Central Bank Communication with Non-Experts – A Road to Nowhere?

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First draft: June 2020

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Abstract

Central banks have started intensifying their communication with non-expert audiences – an endeavour which some have argued is bound to fail. Is this communication received at all, and how does it affect non-experts' views? This paper tries to answer these questions by studying English and German Twitter traffic about the European Central Bank (ECB). It shows that ECB-related tweets are more likely to get retweeted or liked if they express strong views about the ECB or are more subjective. Differentiating experts from non-experts, the paper shows that Twitter traffic is responsive to the ECB's communication, also for non-experts. In particular President Draghi's "Whatever it takes" statement has triggered persistent discussions on Twitter. In response to several ECB communication events, tweets become more factual, and the views expressed become more moderate. A notable exception to this is the discussion following "Whatever it takes" in the German-speaking Twitter community. These findings suggest that central bank communication with non-experts is not a road to nowhere – it manages to reach out to non-experts, and has the potential to make discussions in social media somewhat more factual and moderate.

JEL Codes: E52, E58.
Keywords: monetary policy, central bank communication, social media, non-experts

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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), but most importantly, these changes made monetary policy the focus of an increasingly public debate, which has been more controversial than ever before (Blinder et al. 2017). Public engagement furthermore increased because information has become more easily available, and because new media allow everyone to express their views more easily and with substantially larger reach. In addition, central banks saw an erosion of citizens' trust in them and their policies, which has only sluggishly recovered in the meantime (Bergbauer et al. 2019). 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 new challenges. Experts are easy to reach – they have an intrinsic interest to follow central bank communication, as it affects them professionally. By definition, they also have detailed knowledge and understanding of central banking, making it easy for central banks to convey their messages. Also, they react instantaneously, for instance in financial markets, and in ways that are straightforward to monitor, making it easy 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".

Further to having started their journey along this new road, central banks have also opened it for two-way traffic. While much of the traditional central bank communication has focused on conveying messages from the central bank to the recipients, there is an increasing emphasis on listening. For instance, both the U.S. Federal Reserve and the

[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

ECB have made listening events part and parcel of their ongoing strategy reviews (see, e.g., Powell 2019). Once again, this poses new challenges for central banks. Listening events are a great start, but they are restricted to few people, they will remain relatively infrequent and they can only cover as much ground as their agendas allow.

Focus groups as well as surveys are other options that central banks are pursuing; even laboratory experiments have become part of the central bank toolkit to study how best to communicate with non-experts. 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 laboratory experiments to test the causal effects of central bank communication on economic expectations and their underlying mechanisms (Kryvtsov and Petersen 2019).

These approaches guarantee that the recipient receives the central bank signal – the participants in the survey or in the experiment 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 controlled experiments. 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. It is therefore important to also find ways to observe non-experts' responses to central bank communication and their reaction to it in real life.

Some papers have started along this line of research. Lamla and Vinogradov (2019) conduct a survey among the general public just before and just after press conferences by the U.S. FOMC, and find that these events do not go entirely unnoticed: in the surveys conducted just after the press conferences, relatively more respondents report to have heard news about the monetary policy of the Federal Reserve, even if these do not appear to affect their average beliefs. In contrast, using daily survey data from Gallup, Lewis et al. (2019) provide evidence that monetary policy surprises have instantaneous effects on economic confidence.

In this paper, we follow another 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 (meaning that we do not impose that our non-experts receive central bank signals) which are available at high frequency (therefore allowing us to make causal statements in line with the assumptions underlying the announcement effect literature) and on a continuous basis (such that we are not restricted to a single type of event). Furthermore, it represents many individuals (clearly more than could possibly be invited to listening events or into the laboratory), and it allows us to trace differences and interactions between non-experts and experts, as we observe both of them on Twitter.

At the same time, it is clear 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 do tweet about the ECB (and do so publicly), we do not observe those who have never done so. This clearly needs to be kept in mind when interpreting our results – they cannot and should not be generalised to the entire population.

We study tweets about the ECB in two languages, English and German. We chose English because of its status as global language, because it is the most common language spoken in financial markets and in economics and finance 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]

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.

Our key findings are as follows. First, 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 are considerably more likely to tweet during weekends, 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 shows that ECB-related tweets are more likely to get retweeted or liked if they formulate their opinion in relatively strong language and if they are more subjective.

Third, ECB-related Twitter traffic is responsive to ECB communication events. Typically, this effect is contained to the same day, but the ECB press conference and in particular President Draghi's "Whatever it takes statement" lead to rather persistent discussions on Twitter – the press conference even several days ahead. These two events also show a much larger response than any of the other events, with many more people participating in the debate than usual.

