Do Central Bank Sentiment Shocks Affect Liquidity within the European Monetary Union? A Computational Linguistics Approach.

Abstract

A common feature of recent financial crises has been the "drying up" of financial market liquidity. Increased attention, therefore, has been directed to central bank policy tools which can affect liquidity, even as policy rates approach the zero lower bound. This study examines the role of the European Central Bank (ECB) Governing Council's communication in influencing financial market liquidity. A specialized lexicon is used to extract sentiments on i) monetary policy and ii) economic outlook from ECB Governing Council statements between 2006-2016. The analysis reveals that ECB sentiments on "economic outlook" are more consequential for money market (MM) liquidity than for currency, equity and bond (CEB) liquidity. Sentiments on "monetary policy" produce a statistically significant effect on CEB liquidity; with more "hawkish" sentiments leading to declines in liquidity. Volatility in global financial markets, however, plays a relatively more robust role than ECB sentiments in influencing market liquidity. The results are corroborated using an alternative and more generic quantifier called the Loughran and McDonald (LM) sentiment quantifier. The specialized lexicon provides richer inferences than the LM quantifier, however, since it captures the "hawkishness" or "dovishness" of monetary policy tone and the "positivity" or "negativity" of Governing Council sentiments on economic outlook.

Dr. Robert Mullings

Economics
Nottingham Business School
Nottingham Trent University
robert.mullings@ntu.ac.uk
tel: +44(0)1158582010

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1. Introduction

The issue of financial market liquidity has received heightened focus within the empirical literature and in policy circles in the aftermath of the financial crisis of 2007- 2009 and the relatively more recent European sovereign debt crisis. In fact, a central stylized fact of multiple international crises, which has been confirmed by numerous studies within the economic literature is the lack or "drying up" of liquidity within financial markets (see for example, Rehse, Riordan, Rottke and Zietz, 2019; Dombret, Foos, Plishka and Schulz, 2019). While price stability remains a key goal of monetary policy[1], it is also true that a key goal of broader monetary policy and, more narrowly defined, macroprudential policy in the wake of such crises, has been to ensure that financial markets are liquid. Adequate liquidity has been found to increase the confidence of market participants thereby ensuring financial market stability (Del Negro, Eggertson, Ferrero, Kiyotaki, 2017; Lombardi, Siklos and Amand, 2018).

Given the central importance of liquidity to the proper functioning of financial markets, much economic research has been devoted toward understanding its role during episodes of increased uncertainty, market ambiguity and financial crisis (see for example, Garcia-Macia and Villa-Corta, 2016). At the same time, a parallel literature has emerged exploring the role of sentiments in affecting real economic outcomes. This emerging literature indicates a relationship between the sentiments of economic agents and market expectations and outcomes (Angeletos and La'O, 2013, Liang, 2018). Moreover, this literature suggests that the perceived sentiments of key market participants could influence the expectations of other market participants and may, in turn, affect their own strategies and behaviours thus determining market outcomes (Jansen and De Haan, 2007; Filardo *et al*, 2014; Kohn 2004; Asriyan, Fuchs and Green, 2019).

While the literature on the role of central bank communication in affecting financial markets outcomes has been well established since Blinder (2008), the exact transmission mechanism through which central bank sentiments affect financial markets remains an open question (Hubert and Lebondance, 2017). Gürkayanak, Sack and Swanson (2005), for example, emphasize the role of information contained within central bank communication regarding the bank's future policy path. Two key aspects of central bank communication which are of particular relevance in affecting outcomes in financial markets are often mentioned within the

[1] In fact, the Bank's main aim "to maintain price stability in the Eurozone" is enshrined in Statute 2 of the European Central Bank's Protocol.

literature on this topic. They are i) the central bank's views about the current and future state of the economy and ii) the central bank's views about its policy and reaction function. This study falls within the category of studies quantifying these two dimensions of the ECB Governing Council's statements and then goes on to investigate the link between the quantified sentiments and financial market liquidity. Hubert and Maule (2021) describes how these dimensions can significantly affect inflationary expectations, which in turn, could have differential effects on both short- and long-term interest rates. Hansen et al (2020), provides a concise survey of the role of central bank sentiments in financial markets while identifying an additional channel on in addition to the more traditional forward-guidance channel (Campbell, Evans et al; 2012). Hansen et al (2020) argues that central bank communications can also affect expectations about future market volatility and uncertainty, thereby producing an effect on long-term interest rates. On the other hand, Asriyan, Fuchs and Green, (2019) develops a rational theory of liquidity sentiments within an infinite horizon, discrete time framework, taking into account adverse selection information frictions and resale concerns. Asriyan et al (2019) states that sentiments, along with fundamentals, are both essential in determining asset valuations. On this basis, Asriyan et al (2019) concludes that sentiments, liquidity, and prices are intrinsically connected even when agents are fully rational.

