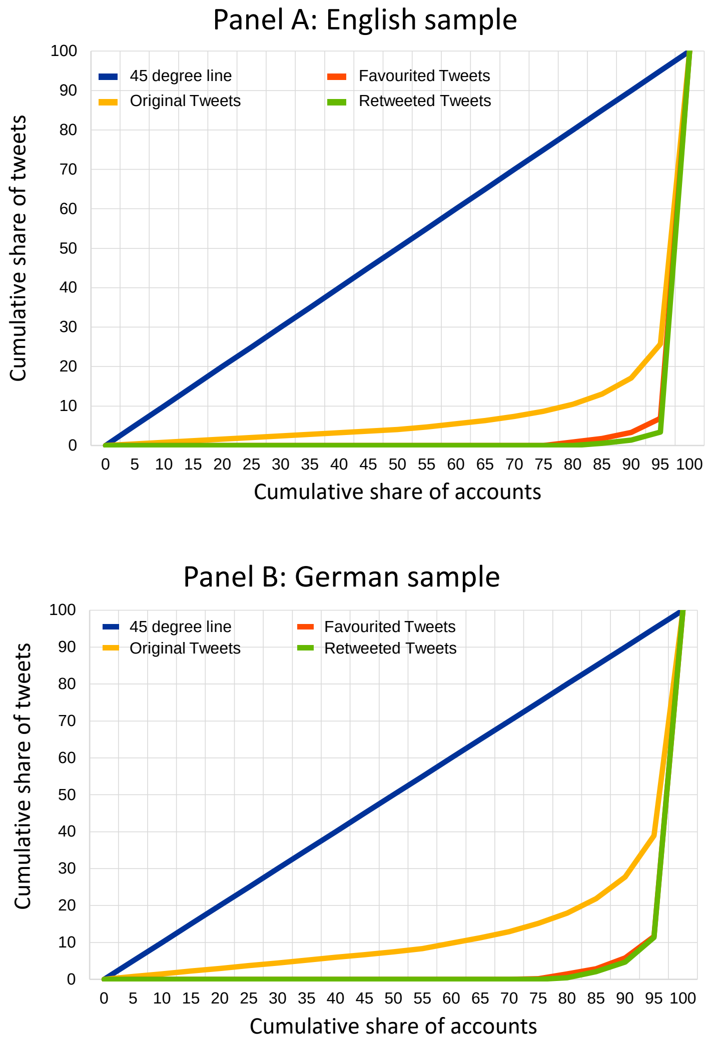
Notes: The table shows coefficient estimates for the contemporaneous effect of the "Whatever it takes" statements (Panel A) and all other speeches by former ECB president Draghi (Panel B) on the average and standard deviation of subjectivity, favourableness and absolute favourableness, based on equation (5), separately for the various account types. The left panel reports results for the views expressed about former ECB president Draghi, the right panel repeats the benchmark results for views about the ECB overall. The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level. The summary statistics at the bottom of the table refer to the mean and the standard deviation of the dependent variable for tweets originating from all accounts.

Figure 1: Interest in the ECB: number of tweets, google searches, newspaper articles



Notes: Panel A: Monthly number of ECB-related tweets in English (left axis) and German (right axis). The vertical lines illustrate the timing of various ECB actions, namely July 2012: "Whatever it takes"; June 2014: Introduction of negative interest rates and credit-easing measures via targeted long-term refinancing operations, then complemented by and an asset-backed securities purchase programme; September 2014: Introduction of third covered bond purchase programme; January 2015: Expansion of asset purchase programme (APP), starting the public sector purchase programme (PSPP); March 2016: ECB lowers rates further and expands its APP considerably.
Panel B: Monthly Google search popularity for the three search terms "ecb", "european central bank" and "draghi". Numbers represent search interest relative to the highest point on the chart for worldwide searches between 2012 and 2018. A value of 100 is the peak popularity for each term. Source: Google Trends (https://www.google.com/trends).
Panel C: Number of newspaper articles related to our key terms in English. The sample is based on 3,075 different news outlets and on over 800 thousand articles. As many online newspapers update the same article several times, there is a possibility for duplicated articles being in the sample. This is why we standardise values, where 100 is the peak of article volume between 2012 and 2018. Source: Factiva DNA.

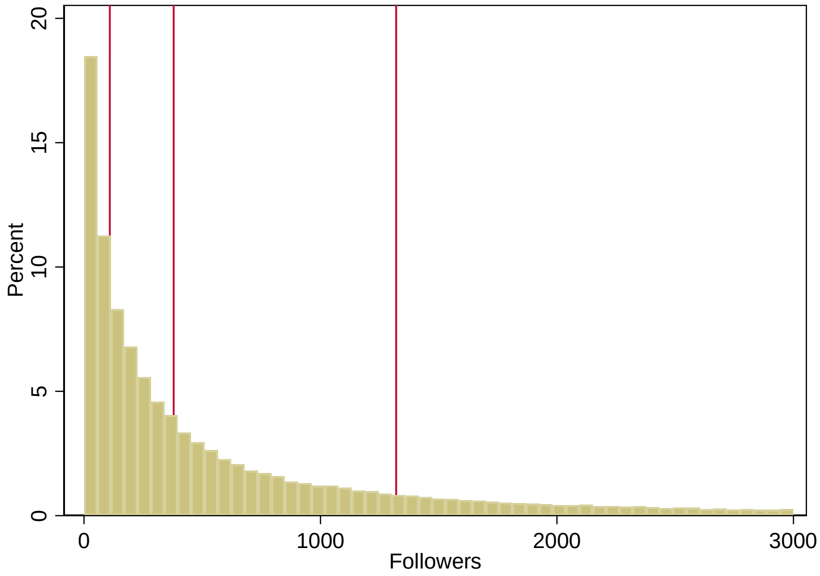
Figure 2: Lorenz curve of Twitter activity



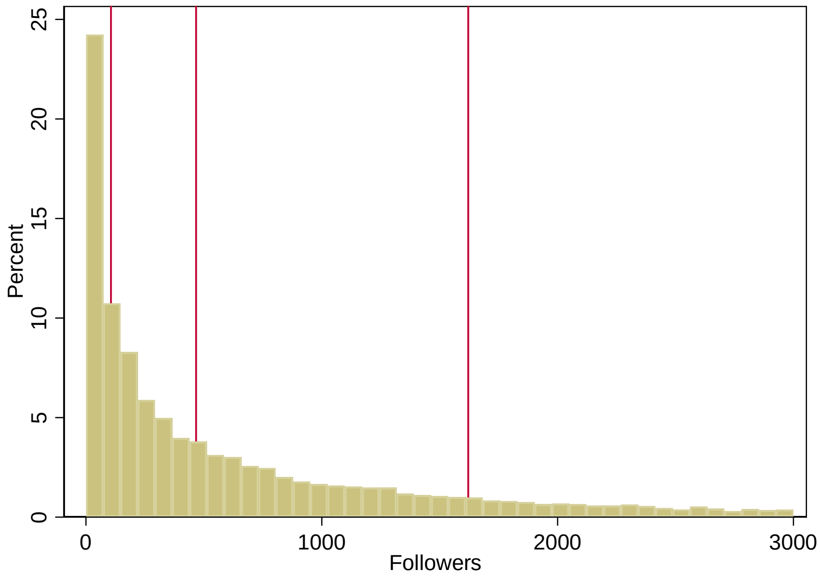
Notes: The figure shows in the top (lower) panel the Lorenz curve of ECB-related Twitter activity for the English (German) sample. The blue line represents the 45-degree line (which represents the line of equality. The yellow line shows the distribution of original tweets about the ECB, the red line the original tweets about the ECB that got “liked” by other Twitter accounts, the green line the original tweets about the ECB that got retweeted by other users.