Fourth, non-experts are less responsive to ECB communication events than experts, because they discuss the ECB press conference with less lead time and because the response coefficients are generally smaller and estimated at lower levels of statistical significance – with "Whatever it takes" being an important exception, as it has led to very similar reactions of experts and non-experts alike.

Fifth, in response to several ECB communication events, tweets by non-experts 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. A notable exception to this is the discussion following "Whatever it takes" in the entire German-speaking Twitter community, where the views expressed by experts and non-experts alike became a lot more dispersed, with regard to the subjectivity, the favourableness and the strength of the views that were expressed.

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

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 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 reposted more often. At the same time, the analysis in this paper also shows that central bank communication has the potential to make discussions in social media somewhat more factual and moderate. So it remains important for central banks to reach out to non-expert audiences, especially if they become part of a substantial and persistent debate among non-experts, as was the case for the “Whatever it takes” statement. Finally, the analysis also lends support to the efforts by central banks to monitor the related social media traffic; especially if the analysis is conducted in a disaggregated fashion, by distinguishing between different types of accounts, it provides a cost-effective and instantaneous way to better understand the views that different audiences hold about the central bank and its monetary policy.

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/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.

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 ECB president Draghi’s 2012 “Whatever it takes” statement), and show that these beliefs are mirrored in financial market

[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.

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) and Tillmann (2020). These papers show that tweets by U.S. president Trump about the Federal Reserve and its monetary policy lead to a reduction in interest rates, suggesting that market participants price in future rate cuts in response to Trump's statements. They also seem to affect long-term inflation expectations and confidence of consumers (Binder 2020).

Furthermore, using an Italian sample of tweets on prices and inflation, Angelico et al. (2019) generate a daily measure of inflation expectations for Italy.

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.

Many recent contributions resort to surveys and lab experiments to test how non-experts understand and respond to central bank communication. 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 2019). 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. 2019). While these statements are addressed to a specialised audience (which might justify a higher level of complexity), Haldane (2016) has pointed out that also speeches by policy makers are not easily readable.

Much effort is currently already devoted to making central bank communication more accessible to non-experts (Haldane and McMahon 2017). However, it is important not to over-simplify messages; assessing the current and future economic environment and the central bank's response to changing conditions is extremely complex, and there is a risk that a simple exposition of these issues makes economic agents take decisions with an unwarranted sense of certainty.

Studies that use focus groups, surveys or lab experiments engineer a situation whereby the intended recipient is sure to actually receive the central bank signals. This might be in stark contrast to reality, where 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. Observations of this nature made Blinder (2018) predict that "central banks will keep trying to communicate with the general public, as they should. But for the most part, they will fail."

For sure, Alan Blinder would be delighted if his prediction was proven wrong. So what can central banks do in that regard? One option might be to ensure that they are trusted by their citizens. Several contributions have studied this issue from various angles. Importantly, it has been shown that agents which have more favorable opinions of the ECB are more likely to be influenced by ECB communications (Baerg et al. 2019), which suggests that enhanced trust might help overcoming some of the difficulties that central banks face in communicating with the general public.

In addition, enhancing trust brings several benefits to central banks. First, it helps anchoring consumers' inflation expectations, by lowering consumers' uncertainty about future price developments and because those who trust are less likely to hold inflation expectations that are far from the inflation target (Christelis et al. 2020). Second, a fall in trust can amplify macroeconomic fluctuations and steepen the sacrifice ratio (Bursian and Faia 2018). Third, low public trust in the ECB increases the likelihood that domestic politicians comment on the ECB's policy not with a euro area perspective, but instead against the background of their national growth performance (Ehrmann and Fratzscher 2011). This poses a risk, as it is important to ensure that the ECB's policy is assessed in the context of the economic performance of the euro area as a whole.

But what determines trust? Several papers study this for the case of the ECB. A consistent finding is that trust in the ECB is largely driven by economic developments (see, e.g., Ehrmann et al. 2013, Bursian and Fürth 2015). At the same time, it is also evident that the performance of policy makers matters (Bergbauer et al. 2020), that uncertainty about economic policy plays a role (Istrefi and Piloiu 2020), and that knowledge about the ECB instils trust (Hayo and Neuenkirch 2014). This suggests that efforts by the central bank to inform the public about its mandate and its performance are a worthwhile endeavour.

This is where the current paper comes in – how successful is the ECB in reaching out to non-experts, and what are the views that these hold of their central bank? We will do so by analysing tweets about the ECB, separately for experts and non-experts.