In light of these developments, this study explores the extent to which central bank sentiments affect financial market liquidity. It adds to the emerging literature which examines how sentiments, expressed in central bank communications, may affect financial markets. This study makes use of tools provided by computational linguistics to clarify the nature of the possible relationship. The increased focus on central bank communication as an important tool of monetary policy coincides with a period in which key policy rates have tended towards the zero-lower bound, thus bringing into stark relief the remaining menu of policy tools which can be used by the central banker to manage the expectations of financial market agents with a view toward influencing market liquidity and other key financial variables.

As is the case in Dombret *et al* (2019), liquidity is defined within this paper as the ability of participants within a given market to buy or sell assets without causing significant price changes. This particular definition of liquidity extends the notion of liquidity beyond changes in the liquidity premium, to include commonalities between liquidity components in the asset returns of related financial markets. Moreover, as pointed out by Dombret *et al* (2019), while market liquidity is closely related to funding liquidity, the ability of an entity to obtain funding is itself a key determinant of market conditions. This paper is therefore focussed on a relatively broad definition of liquidity within asset markets in general, which in turn could have important implications for funding liquidity and broader macroprudential policy. Furthermore, Dombret *et al* (2019) shows that financial market liquidity, thus defined, could significantly impact the real economy[2].

The increased attention being given to less traditional policy tools within the central banker's toolbox has also coincided with the longer-term trend of increasing efforts being made by central bankers to improve transparency (Geraats, 2002). In fact, economic research has shown that through i) managing expectations ii) describing the strategy behind monetary policy actions iii) explaining current policy decisions iv) interpreting economic conditions while giving views on the future economic outlook and v) making statements about future policy, central bankers may impact market outcomes and reduce market instability and risks (see for example Woodford, 2005; Filardo and Hofmann, 2014; Blinder *et al*, 2008; Sturm and De Haan, 2011; Picault and Renault, 2017).

This paper is the first to directly bridge the gap between the literature on central bank communication and financial market liquidity. It achieves this by applying a relatively new methodology proposed by Picault and Renault (2017). The methodology quantifies sentiments expressed by the European Central Bank (ECB) Governing Council using a new approach combining a specialized lexicon with a probability weighting methodology. A novel feature of the Picault and Renault (2017) algorithm is that it combines a probability weighting approach with a multi-word or "*n*-gram" lexicon in order to classify central bank communication into two key areas of policy interest: i) monetary policy sentiments and ii) economic outlook sentiments. The approach introduced by Picault and Renault (2017) differs from prior, more traditional, "bag-of-words" methods which typically assign sentiment scores to statements using a list of "positive" and "negative" single words (unigrams). Moreover, within each of the aforementioned two major categories of sentiment, the field- and ECB-specific lexicon of Picault and Renault (2017) allows for the particular tone inclination of the central bank communication to be quantified. In particular, the answer to questions arising from a given ECB Governing Council statement such as: i) "was the tone of the central bank's sentiments regarding economic outlook positive or negative?" or ii) "was the tone of the central bank's sentiments on monetary policy 'hawkish' or 'dovish'?", are made possible using the lexicon.

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[2] Brunnermeier and Pedersen (2009) also provide a theoretical model relating market liquidity to funding liquidity.

After applying this novel approach to the textual analysis of the European Central Bank (ECB) Governing Council's statements spanning the period January, 2006 to April 2016, this study finds that sentiment shocks from the ECB Governing Council statements do play a statistically significant role in affecting liquidity in financial markets. These fairly robust, statistically significant effects are, however, found to be relatively small when compared to the effects of global market uncertainty. Furthermore, it was discovered that the more pronounced effects of sentiment shocks are observed in a narrowly defined liquidity measure – namely, money market (MM) liquidity as opposed to the much more broadly defined currency, equity and bond (CEB) liquidity. "Hawkish" ECB Governing Council monetary policy sentiment shocks can, over time, lead to a reduction in currency equity and bond (CEB) liquidity and has the opposite effect of "dovish" sentiment shocks regarding monetary policy. Positive economic outlook sentiment shocks by the Governing Council lead to an increase in MM liquidity - a type of liquidity which, as pointed out by Dombret *et al* (2019), pertains to financial markets dominated by banks and other similar financial institutions and not to broader market players. Overall, the study finds that volatility within global financial markets plays a much greater and robust role in affecting financial market liquidity within the euro-area than ECB Governing Council sentiment shocks. The findings from the empirical analysis also prove to be relatively robust, as corroborative evidence was obtained using the more generic, and not as nuanced, Loughran-McDonald (2011, 2015) lexicon.