Figure 3: Distribution of accounts by number of followers

Panel A: Accounts in English-speaking sample

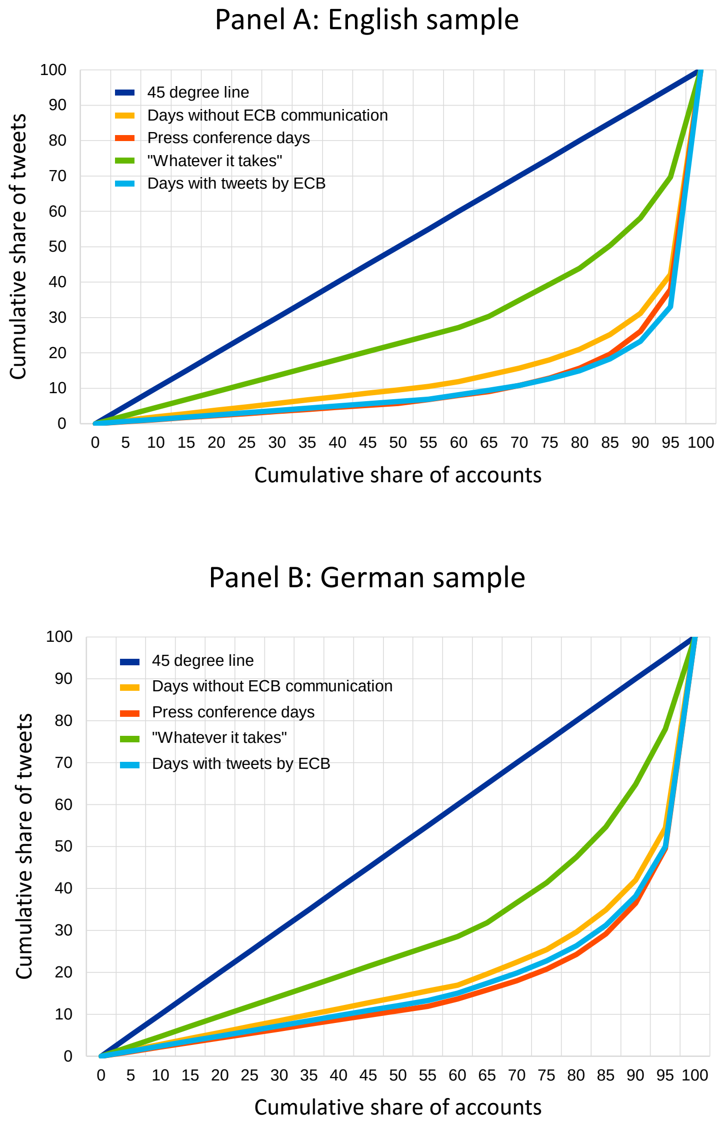


Panel B: Accounts in German-speaking sample



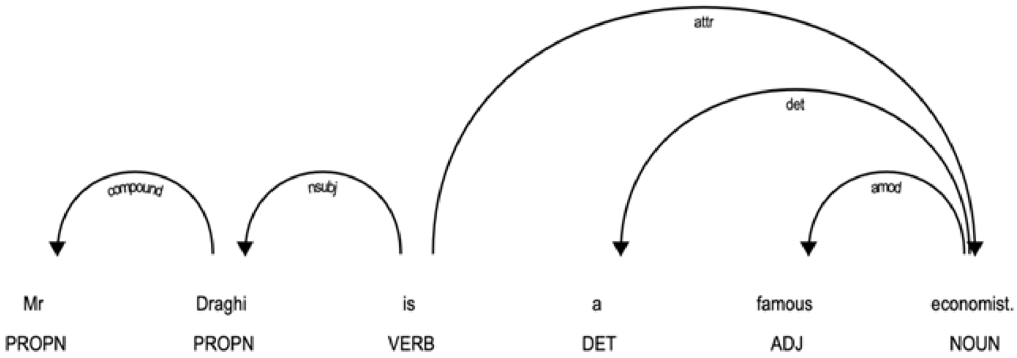
Notes: The figure shows the distribution of accounts by number of followers for the English sample (top panel) and German sample (bottom panel). Red lines denote 25%, 50% and 75% of sample, respectively. For better visualisation, the figure is truncated at 3,000 followers, whereas the actual maximum is 43,844,335 (6,368,598) followers in the English (German) sample.

Figure 4: Lorenz curve of Twitter activity by events



Notes: The figure shows in the top (lower) panel the Lorenz curve of ECB-related Twitter activity for the English (German) sample. The blue line represents the 45-degree line (which represents the line of equality. The yellow line shows the distribution of tweets on days without any ECB communication, the red on press conference days, the green line on the day of former ECB President Draghi's "Whatever it takes" statement and the light blue line on days with tweets by the official ECB account (and no other official communication).

Figure 5: Identification of sentiment relative to Mario Draghi

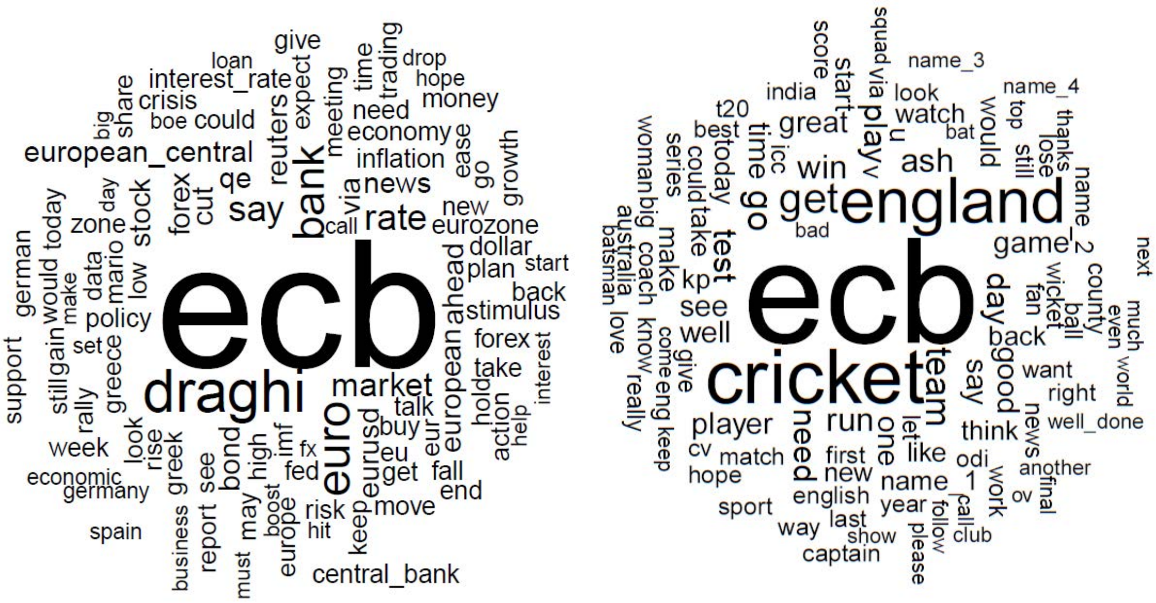


Notes: The chart illustrates the process involved in the Part-of-speech (POS) tagging that is applied in order to identify the sentiment relative to Mario Draghi expressed in a tweet.

Appendix

Figure A1: Word clouds of ECB-related and unrelated tweets

Panel A: English sample



Panel B: German sample

Note: The top word clouds represent the English sample and the bottom clouds represent the German sample. The left word clouds show the 100 most frequent words of the ECB-related tweets. The right word clouds show the 100 most frequent words of the tweets that were identified as unrelated to the ECB. For the word clouds we allow for bigrams (two words often occurring together) and exclude stop words, special characters, punctuation and links to websites. Word sizes indicate frequency. Names of individual persons other than the ECB president are anonymized for data protection reasons.