3. Data

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

Tweets

We filter and scrape tweets via Twitter's Advanced Search using Henrique Jefferson's Python library "GetOldTweets" (Jefferson 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.

We clean our samples in several steps to ensure that the remaining tweets are not contaminated by tweets that are unrelated to the European Central Bank. To do this, we start by looking at random subsamples of our pool of tweets and manually identify unrelated tweets. 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 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",[5] "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

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

“@”), 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”[6] (Danilak 2015) because despite the language filter of the Twitter Advanced Search, numerous tweets in other languages were returned. For the sample of English tweets, we only keep tweets that “langdetect” identifies as English. For the sample of German tweets, 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, and more than 2 million retweets (see Table 1). The sample of tweets in German is considerably smaller; there are only around 110,000 original tweets, and around 50,000 retweets. There are even a few days (thirteen) without any ECB-related tweet in German at all.

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.[7] The first peak corresponds to 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, which can be explained by the comprehensive monetary policy easing strategy starting in June 2014, 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 and an expanded asset purchase programme (APP) in January 2015, 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.[8] 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

[6] 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.
[7] For a detailed review, see Hartmann and Smets (2018).
[8] There is a notable drop in Twitter activity in August 2015, likely because of the absence of an ECB press conference in this month, together with the regular low activity in August.

social medium.[9] 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 highly 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.[10] 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[11] and our German lexicon on the German equivalent GermaNet[12]. Sentiment measures do not have to be only positive or negative; they can also indicate other dimensions of sentiment such as opinionatedness or strength of emotion 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

[9] 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/.

[10] 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.

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

[12] 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.

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 and also the 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 –(1/2), 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.[13] 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 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, the number of accounts which follow this account (“friends”), 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. 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”,

[13] 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.

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. In particular the latter is not surprising, and a standard feature of social media.

Looking at Figure 3, it is evident that the bulk of accounts has only very few followers (the account at the 25th percentile has 109 followers), whereas some accounts have a very large number of followers (the 75th percentile records 1,320 followers, the 95th 10,020 followers). The corresponding numbers for the German sample are similar with 106 at the 25th percentile, 1,621 at the 75th percentile and 12,124 at the 95th percentile.

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:

- 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);
- 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.

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.[14] 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,[15] and

[14] 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.

[15] 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.

$P25(centricity)$ 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 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 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.[16] The ratios in our German sample are similar, with 24% of accounts classified as non-experts and 0.1% as experts.[17]

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-

[16] 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.

[17] 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 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 the accounts of non-experts were, on average, created around 1.5 years earlier, a gap that increases to roughly two years for the German sample. What is interesting, however, is that 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 might be surprising, in particular when we think of non-experts as part of the general public. For that reason, we conduct a robustness test where we impose that non-experts have few followers. While that robustness test might get closer to the idea of the general public, it is important to keep in mind that the views of Twitter users with many followers are generally more influential in shaping the public discourse; 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 opinions (in which case the measure is closer to 1). Mean subjectivity is significantly higher for non-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 the subjectivity should not be compared across languages). This implies that experts issue a mixture of more factual and more opinionated tweets, whereas there is less such variation in the Twitter behaviour of non-experts. Another interesting feature is that, among non-experts, the distribution of subjectivity across accounts has a much higher standard deviation than among 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 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,[18] 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) 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 of these findings are intuitive, and make us comfortable that the differentiation of accounts has indeed succeeded in singling out experts and non-experts. A final statistic shown in Table 3 corroborates this interpretation: 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. Once again, the pattern is

[18] 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.

very similar for the accounts in German, with 20% weekend-activity for non-experts and 8% for experts.[19]

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, and an additional 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, 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 how the semantic content of the original tweet affects the likelihood of being retweeted or liked. In particular, we are interested 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.

[19] These four most pronounced differences, measured by 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). The only exceptions are subjectivity and absolute favourableness for non-experts (few followers) in the English sample, which are not substantially larger than for the experts.

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:

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

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

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,[20] 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.

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).

For each of these regressions, we calculate robust standard errors. Table 4 reports the corresponding results. For the multinomial logit and the probit models, the table reports marginal effects.

Table 4 here

The estimations with the German sample do not yield many noteworthy results, in contrast to those with the English sample. What is found consistently for both languages,

[20] 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).

however, is 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. Tweets from English-speaking 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.

A number of interesting results are obtained regarding the semantic content of the tweets. First, there is only little evidence of a negativity bias. Tweets with a negative sentiment are not more likely to be retweeted. In contrast, they are more likely to be liked. However, the effect is small: the likelihood of being liked increases by 0.2 percentage points. Furthermore, conditional on being retweeted or liked, negative tweets don't travel farther – they are retweeted or liked less often.