In order to achieve its objectives, this paper is organised as follows: Section 2, which follows, briefly outlines the literature on liquidity and central bank communication and introduces the key hypothesis explored within this paper. Section 3 then describes the methodology used to quantify European Central Bank (ECB) Governing Council's sentiments and provides a description of the dataset. Section 3 also explores the nature of the relationship between ECB sentiments and financial market liquidity over the sample period January 2006 to April 2016, which was a period of remarkable developments in financial markets within the European Monetary Union and across the globe. Estimated results are then presented and discussed in Section 4. Finally, Section 5 presents key conclusions drawn from the analysis and prospects for future research.

2. Literature Review and Hypothesis Development

This study provides a link between two key thematic areas of research within the economic literature on central bank communication. On the one hand, there is an emerging literature which makes use of textual analytic methods to extract sentiments from central bank communication. On the other hand, a separate strand of the literature relates the quantified sentiments to real economic and financial outcomes. As previously outlined by Picault and Renault (2017), the aforementioned literature focussed on extracting sentiments from central bank communications can also be further sub-divided into two categories. They are: i) studies focused on the manual classification of the corpus of central bank statements or communications, and ii) studies making use of lexica or dictionary methods in order to analyse the speeches, minutes or other forms of central bank communication. In the former category, manual methods have been employed by Romer and Romer (1989), Boschen and Mills (1995) and Dewachter *et al* (2014), to grade or categorise central bank communications according to key criteria such as the monetary policy tone and inclinations contained within the document. Studies specific to ECB communication have emerged under this branch of the literature also (Musard-Gries, 2006; Rosa and Verga, 2007; Gerlack, 2007). Moreover, Berger *et al*., (2011) and Conrad and Lamla (2010) exemplify studies which employ manual grading schemes in order to quantify central bank tone, inclinations and posture. Manual text classification approaches, however, tend to be highly subjective in nature and therefore generally lack reproducibility. Moreover, it is possible for experts within a particular field to have significant disagreements on the classification of a given statement; a point made by Picault and Renault (2017).

A partial alternative to the manual classification approach is the use of dictionary-based and word count approaches in quantifying central bank sentiments. Jansen and De Haan (2007) exemplify this approach by relating simple frequency counts of the word "vigilance" in ECB communication to inflationary expectations within the Euro Area. Other similar so-called, "bag-of-words" approaches involve the construction and use of lists containing "positive" and "negative" words which are then compared to the corpus in some way in order to generate sentiment scores of ECB statements. Within this branch of the literature, specific lexica have emerged quantifying the sentiments of central bank communication such as those produced by Conrad and Lamla (2010) and Rosa and Verga, (2007). In general, these studies employ dictionaries containing a list of single words (or unigrams) to assess the extent and impact of the "hawkishness" or "dovishness" of central bank sentiment or tone.

Yet other dictionary-based studies have emerged, which have exploited generic financial lexica in order to quantify sentiments contained within central bank communications. This dictionary-based approach is exemplified by Tetlock (2007), Hansen *et al* (2014), Cannon (2015) and

Jensen *et al* (2016). These papers make use of either the Harvard IV-4 psycho-sociological dictionary or the Loughran – McDonald (LM) financial lexicon to extract sentiments from Federal Open Market Committee (FOMC) or ECB corpora[3]. Nevertheless, questions have been raised regarding the degree to which psycho-sociological or generic financial lexica are suitable for the analysis of sentiments contained in central bank communication or statements. For example, as pointed out by Picault and Renault (2017), the term "lower unemployment" would be classified as a negative sentiment in the generic financial lexicon of Loughran-McDonald due to the presence of the negative word "unemployment", whereas- in reality - the term expresses a positive economic sentiment within the context and jargon of central banking.