Table A1: Examples of words in English sentiment lexicon

selection of words high in favourability				selection of words low in subjectivity			
word	*favourability*	*subjectivity*	*sense*	*word*	*favourability*	*subjectivity*	*sense*
astonishing	1	1	so surprising as to stun or overwhelm	drag	-0.2	0	move slowly and as if with great effort
best	1	0.3	(superlative) having the most positive qualities	stretched	-0.1	0	extended spread over a wide area or distance
breathtaking	1	1	tending to cause suspension of regular breathing	unexplained	-0.1	0	having the reason or cause not made clear
consummate	1	1	having or revealing supreme mastery or skill	vacuum	-0.05	0	a region that is devoid of matter
delicious	1	1	extremely pleasing to the sense of taste	20th	0	0	coming next after the nineteenth in position
exceptional	1	1	surpassing what is common or usual or expected	academic	0	0	associated with academia or an academy
exceptional	1	1	far beyond what is usual in magnitude or degree	actual	0	0	being or existing at the present moment
impressed	1	1	deeply or markedly affected or influenced	aforementioned	0	0	being the one previously mentioned or spoken of
marvelous	1	1	too improbable to admit of belief	alternate	0	0	serving or used in place of another
marvelous	1	1	being or having the character of a miracle	atmospheric	0	0	relating to or located in the atmosphere
masterful	1	1	having or revealing supreme mastery or skill	back	0	0	relating to or located at the back
overwhelming	1	1	so strong as to be irresistible	basic	0	0	serving as a base or starting point
priceless	1	1	having incalculable monetary, intellectual or spiritual worth	basic	0	0	pertaining to or constituting a base or basis
bewitching	0.9	1	capturing interest as if by a spell	chronological	0	0	relating to or arranged according to temporal order
consummate	0.9	1	having or revealing supreme mastery or skill	comic	0	0	of or relating to or characteristic of comedy
favored	0.8	0.9	preferred above all others and treated with partiality	consistent	0	0	the same throughout in structure or composition
fly	0.8	0.9	(British informal) not to be deceived or hoodwinked	contemporary	0	0	occurring in the same period of time
joy	0.8	0.2	something that provides a source of happiness	daily	0	0	of or belonging to or occurring every day

selection of words high in subjectivity				selection of words low in favourability			
word	*favourability*	*subjectivity*	*sense*	*word*	*favourability*	*subjectivity*	*sense*
consummate	0.9	1	having or revealing supreme mastery or skill	awful	-1	1	causing fear or dread or terror
bewitching	0.7	1	capturing interest as if by a spell	deadly	-1	1	involving loss of divine grace or spiritual death
controversial	0.7	1	marked by or capable of arousing controversy	devastating	-1	1	wreaking or capable of wreaking complete destruction
astounding	0.6	1	bewildering or striking dumb with wonder	dreadful	-1	1	causing fear or dread or terror
bewitching	0.6	1	capturing interest as if by a spell	evil	-1	1	having or exerting a malignant influence
loving	0.6	1	feeling or showing love and affection	grim	-1	1	harshly uninviting or formidable in manner or appearance
mouth-watering	0.6	1	pleasing to the sense of taste	grotesque	-1	1	distorted and unnatural in shape or size
rose	0.6	1	of something having a dusty purplish pink color	horrific	-1	1	causing fear or dread or terror
adorable	0.5	1	lovely especially in a childlike or naïve way	hysterical	-1	1	characterized by or arising from psychoneurotic behavior
authentic	0.5	1	conforming to fact and therefore worthy of belief	impossible	-1	1	used of persons or their behavior
avid	0.5	1	marked by active interest and enthusiasm	insane	-1	1	afflicted with or characterized of mental derangement
capable	0.5	1	have the skills and qualification to do things well	menacing	-1	1	threatening or foreshadow evil or tragic development
captivating	0.5	1	capturing interest as if by a spell	nasty	-1	1	exasperatingly difficult to handle or circumvent
certain	0.5	1	having or feeling no doubt or uncertainty	outrageous	-1	1	greatly exceeding bounds of reason or moderation
challenging	0.5	1	requiring full use of your abilities or resources	terrible	-1	1	causing fear or dread or terror
charismatic	0.5	1	possessing an extraordinary ability to attract	violent	-1	1	effected by force or injury rather than natural causes
competent	0.5	1	properly sufficiently qualified or capable or efficient	malevolent	-0.9	1	wishing or appearing to wish evil to others
confident	0.5	1	having or marked by confidence or assurance	repellent	-0.9	1	incapable of absorbing or missing with
inconvenient	-0.6	1	not suited to your comfort, purpose or needs	stupid	-0.9	1	lacking or marked by lack of intellectual acuity

Notes: This table lists selected words and their favourability and subjectivity scores. Multiple entries of the same word are generally due to multiple meanings and in these cases average score is taken by default. Source: Princeton University’s WordNet, https://wordnet.princeton.edu/

Table A2: Characteristics of account types, robustness

	Number of accounts	Average date of account creation	Average percentile followers	Average percentile ECB centricity	Average subjectivity	Average standard deviation of subjectivity	Standard deviation of average subjectivity	Average favourable-ness	Average standard deviation of favourable-ness	Standard deviation of average favourable-ness	Average absolute favourable-ness	Average standard deviation of absolute favourable-ness	Standard deviation of average absolute favourable-ness	Average weekend activity
Panel A: English														
Non-expert (benchmark)	69,031	28/08/2011	68	12	0.2746	0.2153	0.2756	0.0544	0.1526	0.2247	0.1389	0.1306	0.1311	0.1835
Non-expert (excl. centricity)	286,366	09/01/2012	50	47	0.2830	0.2337	0.2534	0.0573	0.1686	0.2075	0.1400	0.1431	0.1162	0.1652
Non-expert (few followers)	5,010	27/06/2013	12	13	0.2270	0.1813	0.2583	0.0479	0.1176	0.1953	0.1096	0.1065	0.1216	0.1866
Expert (benchmark)	1,282	03/02/2013	68	84	0.2434	0.2579	0.0954	0.0418	0.1714	0.0627	0.0994	0.1491	0.0405	0.0716
Expert (0.33)	2,803	27/11/2012	66	81	0.2407	0.2560	0.0897	0.0416	0.1726	0.0540	0.0994	0.1500	0.0412	0.0739
Expert (0.75)	369	18/10/2013	66	86	0.2478	0.2619	0.1093	0.0464	0.1718	0.0732	0.1026	0.1499	0.0475	0.0624
Expert (ECB-centric)	1,087	10/11/2012	69	89	0.2447	0.2600	0.0882	0.0416	0.1736	0.0588	0.1002	0.1506	0.0358	0.0684
Panel B: German														
Non-expert (benchmark)	3,921	22/09/2011	65	12	0.1305	0.1172	0.2592	0.0472	0.0735	0.1811	0.0734	0.0717	0.1337	0.2024
Non-expert (excl. centricity)	16,313	17/02/2012	50	49	0.0738	0.0756	0.1960	0.0210	0.0444	0.1304	0.0405	0.0432	0.0976	0.1722
Non-expert (few followers)	327	26/08/2012	14	14	0.2053	0.1322	0.2992	0.0974	0.0852	0.2073	0.1072	0.0801	0.1361	0.2660
Expert (benchmark)	23	03/07/2013	63	84	0.0309	0.1278	0.0459	0.0013	0.0661	0.0209	0.0156	0.0645	0.0599	0.0755
Expert (0.33)	80	27/05/2012	66	82	0.0218	0.0996	0.0296	0.0020	0.0489	0.0122	0.0099	0.0480	0.0431	0.0912
Expert (0.75)	4	26/10/2013	54	95	0.0218	0.1410	0.0155	0.0000	0.0666	0.0014	0.0090	0.0655	0.0338	0.0125
Expert (ECB-centric)	19	02/02/2013	68	89	0.0248	0.1106	0.0377	-0.0020	0.0564	0.0117	0.0125	0.0547	0.0527	0.0618

Notes: The table shows summary statistics for the various account types, in the English sample (Panel A) and the German sample (Panel B).

Table A3: Determinants of Retweets and Likes, full sample

	English							German						
	Probit	OLS	Probit	OLS	Multinomial Logit			Probit	OLS	Probit	OLS	Multinomial Logit		
	Retweet		Like		Retweet	Like	R & L	Retweet		Like		Retweet	Like	R & L
Negative sentiment	0.001	-0.008**	0.002***	-0.021***	0.001**	0.003***	-0.000	0.002	0.092	-0.010	0.083	-0.002	-0.011***	0.004
	(0.000)	(0.004)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.008)	(0.060)	(0.007)	(0.061)	(0.006)	(0.004)	(0.006)
Abs(favourableness)	0.030***	0.049***	0.049***	0.118***	0.004***	0.021***	0.024***	-0.003	-0.039	0.039**	0.097	-0.006	0.030***	0.003
	(0.001)	(0.010)	(0.001)	(0.009)	(0.001)	(0.001)	(0.001)	(0.020)	(0.131)	(0.017)	(0.130)	(0.016)	(0.011)	(0.015)
Subjectivity	0.014***	-0.000	0.026***	0.004	0.005***	0.018***	0.008***	0.001	0.046	0.020*	-0.032	-0.001	0.017**	0.004
	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.000)	(0.001)	(0.012)	(0.073)	(0.011)	(0.072)	(0.009)	(0.007)	(0.009)
Percentile Followers	0.005***	0.014***	0.003***	0.010***	0.002***	0.000***	0.004***	0.004***	0.011***	0.003***	0.010***	0.002***	0.000***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-expert	-0.047***	-0.109***	-0.022***	-0.070***	-0.023***	0.001**	-0.025***	-0.057***	0.062*	-0.017***	0.079**	-0.039***	0.004	-0.019***
	(0.001)	(0.007)	(0.001)	(0.006)	(0.001)	(0.000)	(0.001)	(0.004)	(0.032)	(0.004)	(0.031)	(0.004)	(0.003)	(0.003)
Expert	0.036***	0.237***	0.008***	0.143***	0.015***	-0.019***	0.020***	-0.149***	-0.494***	-0.141***	-0.521***	-0.040***	-0.032***	-0.120***
	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.004)	(0.020)	(0.004)	(0.020)	(0.003)	(0.003)	(0.005)
No. of Characters	0.000***	0.001***	0.000***	0.001***	0.000***	-0.000***	0.000***	0.000***	0.001***	0.000***	0.001***	0.000***	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,610,722	463,973	3,610,722	417,903		3,610,722		109,931	14,763	109,931	13,612		109,931	
R-squared		0.113		0.124					0.110		0.125			