Second, strong views are much more likely to generate retweets and likes, consistently throughout all the estimations in the English sample, both unconditionally and 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 3.0 (4.9) 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 a 3 or 5 percentage point increase is 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 1.4 percentage points more likely to be retweeted and 2.6 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

Specification of the econometric model

To study determinants of Twitter behaviour, we resort to aggregated data, at a daily frequency, yielding 2,537 observations. We do so first for all accounts, and subsequently separately for each identified user group. We study Twitter activity as measured by the (log) number of tweets issued each day[21] and by the Herfindahl-Hirschman indicator (which provides a measure of concentration – the larger the indicator, the larger the

[21] We drop retweets from 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.

"market share" of the participating accounts on a given day).[22] Subsequently, we analyse the content of tweets, by studying subjectivity, favourableness and absolute favourableness, each time looking at the average for a given day and the standard deviation across tweets.

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

$$x_t = \alpha_{dow} + \alpha_{moy} + \alpha_{hol} + \alpha_t t + \alpha_{t^2} t^2 + \beta^e_{c,l} C^e_{t,l} + \varepsilon_t, \tag{5}$$

where $t$he variables of interest are $C^e_{t,l}$, 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 linear 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,[23] we also find that Twitter activity intensifies already several days ahead of the press conferences, therefore warranting the 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 on Twitter for a total of 10 days, in the English sample. 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).

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 A3.

Starting with the results for Twitter volume originating from all accounts, it is apparent that there is a simultaneous reaction to all events. The press conference and "Whatever it

[22] $Herfindahl - Hirschman\ indicator_t = \sum_{i=1,t}^{N_t} s_{i,t}^2$, 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.

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

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 20 to 60 percent). 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 each of these days, Twitter volume about the ECB is 60% higher than on normal days.[24] "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.

For the German sample, very similar patterns arise. The main communication events that trigger ECB-related Twitter traffic are the press conference (with very similar magnitudes to those estimated in the English sample) and "Whatever it takes", which led to an even stronger response in the German-speaking Twitter community (more than 1.5 times the response in the English sample). There is no discernable response to the Economic Bulletin or the Monetary Policy Accounts, and even the response to ECB tweets is smaller in magnitude and estimated at lower levels of statistical significance. German speakers tend to differentiate even more strongly between speeches by the ECB president and other Executive Board members, with the former coefficient being more than double the one in the English sample, and the latter being only 60% of the English counterpart.

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 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. The estimated coefficients for the German sample are considerably larger – but it is important to keep in mind that the concentration ratio is a lot higher, with a mean of 0.1318 and a standard deviation of 0.1602, meaning that the estimated effects are, in economic terms, broadly comparable across the two languages. This pattern can also be identified in Figure 4, which shows the

[24] 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.

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 A3, 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. In the English sample, they seem to be responsive to the Monetary Policy Accounts, but no response to this specialised event is visible in the German sample. 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% (40%) of the variation in the English (German) expert sample, they explain roughly half of this (namely 35% and 20%) 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; for the German sample, the overall coefficient for non-experts is, at 26, even much larger than the one for experts, which stands at 17. 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" has had a lasting effect on both groups, and in particular got noticed and discussed by the general public in the German-speaking community.

The content of tweets

After having studied the amount of Twitter traffic and the degree to which the Twitter discussion is concentrated among many or few individuals, we 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). Please be reminded that the levels of these three measures of sentiment in the English sample cannot directly be compared to the German sample.

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 a response in sentiment is inherently harder to achieve. 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, we argue, is good news, as it implies that ECB communication events lead to a more factual discussion about the ECB on Twitter.

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). This is much less the case for experts, where average subjectivity and its standard deviation are generally less responsive, and no consistent pattern emerges. Interestingly, the standard deviation of subjectivity for the experts increases around the press conference, which suggests that experts, on the one hand, provide relatively more factual information, while, on the other hand, they also use this occasion to express their opinions on the ECB’s monetary policy.

A very different picture emerges in the German sample, where the subjectivity in the tweets issued by non-experts is hardly responsive to the various communication events, whereas experts’ tweets become more subjective, and more diverse (as reflected in a higher standard deviation). As before, “Whatever it takes” yields interesting results for the German sample – it consistently raises 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.

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 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. “Whatever it takes” could be different in that regard, as it is only one event that might have led to a particularly positive or negative response. We find this to be the case to some extent – German tweets overall, and those by non-experts in particular, seem to have been relatively more negative during the ensuing discussion.