Notes: The table shows coefficient estimates for the determinants of Retweets and Likes, using the full sample. The left panel reports results for English sample, the right panel for the German sample. Results for probit and multinomial logit models are marginal effects. The OLS models explain the log of the number of Retweets and Likes and are thus conditional on a tweet being retweeted or liked, respectively. The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table A4: Twitter traffic, leads and lags of press conference and "Whatever it takes"

	Log number of tweets					
		English			German	
	All	Non-experts	Experts	All	Non-experts	Experts
Press Conference, t-5	0.168**	-0.038	0.450***	--	--	--
	(0.067)	(0.077)	(0.083)			
Press Conference, t-4	0.302***	0.084	0.644***	--	--	--
	(0.082)	(0.087)	(0.096)			
Press Conference, t-3	0.292***	0.031	0.414***	--	--	--
	(0.071)	(0.089)	(0.073)			
Press Conference, t-2	0.259***	0.111	0.344***	--	--	--
	(0.076)	(0.091)	(0.076)			
Press Conference, t-1	0.610***	0.254***	0.767***	0.438***	0.119	0.572***
	(0.081)	(0.088)	(0.082)	(0.108)	(0.134)	(0.148)
Press Conference, t	2.475***	2.059***	2.847***	2.475***	1.194***	2.735***
	(0.075)	(0.109)	(0.076)	(0.120)	(0.163)	(0.150)
Press Conference, t+1	1.055***	1.012***	1.055***	1.266***	0.665***	1.012***
	(0.086)	(0.111)	(0.086)	(0.105)	(0.141)	(0.142)
Press Conference, t+2	0.412***	0.351***	0.526***	0.409***	0.166	0.305*
	(0.085)	(0.086)	(0.100)	(0.144)	(0.173)	(0.176)
Press Conference, t+3	0.261***	0.217**	0.365***	--	--	--
	(0.088)	(0.098)	(0.106)			
Press Conference, t+4	0.132*	0.087	0.081	--	--	--
	(0.075)	(0.095)	(0.081)			
Whatever it takes, t	2.020***	1.883***	1.740***	3.239***	1.590***	2.413***
	(0.073)	(0.094)	(0.080)	(0.126)	(0.154)	(0.158)
Whatever it takes, t+1	2.850***	2.442***	2.775***	4.109***	2.806***	2.800***
	(0.064)	(0.077)	(0.070)	(0.106)	(0.119)	(0.136)
Whatever it takes, t+2	1.774***	1.273***	1.434***	3.345***	2.545***	0.894***
	(0.073)	(0.085)	(0.084)	(0.089)	(0.100)	(0.130)
Whatever it takes, t+3	1.258***	1.269***	0.912***	2.002***	1.041***	1.098***
	(0.086)	(0.092)	(0.094)	(0.091)	(0.103)	(0.128)
Whatever it takes, t+4	1.875***	1.781***	1.551***	3.811***	3.661***	2.313***
	(0.077)	(0.095)	(0.080)	(0.089)	(0.106)	(0.118)
Whatever it takes, t+5	1.992***	1.870***	1.737***	3.394***	2.500***	2.736***
	(0.088)	(0.104)	(0.091)	(0.102)	(0.113)	(0.128)
Whatever it takes, t+6	1.358***	1.329***	1.162***	2.367***	1.841***	1.296***
	(0.095)	(0.098)	(0.101)	(0.135)	(0.161)	(0.182)
Whatever it takes, t+7	1.320***	1.542***	0.985***	2.749***	2.452***	1.117***
	(0.081)	(0.104)	(0.084)	(0.125)	(0.164)	(0.156)
Whatever it takes, t+8	1.571***	1.573***	1.466***	2.792***	1.978***	1.268***
	(0.105)	(0.124)	(0.109)	(0.139)	(0.177)	(0.186)
Whatever it takes, t+9	1.407***	1.346***	1.387***	3.328***	1.794***	0.823***
	(0.096)	(0.094)	(0.109)	(0.165)	(0.200)	(0.199)
Whatever it takes, t+10	1.250***	0.719***	1.176***	2.425***	0.949***	-0.172
	(0.098)	(0.103)	(0.114)	(0.107)	(0.116)	(0.145)
Whatever it takes, t+11	1.551***	1.126***	1.606***	2.909***	2.374***	0.676***
	(0.090)	(0.100)	(0.099)	(0.104)	(0.116)	(0.142)
Whatever it takes, t+12	1.644***	1.242***	1.597***	2.742***	0.415***	-0.208
	(0.071)	(0.073)	(0.078)	(0.112)	(0.128)	(0.140)
Whatever it takes, t+13	0.972***	0.338***	1.062***	1.223***	-0.057	--
	(0.067)	(0.067)	(0.076)	(0.105)	(0.119)	
Whatever it takes, t+14	1.278***	0.718***	1.360***	1.996***	1.020***	--
	(0.088)	(0.102)	(0.093)	(0.135)	(0.174)	
Whatever it takes, t+15	0.681***	0.448***	0.497***	0.597***	-0.708***	--
	(0.069)	(0.068)	(0.077)	(0.109)	(0.125)	

Notes: The table shows the coefficient estimates for leads and lags of the ECB press conference and "Whatever it takes" omitted from Table 5. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table A5: Twitter traffic, robustness tests

	Log number of tweets													
	English							German						
	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)
Panel A: Contemporaneous response														
Press Conference	2.059***	2.343***	1.831***	2.847***	2.806***	2.871***	2.824***	1.194***	2.346***	0.030	2.735***	3.096***	2.210***	2.596***
	(0.109)	(0.081)	(0.132)	(0.076)	(0.073)	(0.074)	(0.075)	(0.163)	(0.121)	(0.235)	(0.150)	(0.155)	(0.154)	(0.150)
Whatever it takes	1.883***	2.112***	1.860***	1.740***	1.915***	1.618***	1.700***	1.590***	3.290***	-0.088	2.413***	2.759***	1.899***	2.234***
	(0.094)	(0.075)	(0.132)	(0.080)	(0.079)	(0.078)	(0.078)	(0.154)	(0.126)	(0.226)	(0.158)	(0.168)	(0.181)	(0.154)
Economic Bulletin	0.142	0.200**	-0.045	0.362***	0.334***	0.415***	0.371***	-0.185	-0.159	-0.422**	-0.209	-0.265	-0.106	-0.248
	(0.102)	(0.084)	(0.131)	(0.084)	(0.084)	(0.078)	(0.082)	(0.166)	(0.122)	(0.192)	(0.165)	(0.173)	(0.152)	(0.160)
Accounts	0.324***	0.481***	0.166	0.986***	0.900***	1.018***	0.985***	0.054	0.028	0.079	-0.103	-0.044	-0.119	-0.163
	(0.097)	(0.078)	(0.156)	(0.091)	(0.084)	(0.096)	(0.090)	(0.196)	(0.138)	(0.466)	(0.185)	(0.198)	(0.181)	(0.176)
Speeches by others	0.080	0.224***	0.019	0.450***	0.414***	0.468***	0.451***	0.050	0.154**	0.027	0.129	0.179*	0.129	0.093
	(0.052)	(0.043)	(0.070)	(0.047)	(0.046)	(0.046)	(0.046)	(0.081)	(0.070)	(0.188)	(0.091)	(0.096)	(0.095)	(0.089)
Speeches by president	0.385***	0.407***	0.406***	0.499***	0.489***	0.507***	0.489***	0.453***	0.812***	0.270	1.223***	1.302***	0.921***	1.200***
	(0.067)	(0.051)	(0.099)	(0.055)	(0.054)	(0.053)	(0.053)	(0.115)	(0.088)	(0.191)	(0.107)	(0.116)	(0.104)	(0.107)
Tweet	0.157***	0.175***	0.084	0.274***	0.265***	0.285***	0.271***	0.053	0.111*	-0.133	0.169**	0.157*	0.155*	0.149*
	(0.048)	(0.042)	(0.062)	(0.046)	(0.045)	(0.046)	(0.045)	(0.071)	(0.066)	(0.150)	(0.084)	(0.090)	(0.089)	(0.083)
Panel B: Overall response														
Press Conference	**4.169**	**5.612**	**3.694**	**7.494**	**7.307**	**7.448**	**7.454**	**2.144**	**4.378**	0.774	**4.624**	**5.167**	**2.911**	**4.455**
Std. error	0.325	0.277	0.437	0.303	0.298	0.304	0.296	0.316	0.246	0.691	0.315	0.346	0.307	0.317
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.264	0.000	0.000	0.000	0.000
Whatever it takes	**20.901**	**25.491**	**18.062**	**22.446**	**24.779**	**20.058**	**21.861**	**26.200**	**42.957**	**3.997**	**17.056**	**26.457**	**4.755**	**15.909**
Std. error	0.739	0.754	0.956	0.833	0.831	0.814	0.816	1.338	1.174	1.737	1.186	1.576	0.862	1.198
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.022	0.000	0.000	0.000	0.000
Observations	2,537	2,537	2,033	2,537	2,537	2,534	2,537	1,551	2,531	273	1,284	1,596	677	1,254
R-squared	0.365	0.587	0.260	0.717	0.709	0.736	0.728	0.219	0.355	0.233	0.434	0.390	0.524	0.434

Notes: The table shows coefficient estimates for the effect of ECB communication events on log number of tweets, based on equation (5), for different definitions of non-experts and experts. The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for “Whatever it takes” (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table A6: Concentration index, robustness tests

	Concentration index													
	English							German						
	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)
Panel A: Contemporaneous response														
Press Conference	-0.037***	-0.005***	-0.379***	-0.022***	-0.017***	-0.054***	-0.023***	-0.388***	-0.119***	-0.076	-0.536***	-0.476***	-0.467***	-0.519***
	(0.003)	(0.001)	(0.034)	(0.003)	(0.002)	(0.006)	(0.003)	(0.047)	(0.014)	(0.096)	(0.041)	(0.040)	(0.036)	(0.039)
Whatever it takes	-0.016***	-0.002***	-0.202***	-0.012***	-0.010***	-0.027***	-0.011***	-0.441***	-0.098***	-0.258**	-0.416***	-0.316***	-0.414***	-0.405***
	(0.003)	(0.001)	(0.045)	(0.003)	(0.002)	(0.008)	(0.003)	(0.058)	(0.017)	(0.108)	(0.052)	(0.050)	(0.050)	(0.052)
Economic Bulletin	-0.006*	-0.001	0.026	-0.006**	-0.005***	-0.018***	-0.006**	0.063	0.007	0.139	0.010	0.046	-0.054	0.018
	(0.003)	(0.001)	(0.048)	(0.003)	(0.002)	(0.006)	(0.003)	(0.071)	(0.019)	(0.084)	(0.057)	(0.058)	(0.051)	(0.056)
Accounts	-0.016***	-0.001**	-0.088	-0.016***	-0.011***	-0.033***	-0.017***	-0.069	-0.022	-0.002	0.009	0.006	0.019	0.009
	(0.003)	(0.001)	(0.064)	(0.003)	(0.002)	(0.007)	(0.004)	(0.077)	(0.022)	(0.140)	(0.067)	(0.074)	(0.060)	(0.066)
Speeches by others	-0.004**	-0.001**	-0.008	-0.014***	-0.009***	-0.036***	-0.015***	-0.037	-0.030**	-0.010	-0.054	-0.076**	-0.065***	-0.043
	(0.002)	(0.001)	(0.027)	(0.003)	(0.001)	(0.006)	(0.003)	(0.033)	(0.012)	(0.071)	(0.033)	(0.033)	(0.025)	(0.033)
Speeches by president	-0.012***	-0.001***	-0.120***	-0.001	-0.001*	-0.003	-0.001	-0.150***	-0.049***	-0.127	-0.307***	-0.274***	-0.224***	-0.299***
	(0.002)	(0.000)	(0.035)	(0.001)	(0.001)	(0.003)	(0.001)	(0.040)	(0.008)	(0.084)	(0.030)	(0.028)	(0.030)	(0.031)
Tweet	-0.006**	-0.001**	-0.015	-0.012***	-0.007***	-0.031***	-0.013***	-0.051*	-0.023*	0.022	-0.076**	-0.066**	-0.061***	-0.077**
	(0.002)	(0.001)	(0.024)	(0.003)	(0.001)	(0.006)	(0.003)	(0.030)	(0.012)	(0.060)	(0.031)	(0.030)	(0.020)	(0.031)
Panel B: Overall response														
Press Conference	**-0.125**	**-0.021**	**-1.160**	**-0.205**	**-0.124**	**-0.453**	**-0.219**	**-0.755**	**-0.317**	**-0.432**	**-1.044**	**-0.973**	**-0.608**	**-1.009**
Std. error	0.013	0.003	0.172	0.021	0.012	0.048	0.023	0.107	0.030	0.237	0.104	0.101	0.080	0.106
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.070	0.000	0.000	0.000	0.000
Whatever it takes	**-0.433**	**-0.062**	**-3.426**	**-0.527**	**-0.332**	**-1.304**	**-0.551**	**-6.984**	**-2.765**	**-2.467**	**-4.759**	**-6.022**	**-1.402**	**-3.942**
Std. error	0.038	0.008	0.365	0.059	0.040	0.133	0.062	0.485	0.190	0.682	0.416	0.526	0.209	0.414
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	2,537	2,537	2,033	2,537	2,537	2,534	2,537	1,551	2,531	273	1,284	1,596	677	1,254
R-squared	0.241	0.185	0.157	0.395	0.397	0.415	0.406	0.165	0.174	0.230	0.256	0.190	0.414	0.256

Notes: The table shows coefficient estimates for the effect of ECB communication events on the concentration index, based on equation (5), for different definitions of non-experts and experts. The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for "Whatever it takes" (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table A7: Average subjectivity, robustness tests