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. Tweets in German are different – here, the spectrum of views widens up, especially for experts. Once again, this is particularly the case for the “Whatever it takes” statement, which both simultaneously and over the subsequent days has increased the diversity of opinions expressed in German tweets. The effect is economically large – for instance, the standard deviation of experts has increased by one standard deviation on the day of “Whatever it takes”.

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 more opinionated on average. These findings do therefore suggest that ECB communication might be helpful in containing the strength of views expressed by non-experts.

Also in this respect, tweets in German behave rather differently than those in English. Average absolute favourableness and the standard deviation tend to increase for tweets written by experts. Once again, "Whatever it takes" shows a distinct pattern, having increased the standard deviation of absolute favourableness for experts and non-experts alike (e.g. by one standard deviation for the experts on the day of the statement alone), meaning that the strength of opinions expressed got considerably more varied.

Robustness

Appendix Tables A4-A11 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 issued, 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 main findings (non-experts are not responsive to some, more specialised, types of ECB communication; if they respond, the coefficients are smaller in magnitude; the smaller responsiveness is also reflected in a lower R^2; 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 A3).

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 himself. 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 only the adjectives (with their negation whenever applicable) that our method identifies to refer to Mario Draghi.[25]

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

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

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 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 more opinionated, 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 a number of 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, it has already been 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.

The paper has provided ample evidence that Twitter traffic by experts and non-experts is responsive to the ECB's communication. This has particularly been the case for President Draghi's "Whatever it takes" statement, which has led to rather persistent discussions on Twitter. In general, following communication events by the ECB, the discussion on Twitter becomes more factual, with more moderate views being expressed. However, this has not been the case for the discussion about the "Whatever it takes" statement in the German-speaking Twitter community.

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 heard more often. At the same time, the analysis in this paper also shows that central bank communication has the potential to make discussions in social media somewhat more factual and moderate. So it remains important for central banks to reach out to non-expert audiences, especially if they become part of a substantial and persistent debate among non-experts, as was the case for the "Whatever it takes" statement. Finally, the analysis also lends support to the efforts by central banks to monitor the related social media traffic; especially if the analysis is conducted in a disaggregated fashion, by distinguishing between different types of accounts, it provides a cost-effective and instantaneous way to better understand the views that different audiences hold about the central bank and its monetary policy.

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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: Summary statistics for different account types

	Non-experts		Experts
Panel A: English			
Number of accounts	69,031		1,282
Average date of account creation	28.08.2011	***	03.02.2013
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 favourable	0.1306	***	0.1491
Standard deviation of average absolute favourable	0.1922	***	0.0564
Average weekend activity	0.1835	***	0.0716
Panel B: German			
Number of accounts	3,921		23
Average date of account creation	22.09.2011	***	03.07.2013
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 favourable	0.0717		0.0645
Standard deviation of average absolute favourable	0.1727	***	0.0279
Average weekend activity	0.2024	*	0.0755

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 3: 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 4: Determinants of Retweets and Likes

	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. 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