	Average subjectivity													
	English							German						
	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)
Panel A: Contemporaneous response														
Press Conference	-0.016***	-0.029***	0.031	0.012**	0.015***	0.028***	0.013**	-0.038	-0.010	0.028	0.040***	0.031***	0.051***	0.041***
	(0.005)	(0.009)	(0.024)	(0.006)	(0.006)	(0.006)	(0.006)	(0.030)	(0.007)	(0.033)	(0.009)	(0.007)	(0.014)	(0.010)
Whatever it takes	-0.010	-0.045***	0.099***	0.010	0.007	0.003	0.009	0.020	-0.009	-0.023	0.093***	0.065***	0.108***	0.036***
	(0.006)	(0.012)	(0.029)	(0.008)	(0.007)	(0.008)	(0.007)	(0.031)	(0.008)	(0.072)	(0.011)	(0.010)	(0.014)	(0.011)
Economic Bulletin	-0.011*	-0.010	-0.001	-0.003	-0.005	0.002	-0.004	-0.010	0.014	-0.020	0.057***	0.047***	0.011	0.068***
	(0.006)	(0.012)	(0.032)	(0.007)	(0.006)	(0.007)	(0.006)	(0.041)	(0.011)	(0.033)	(0.019)	(0.015)	(0.018)	(0.018)
Accounts	-0.027***	-0.026*	-0.026	-0.018**	-0.012*	-0.013	-0.020***	-0.059**	-0.008	0.004	0.109**	0.108**	0.042	0.119**
	(0.006)	(0.016)	(0.046)	(0.008)	(0.007)	(0.008)	(0.007)	(0.029)	(0.008)	(0.046)	(0.055)	(0.054)	(0.041)	(0.058)
Speeches by others	0.000	0.004	0.018	0.007	0.008*	0.011**	0.006	0.001	0.006	0.070	0.021**	0.018**	0.020	0.023**
	(0.004)	(0.006)	(0.018)	(0.005)	(0.005)	(0.005)	(0.005)	(0.017)	(0.008)	(0.048)	(0.011)	(0.009)	(0.013)	(0.011)
Speeches by president	-0.010**	-0.024***	-0.063***	-0.003	-0.001	0.005	-0.002	-0.019	-0.012**	-0.065	-0.013	-0.012	-0.009	-0.010
	(0.004)	(0.008)	(0.021)	(0.005)	(0.004)	(0.005)	(0.005)	(0.017)	(0.005)	(0.040)	(0.011)	(0.009)	(0.013)	(0.011)
Tweet	-0.004	0.005	-0.012	-0.004	-0.004	-0.002	-0.004	0.011	-0.000	0.035	0.012	0.010	0.020**	0.015*
	(0.003)	(0.006)	(0.015)	(0.005)	(0.004)	(0.005)	(0.005)	(0.016)	(0.006)	(0.030)	(0.008)	(0.007)	(0.009)	(0.008)
Panel B: Overall response														
Press Conference	**-0.073**	**-0.098**	0.025	0.010	0.034	0.041	0.010	-0.028	-0.019	0.216	**0.086**	**0.066**	0.125	**0.057**
Std. error	0.023	0.040	0.117	0.033	0.030	0.038	0.033	0.058	0.020	0.179	0.039	0.031	0.106	0.028
p-value	0.002	0.014	0.829	0.754	0.267	0.277	0.769	0.633	0.337	0.228	0.026	0.035	0.240	0.040
Whatever it takes	**-0.096**	-0.087	**0.928**	**0.362**	**0.365**	**0.633**	**0.389**	-0.292	**-0.346**	-0.106	-0.006	**-0.268**	**0.291**	0.018
Std. error	0.054	0.090	0.229	0.073	0.068	0.090	0.072	0.272	0.087	0.370	0.143	0.162	0.066	0.122
p-value	0.076	0.331	0.000	0.000	0.000	0.000	0.000	0.282	0.000	0.774	0.968	0.098	0.000	0.881
Observations	2,537	2,537	2,033	2,537	2,537	2,534	2,537	1,551	2,531	273	1,284	1,596	677	1,254
R-squared	0.189	0.075	0.046	0.084	0.059	0.127	0.086	0.035	0.032	0.180	0.096	0.068	0.055	0.098

Notes: The table shows coefficient estimates for the effect of ECB communication events on average subjectivity, based on equation (5), for different definitions of non-experts and experts. The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for "Whatever it takes" (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table A8: Standard deviation of subjectivity, robustness tests

	Standard deviation of subjectivity													
	English							German						
	Non-experts (bm)	**Non-experts (excl centr.)**	**Non-experts (few follow.)**	**Experts (bm)**	**Experts (0.33)**	**Experts (0.75)**	**Experts (ECB centric)**	**Non-experts (bm)**	**Non-experts (excl centr.)**	**Non-experts (few follow.)**	**Experts (bm)**	**Experts (0.33)**	**Experts (0.75)**	**Experts (ECB centric)**
Panel A: Contemporaneous response														
Press Conference	-0.015***	-0.014***	0.120***	0.001	-0.002	0.010**	0.001	0.062***	0.018*	0.004	0.130***	0.120***	0.111***	0.121***
	(0.006)	(0.003)	(0.015)	(0.004)	(0.003)	(0.004)	(0.004)	(0.019)	(0.010)	(0.023)	(0.014)	(0.011)	(0.018)	(0.014)
Whatever it takes	-0.005	-0.008**	0.151***	0.003	0.001	0.002	0.001	0.134***	0.025*	-0.047	0.170***	0.142***	0.225***	0.111***
	(0.007)	(0.003)	(0.019)	(0.005)	(0.005)	(0.006)	(0.005)	(0.019)	(0.013)	(0.032)	(0.013)	(0.013)	(0.016)	(0.014)
Economic Bulletin	-0.013*	-0.009***	0.000	-0.009**	-0.011**	-0.010**	-0.010**	-0.006	0.012	-0.015	0.040**	0.032**	0.007	0.041**
	(0.008)	(0.003)	(0.021)	(0.004)	(0.004)	(0.005)	(0.004)	(0.019)	(0.015)	(0.018)	(0.018)	(0.016)	(0.027)	(0.018)
Accounts	-0.005	-0.012***	0.009	-0.009*	-0.010*	-0.004	-0.010*	-0.004	-0.014	-0.004	0.027	0.018	0.030	0.027
	(0.010)	(0.004)	(0.027)	(0.005)	(0.005)	(0.006)	(0.005)	(0.023)	(0.018)	(0.015)	(0.026)	(0.025)	(0.041)	(0.028)
Speeches by others	0.004	-0.001	0.003	0.003	0.000	0.009**	0.003	-0.000	0.006	0.004	0.021***	0.018**	0.014	0.022***
	(0.004)	(0.002)	(0.012)	(0.003)	(0.003)	(0.004)	(0.003)	(0.010)	(0.008)	(0.015)	(0.008)	(0.007)	(0.012)	(0.008)
Speeches by president	-0.012**	-0.004**	0.005	-0.003	-0.002	0.000	-0.003	0.022	0.007	0.002	0.037***	0.039***	0.023*	0.037***
	(0.005)	(0.002)	(0.014)	(0.003)	(0.003)	(0.003)	(0.003)	(0.014)	(0.009)	(0.014)	(0.012)	(0.011)	(0.014)	(0.012)
Tweet	0.003	-0.002	0.006	-0.002	-0.005**	0.001	-0.002	-0.003	0.002	-0.003	0.020***	0.015***	0.010	0.019***
	(0.003)	(0.002)	(0.010)	(0.003)	(0.002)	(0.004)	(0.003)	(0.009)	(0.007)	(0.011)	(0.007)	(0.006)	(0.009)	(0.007)
Panel B: Overall response														
Press Conference	**-0.040**	**-0.030**	**0.416**	**0.046**	0.030	**0.122**	**0.046**	**0.140**	0.039	-0.013	**0.189**	**0.191**	**0.092**	**0.180**
Std. error	0.023	0.013	0.072	0.021	0.019	0.028	0.021	0.038	0.025	0.032	0.033	0.027	0.035	0.033
p-value	0.087	0.018	0.000	0.026	0.108	0.000	0.027	0.000	0.117	0.690	0.000	0.000	0.009	0.000
Whatever it takes	-0.061	**-0.177**	**1.012**	0.011	-0.031	**0.211**	0.020	**1.298**	**0.614**	-0.103	**0.576**	**0.573**	**0.339**	**0.552**
Std. error	0.050	0.028	0.151	0.048	0.044	0.067	0.048	0.138	0.114	0.137	0.091	0.084	0.072	0.095
p-value	0.225	0.000	0.000	0.822	0.491	0.002	0.677	0.000	0.000	0.454	0.000	0.000	0.000	0.000
Observations	2,537	2,537	2,033	2,537	2,537	2,534	2,537	1,551	2,531	273	1,284	1,596	677	1,254
R-squared	0.029	0.077	0.087	0.096	0.067	0.160	0.099	0.072	0.040	0.128	0.162	0.145	0.153	0.151

Notes: The table shows coefficient estimates for the effect of ECB communication events on the standard deviation of subjectivity, based on equation (5), for different definitions of non-experts and experts. The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for "Whatever it takes" (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table A9: Average favourableness, robustness tests