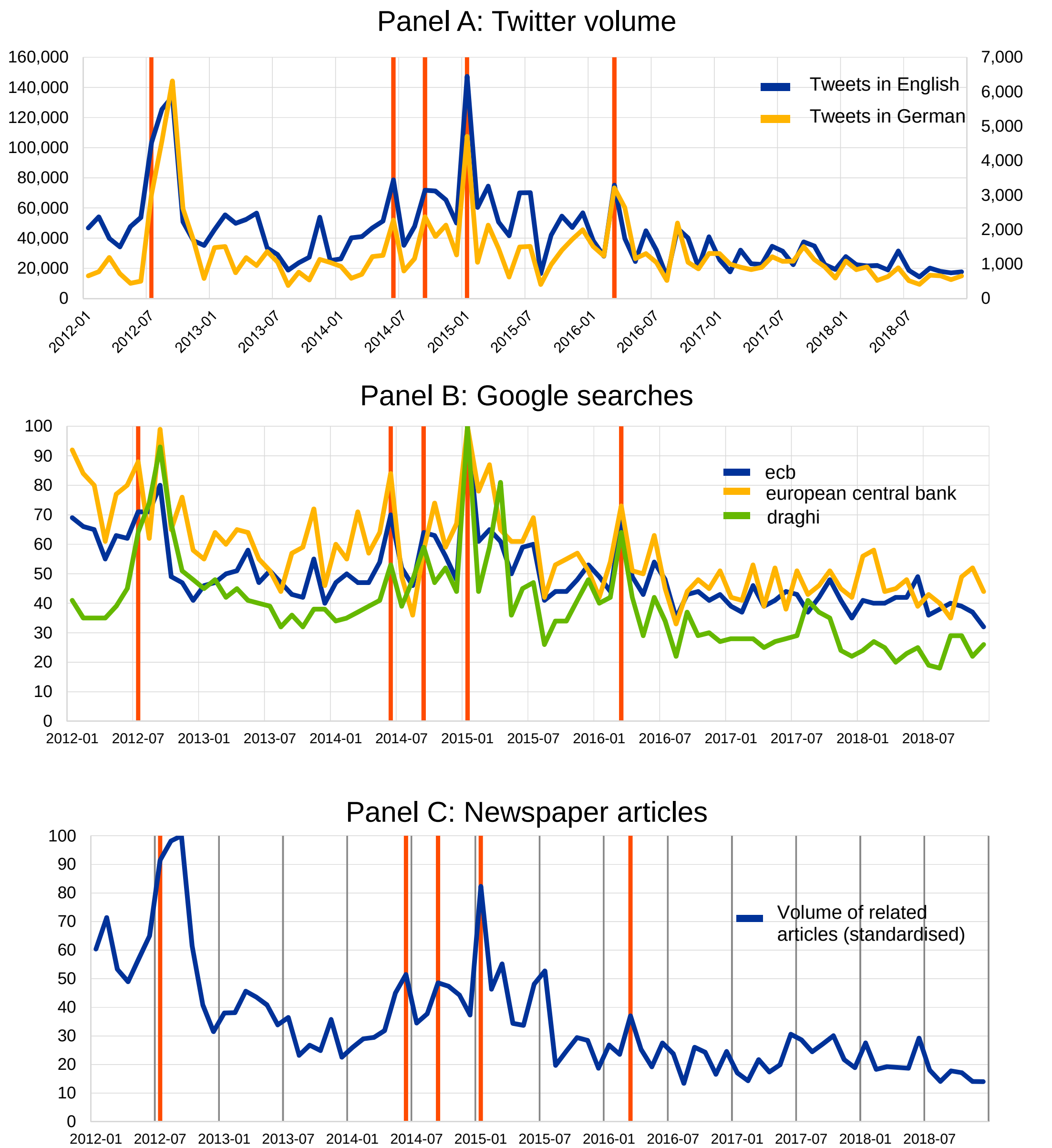
Notes: The table shows coefficient estimates for the effect of ECB communication events on the average and standard deviation of absolute favourableness, based on equation (5). The models control for day of week, month of year and holiday effects and allow for a linear and quadratic time trend. They 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 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 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

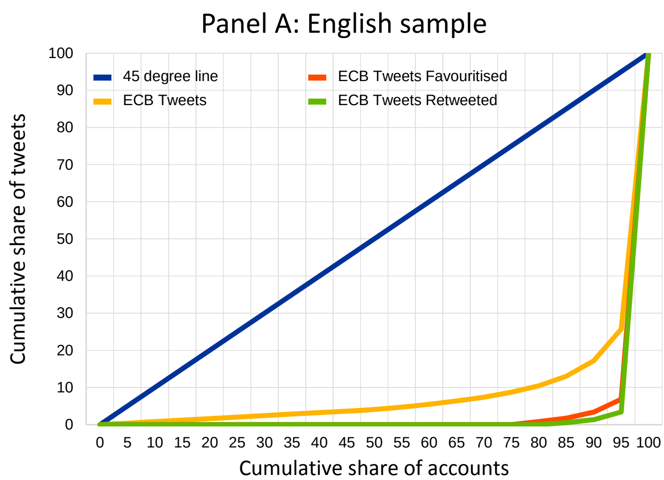


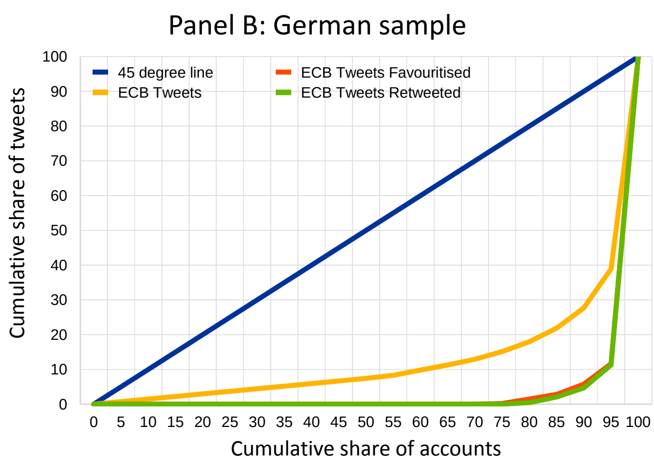
Notes: Panel A: Monthly number of ECB-related tweets in English (left axis) and German (right axis). The vertical lines illustrate the timing of various ECB actions, namely July 2012: "Whatever it takes"; June 2014: Introduction of negative interest rates and credit-easing measures via targeted long-term 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

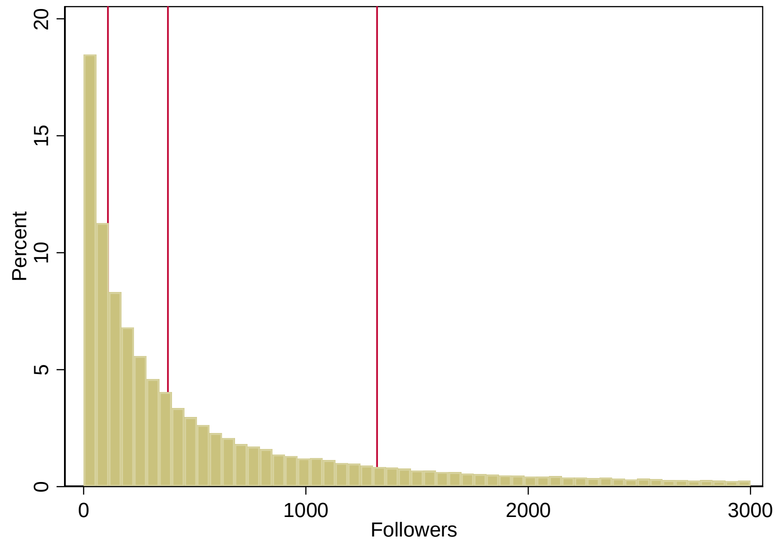




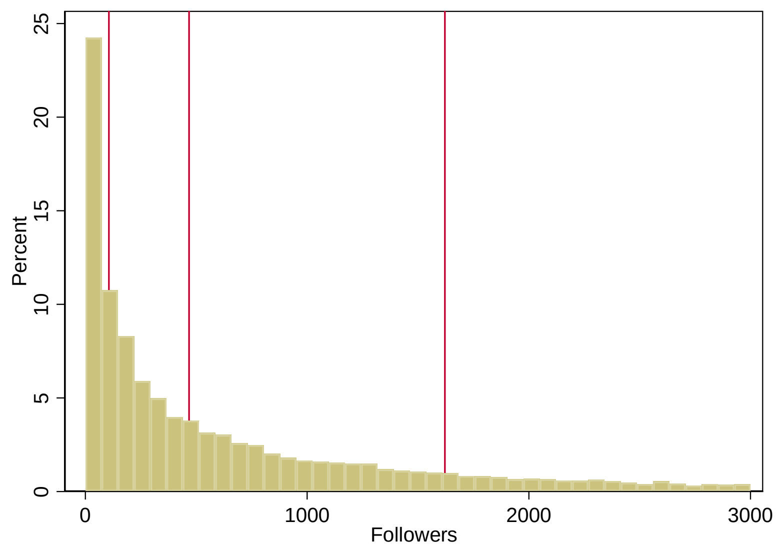
Notes: The figure shows in the top (lower) panel the Lorenz curve of ECB-related Twitter activity for the English (German) sample. The blue line represents the 45 degree line (which represents the line of equality. The yellow line shows the distribution of original tweets about the ECB, the red line 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



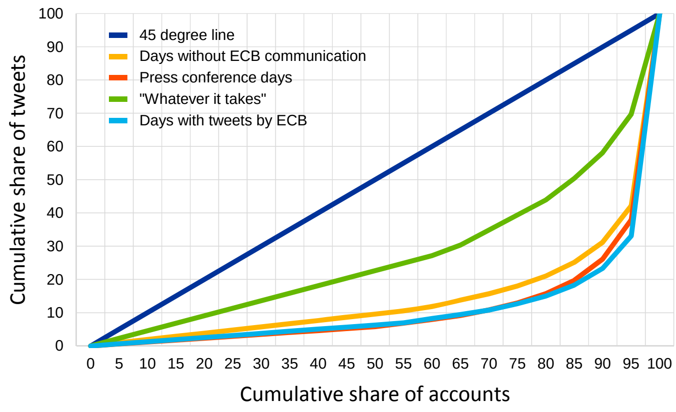
Panel B: Accounts in German-speaking sample