	Average favourableness													
	English							German						
	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)
Panel A: Contemporaneous response														
Press Conference	-0.014*	-0.005	-0.008	0.004	0.007*	0.005	0.004	-0.037**	-0.005	0.019	-0.003	-0.002	0.000	-0.000
	(0.008)	(0.004)	(0.016)	(0.004)	(0.004)	(0.004)	(0.004)	(0.018)	(0.004)	(0.027)	(0.006)	(0.005)	(0.007)	(0.006)
Whatever it takes	0.015	0.018***	-0.006	0.022***	0.024***	0.020***	0.019***	0.003	-0.005	-0.011	0.013*	0.010	-0.023***	0.004
	(0.009)	(0.005)	(0.024)	(0.005)	(0.005)	(0.005)	(0.005)	(0.020)	(0.005)	(0.034)	(0.007)	(0.007)	(0.007)	(0.007)
Economic Bulletin	0.005	0.004	-0.027	0.007*	0.008*	0.009*	0.007	0.023	0.012	-0.018	0.024	0.021	0.004	0.023
	(0.009)	(0.004)	(0.022)	(0.004)	(0.004)	(0.005)	(0.004)	(0.026)	(0.008)	(0.018)	(0.016)	(0.013)	(0.008)	(0.017)
Accounts	-0.006	0.007	0.009	0.005	0.008*	0.004	0.004	-0.015	0.002	0.025	-0.080*	-0.083**	-0.003	-0.084*
	(0.012)	(0.005)	(0.033)	(0.005)	(0.005)	(0.005)	(0.005)	(0.018)	(0.004)	(0.025)	(0.043)	(0.041)	(0.006)	(0.044)
Speeches by others	-0.001	0.002	0.012	0.002	0.003	0.003	0.002	-0.012	-0.002	0.041	-0.007	-0.005	0.005	-0.004
	(0.005)	(0.003)	(0.013)	(0.003)	(0.003)	(0.003)	(0.003)	(0.011)	(0.005)	(0.044)	(0.008)	(0.007)	(0.006)	(0.008)
Speeches by president	0.003	0.003	-0.033*	0.006**	0.007**	0.006**	0.006**	-0.000	-0.006*	-0.037	-0.007	-0.002	-0.013**	-0.008
	(0.006)	(0.003)	(0.018)	(0.003)	(0.003)	(0.003)	(0.003)	(0.012)	(0.003)	(0.030)	(0.008)	(0.007)	(0.006)	(0.008)
Tweet	-0.003	-0.000	-0.010	0.001	0.002	0.002	0.001	-0.005	-0.006*	0.013	-0.003	-0.002	0.002	-0.001
	(0.005)	(0.003)	(0.011)	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.003)	(0.022)	(0.006)	(0.005)	(0.004)	(0.006)
Panel B: Overall response														
Press Conference	-0.033	-0.012	0.040	**0.039**	**0.039**	0.021	**0.036**	-0.035	0.015	0.096	0.012	0.005	0.067	-0.003
Std. error	0.031	0.019	0.089	0.022	0.020	0.023	0.021	0.038	0.012	0.114	0.026	0.021	0.052	0.017
p-value	0.291	0.546	0.653	0.070	0.056	0.350	0.093	0.348	0.237	0.398	0.648	0.805	0.200	0.849
Whatever it takes	-0.087	-0.061	0.164	0.000	**0.075**	**0.155**	-0.020	**-0.569**	**-0.325**	-0.250	0.071	-0.020	**-0.081**	**0.149**
Std. error	0.067	0.040	0.163	0.046	0.042	0.052	0.045	0.160	0.055	0.190	0.099	0.116	0.032	0.085
p-value	0.192	0.129	0.316	0.996	0.076	0.003	0.659	0.000	0.000	0.188	0.477	0.861	0.011	0.080
Observations	2,537	2,537	2,033	2,537	2,537	2,534	2,537	1,551	2,531	273	1,284	1,596	677	1,254
R-squared	0.033	0.084	0.026	0.042	0.049	0.043	0.042	0.021	0.022	0.133	0.072	0.050	0.041	0.081

Notes: The table shows coefficient estimates for the effect of ECB communication events on average favourableness, based on equation (5), for different definitions of non-experts and experts. The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for "Whatever it takes" (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table A10: Standard deviation of favourableness, robustness tests

	Standard deviation of favourableness													
	English							German						
	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)
Panel A: Contemporaneous response														
Press Conference	-0.031***	-0.034***	0.062***	-0.010**	-0.010**	0.003	-0.008*	0.015	0.003	-0.001	0.065***	0.059***	0.047***	0.060***
	(0.007)	(0.004)	(0.014)	(0.004)	(0.004)	(0.005)	(0.004)	(0.015)	(0.008)	(0.013)	(0.009)	(0.008)	(0.010)	(0.008)
Whatever it takes	-0.027***	-0.013***	0.176***	0.010*	0.008	0.019***	0.009*	0.036**	-0.007	-0.033	0.051***	0.033***	0.076***	0.027***
	(0.009)	(0.005)	(0.014)	(0.005)	(0.005)	(0.006)	(0.005)	(0.015)	(0.010)	(0.024)	(0.008)	(0.008)	(0.009)	(0.008)
Economic Bulletin	0.001	-0.008*	0.005	-0.004	-0.006	-0.005	-0.005	-0.006	0.012	-0.013	0.027***	0.018*	0.002	0.029***
	(0.010)	(0.005)	(0.016)	(0.005)	(0.005)	(0.005)	(0.005)	(0.017)	(0.012)	(0.012)	(0.010)	(0.009)	(0.013)	(0.010)
Accounts	-0.011	-0.015**	-0.009	-0.017***	-0.015***	-0.007	-0.018***	-0.031**	-0.018	-0.004	0.009	0.002	-0.003	0.009
	(0.009)	(0.006)	(0.018)	(0.005)	(0.005)	(0.006)	(0.005)	(0.012)	(0.012)	(0.009)	(0.015)	(0.014)	(0.006)	(0.015)
Speeches by others	0.005	-0.003	-0.000	0.000	-0.002	0.009**	0.001	-0.001	0.003	-0.000	0.010**	0.007*	0.002	0.010**
	(0.005)	(0.003)	(0.009)	(0.003)	(0.003)	(0.004)	(0.003)	(0.008)	(0.006)	(0.007)	(0.005)	(0.004)	(0.005)	(0.005)
Speeches by president	-0.015**	-0.012***	-0.011	-0.007**	-0.005*	-0.006*	-0.007**	0.018	-0.002	0.001	0.027***	0.027***	0.019**	0.028***
	(0.006)	(0.003)	(0.010)	(0.003)	(0.003)	(0.003)	(0.003)	(0.011)	(0.006)	(0.011)	(0.007)	(0.007)	(0.008)	(0.007)
Tweet	0.010**	-0.002	0.006	-0.003	-0.004	0.002	-0.003	-0.004	-0.001	-0.005	0.011***	0.006*	0.003	0.011**
	(0.005)	(0.003)	(0.008)	(0.003)	(0.003)	(0.004)	(0.003)	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)
Panel B: Overall response														
Press Conference	**-0.075**	**-0.128**	**0.193**	0.001	-0.018	**0.076**	0.005	**0.051**	0.010	-0.017	**0.102**	**0.100**	**0.035**	**0.096**
Std. error	0.032	0.019	0.059	0.022	0.021	0.027	0.022	0.027	0.018	0.020	0.021	0.017	0.017	0.021
p-value	0.020	0.000	0.001	0.948	0.391	0.004	0.806	0.063	0.575	0.402	0.000	0.000	0.037	0.000
Whatever it takes	-0.118	**-0.079**	**1.028**	**0.186**	**0.235**	**0.365**	**0.191**	**0.929**	**0.385**	-0.078	**0.424**	**0.190**	**0.128**	**0.411**
Std. error	0.074	0.041	0.114	0.049	0.046	0.060	0.049	0.093	0.079	0.104	0.047	0.053	0.038	0.049
p-value	0.108	0.051	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.456	0.000	0.000	0.001	0.000
Observations	2,537	2,537	2,033	2,537	2,537	2,534	2,537	1,551	2,531	273	1,284	1,596	677	1,254
R-squared	0.046	0.157	0.065	0.083	0.054	0.136	0.082	0.057	0.030	0.123	0.162	0.123	0.114	0.161

Notes: The table shows coefficient estimates for the effect of ECB communication events on the standard deviation of favourableness, based on equation (5), for different definitions of non-experts and experts. The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for "Whatever it takes" (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table A11: Average absolute favourableness, robustness tests