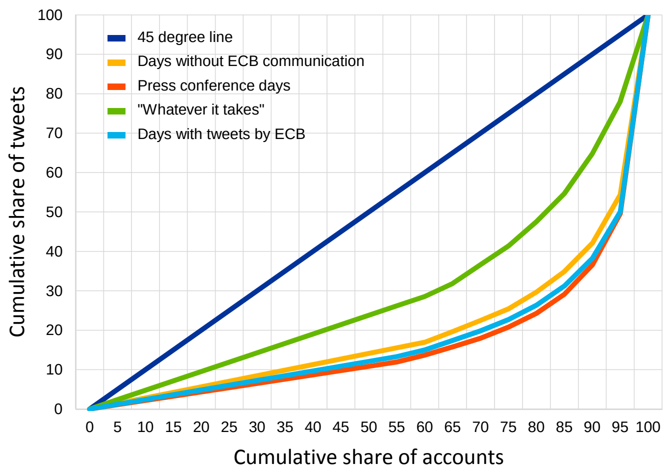
Notes: The figure shows the distribution of accounts by number of followers for the English sample (top panel) and German sample (bottom panel). Red lines denote 25%, 50% and 75% of sample, respectively. For better visualisation, the figure is truncated at 3,000 followers, whereas the actual maximum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

Figure 4: Lorenz curve of Twitter activity by events

Panel A: English sample

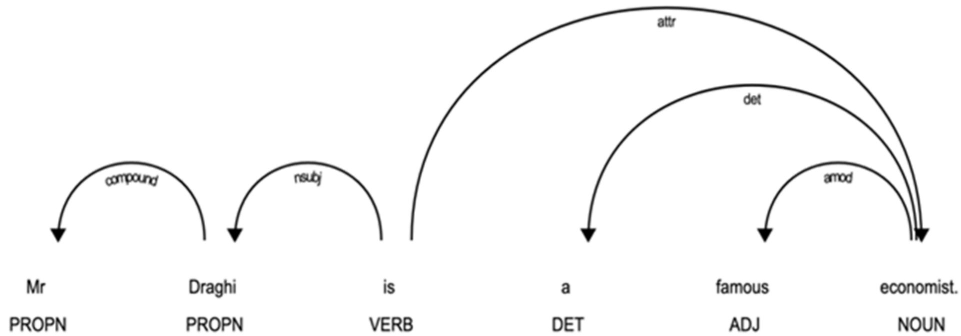


Panel B: German sample



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 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

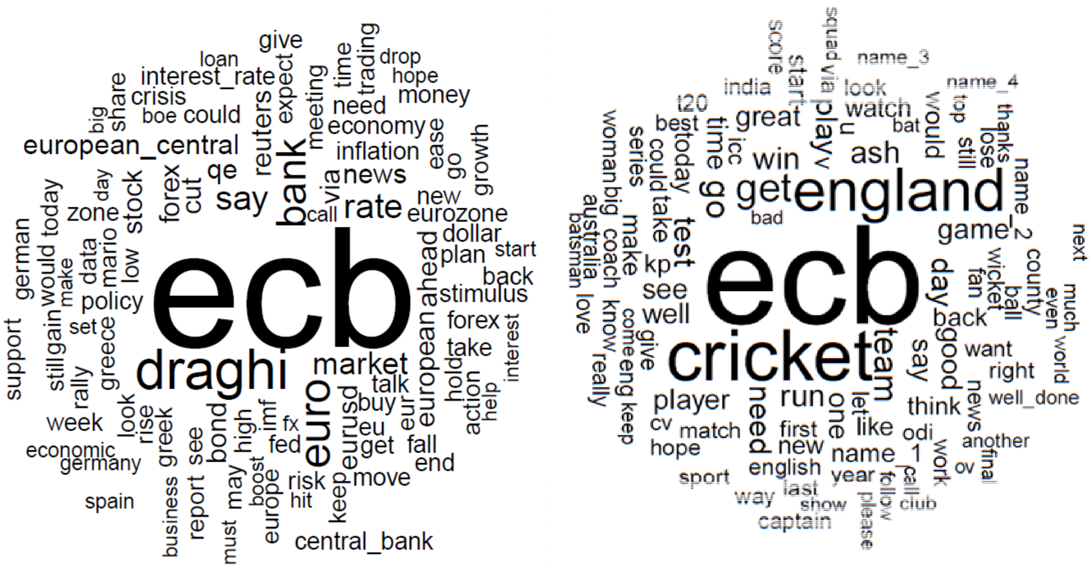


Notes: The chart illustrates the process involved in the Part-of-speech (POS) tagging that is applied in order to identify the sentiment relative to Mario Draghi expressed in a tweet.

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: 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 A4: 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 A5: 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 A6: 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 A7: 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 A8: 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 A9: 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 A10: 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 A11: 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.