	Average absolute favourableness													
	English							German						
	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)
Panel A: Contemporaneous response														
Press Conference	-0.035***	-0.026***	-0.014	-0.008**	-0.007**	0.002	-0.006*	-0.025	-0.009**	0.025	0.017***	0.014***	0.019***	0.018***
	(0.007)	(0.004)	(0.014)	(0.003)	(0.003)	(0.003)	(0.003)	(0.018)	(0.004)	(0.026)	(0.006)	(0.004)	(0.006)	(0.006)
Whatever it takes	-0.021***	-0.006	0.075***	0.009**	0.007*	0.013***	0.008*	0.007	-0.011**	-0.023	0.028***	0.018***	0.037***	0.011
	(0.008)	(0.004)	(0.022)	(0.004)	(0.004)	(0.004)	(0.004)	(0.019)	(0.005)	(0.033)	(0.007)	(0.007)	(0.007)	(0.007)
Economic Bulletin	-0.000	-0.005	-0.003	-0.000	-0.001	0.003	0.000	0.009	0.011	-0.011	0.046***	0.040***	0.004	0.052***
	(0.008)	(0.004)	(0.019)	(0.004)	(0.004)	(0.004)	(0.004)	(0.026)	(0.008)	(0.018)	(0.013)	(0.011)	(0.009)	(0.013)
Accounts	-0.016*	-0.014***	-0.015	-0.014***	-0.011***	-0.008*	-0.015***	-0.036*	-0.008*	0.031	0.075*	0.074*	-0.001	0.080*
	(0.009)	(0.005)	(0.029)	(0.004)	(0.004)	(0.004)	(0.004)	(0.018)	(0.005)	(0.025)	(0.042)	(0.041)	(0.006)	(0.044)
Speeches by others	0.001	-0.004	0.003	-0.001	-0.001	0.004	-0.001	-0.001	0.002	0.060	0.014*	0.011*	0.005	0.016*
	(0.005)	(0.003)	(0.011)	(0.003)	(0.003)	(0.003)	(0.003)	(0.011)	(0.004)	(0.043)	(0.008)	(0.006)	(0.006)	(0.008)
Speeches by president	-0.012**	-0.007***	-0.038**	-0.003	-0.001	-0.001	-0.002	-0.011	-0.009***	-0.032	-0.009	-0.008	-0.000	-0.007
	(0.005)	(0.002)	(0.016)	(0.002)	(0.002)	(0.002)	(0.002)	(0.011)	(0.003)	(0.029)	(0.008)	(0.007)	(0.006)	(0.008)
Tweet	0.005	-0.002	-0.009	-0.004	-0.004*	-0.001	-0.003	0.003	-0.002	0.013	0.005	0.005	0.007*	0.007
	(0.004)	(0.002)	(0.010)	(0.002)	(0.002)	(0.003)	(0.002)	(0.009)	(0.003)	(0.022)	(0.006)	(0.005)	(0.004)	(0.006)
Panel B: Overall response														
Press Conference	**-0.092**	**-0.091**	-0.103	-0.015	-0.012	-0.003	-0.014	-0.032	-0.011	0.083	**0.053**	**0.042**	0.063	**0.033**
Std. error	0.027	0.016	0.080	0.019	0.018	0.021	0.018	0.036	0.012	0.113	0.025	0.020	0.053	0.017
p-value	0.001	0.000	0.200	0.427	0.487	0.891	0.455	0.372	0.348	0.462	0.035	0.041	0.234	0.050
Whatever it takes	**-0.173**	-0.022	**0.447**	**0.219**	**0.281**	**0.334**	**0.222**	-0.033	**-0.216**	0.004	-0.014	**-0.289**	**0.052**	0.027
Std. error	0.063	0.036	0.145	0.039	0.037	0.047	0.039	0.156	0.054	0.187	0.098	0.114	0.031	0.085
p-value	0.006	0.545	0.002	0.000	0.000	0.000	0.000	0.832	0.000	0.981	0.886	0.011	0.099	0.747
Observations	2,537	2,537	2,033	2,537	2,537	2,534	2,537	1,551	2,531	273	1,284	1,596	677	1,254
R-squared	0.060	0.151	0.047	0.063	0.046	0.068	0.063	0.028	0.029	0.145	0.097	0.065	0.049	0.099

Notes: The table shows coefficient estimates for the effect of ECB communication events on average absolute favourableness, based on equation (5), for different definitions of non-experts and experts. The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for "Whatever it takes" (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

Table A12: Standard deviation of absolute favourableness, robustness tests

	Standard deviation of absolute favourableness													
	English							German						
	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)	Non-experts (bm)	Non-experts (excl centr.)	Non-experts (few follow.)	Experts (bm)	Experts (0.33)	Experts (0.75)	Experts (ECB centric)
Panel A: Contemporaneous response														
Press Conference	-0.024***	-0.027***	0.062***	-0.009**	-0.010***	-0.000	-0.008**	0.020	0.003	-0.001	0.064***	0.058***	0.047***	0.060***
	(0.006)	(0.004)	(0.012)	(0.004)	(0.003)	(0.004)	(0.004)	(0.014)	(0.007)	(0.013)	(0.008)	(0.008)	(0.010)	(0.008)
Whatever it takes	-0.015**	-0.007*	0.157***	0.011**	0.009**	0.020***	0.010**	0.031**	-0.007	-0.033	0.044***	0.029***	0.076***	0.027***
	(0.007)	(0.004)	(0.013)	(0.004)	(0.004)	(0.005)	(0.004)	(0.014)	(0.010)	(0.024)	(0.008)	(0.008)	(0.009)	(0.008)
Economic Bulletin	-0.000	-0.008*	0.007	-0.005	-0.006	-0.007	-0.005	-0.000	0.010	-0.013	0.027***	0.018*	0.003	0.029***
	(0.008)	(0.004)	(0.014)	(0.004)	(0.004)	(0.005)	(0.004)	(0.016)	(0.012)	(0.012)	(0.010)	(0.009)	(0.013)	(0.010)
Accounts	-0.007	-0.007	-0.000	-0.012***	-0.011**	-0.004	-0.013***	-0.026**	-0.017	-0.004	0.009	0.002	-0.003	0.009
	(0.008)	(0.006)	(0.017)	(0.004)	(0.004)	(0.005)	(0.004)	(0.011)	(0.011)	(0.009)	(0.015)	(0.014)	(0.006)	(0.015)
Speeches by others	0.003	-0.003	0.003	0.000	-0.002	0.006*	0.001	-0.002	0.002	-0.000	0.010**	0.007	0.002	0.010**
	(0.004)	(0.003)	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.006)	(0.007)	(0.005)	(0.004)	(0.005)	(0.005)
Speeches by president	-0.008	-0.008***	-0.008	-0.006**	-0.004*	-0.005*	-0.006**	0.021*	-0.001	0.001	0.027***	0.027***	0.018**	0.027***
	(0.005)	(0.003)	(0.009)	(0.003)	(0.002)	(0.003)	(0.002)	(0.011)	(0.006)	(0.011)	(0.007)	(0.007)	(0.007)	(0.007)
Tweet	0.006*	-0.002	0.008	-0.003	-0.004*	0.001	-0.002	-0.004	-0.001	-0.005	0.011***	0.006*	0.003	0.011**
	(0.004)	(0.002)	(0.007)	(0.003)	(0.002)	(0.003)	(0.003)	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)
Panel B: Overall response														
Press Conference	-0.043	**-0.104**	**0.209**	0.001	-0.021	**0.069**	0.003	**0.057**	0.011	-0.017	**0.098**	**0.097**	**0.034**	**0.093**
Std. error	0.026	0.016	0.053	0.019	0.018	0.023	0.019	0.026	0.017	0.020	0.020	0.016	0.017	0.020
p-value	0.101	0.000	0.000	0.968	0.244	0.004	0.886	0.030	0.543	0.402	0.000	0.000	0.038	0.000
Whatever it takes	-0.089	**-0.101**	**0.873**	0.063	**0.090**	**0.234**	0.066	**0.877**	**0.394**	-0.078	**0.419**	**0.187**	**0.129**	**0.412**
Std. error	0.058	0.033	0.104	0.042	0.039	0.053	0.042	0.090	0.077	0.104	0.046	0.053	0.038	0.049
p-value	0.121	0.003	0.000	0.133	0.021	0.000	0.114	0.000	0.000	0.456	0.000	0.000	0.001	0.000
Observations	2,537	2,537	2,033	2,537	2,537	2,534	2,537	1,551	2,531	273	1,284	1,596	677	1,254
R-squared	0.036	0.152	0.066	0.073	0.048	0.128	0.072	0.059	0.030	0.123	0.164	0.123	0.114	0.164

Notes: The table shows coefficient estimates for the effect of ECB communication events on the standard deviation of absolute favourableness, based on equation (5), for different definitions of non-experts and experts. The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They contain 5 (1) leads and 4 (2) lags for the press conference in the English (German) sample, and 15 lags for "Whatever it takes" (not reported for brevity). Panel B reports the accumulated response coefficients over all leads and lags, with coefficients that are statistically significant at least at the 10% level printed in bold. Numbers in brackets are standard errors. ***/**/* denote statistical significance at the 1%/5%/10% level.

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