To avoid such misclassification issues, the present study makes use of the most recent, specialized European Central Bank (ECB) communication lexicon to explore the relationship between sentiments expressed within the statements made by the ECB Governing Council and financial market liquidity. So far, the lexicon has been introduced and applied in Picault and Renault (2017). As alluded to earlier, the lexicon is also unique in the sense that it allows for sentiments to be extracted from ECB's Governing Council statements relating to two key dimensions i) monetary policy and ii) economic outlook. Note that this unique feature contrasts with generic financial lexica like the Loughran-McDonald lexicon which assesses mainly the aggregate "positivity" or "negativity" of a given statement. Moreover, the Picault and Renault (2017) lexicon, in contrast, is detailed enough to allow for the identification of inclinations within the two main categories of detectable types of sentiments: i) monetary policy and ii) economic outlook. For example, the prevalence of "hawkish" over "dovish" sentiments on monetary policy and likewise the degree of "positivity" or "negativity" of the ECB Governing Council's sentiments regarding economic outlook can be quantified using the Picault and Renault (2017) lexicon. This feature highlights the advantages of using a lexicon specific to ECB governing council statements.

Picault and Renault (2017) provide preliminary empirical evidence that ECB Governing Council sentiments, quantified using their approach, could be useful predictors of ECB monetary policy decisions, stock market returns and volatility. This paper, in contrast, focuses on the role of sentiments as a determinant of financial market liquidity which is a major and often the ultimate target of monetary policy, especially during times of crisis (Lombardi, Siklos and Amand; 2018). Despite the recent focus on various aspects of liquidity in the aftermath of

[3] Kearney and Liu (2014) provide a useful review of approaches which have been used to conduct textual analysis making use of computational linguistic methods within the, more broadly-defined, financial literature.

recent financial crises (International Monetary Fund, 2015), very few studies have explored the link between central bank communication and market liquidity. One exception, which explores this link is Lee, Ryu and Kutan (2016) which employs an event study methodology in order to investigate the effects of monetary policy announcements on stock market liquidity in South Korea, using high-frequency data. Lee et al (2016) finds evidence that there were significant changes in stock market liquidity conditions around central bank announcements. A key difference between the approach used by Lee et al (2016) and the approach taken within the current study is that, Lee et al (2016) does not qualitatively assess the actual content of the central bank statements. Instead, Lee et al (2016) uses the timing of the statements as the basis for the inferences made within that study. This study, on the other hand, explores the differential impact of ECB governing council statements on i) economic outlook or ii) monetary policy on broadly defined, financial market liquidity. The impact of central bank communication on financial market liquidity is of interest since, according to Dombret *et al* (2019), financial market liquidity risks could have direct implications for bank lending, financial intermediary viability (Dombret et al 2017), bond markets (International Monetary Fund, 2015), equity markets (Toh, Gan and Li, 2019) and the real economy (Chu and Chu, 2019).

3. Methodology and Data Description

3.1 Quantifying Financial Market Liquidity and Central Bank Sentiments

According to Elliot (2015), financial market liquidity refers to the ability of buyers and sellers of securities to transact efficiently. Liquidity can be measured by the speed with which large purchases and sales can be executed and the concomitant transaction costs incurred in doing so. Currency, equity and bond (CEB) and money market (MM) liquidity indicators sourced from the European Systemic Risk Board (ESRB) are used to measure financial market liquidity within the context of the present study. The reason for this choice, as emphasized by Dombret et al (2019), is that both CEB and MM liquidity indicators encompass tightness, depth or resilience and liquidity premiums (Kyle, 1985)[4] which are key definitional aspects of financial market liquidity. Tightness refers to the magnitude of risk premiums required by market makers to hold inventories of securities. It is captured by the width of the bid-ask spreads. Depth and resilience encompass the degree to which trading affects asset prices and the availability of

[4] Sarr and Lybek (2002) provide a concise discussion of the underlying theoretical concepts underpinning financial market liquidity and also provides a discussion of some of the benefits of financial market liquidity for well-functioning financial markets.

many orders both above and below buy and sell prices, and can be measured using ratios of price movements to transaction volumes in the relevant markets (e. g. ratio of absolute return of an asset to its trading volume). On the other hand, liquidity premiums capture the compensation required by investors to cover the risk of the potential need to exit positions which could be challenged by uncertain market conditions in the future. Both CEB and MM liquidity indicators, therefore, capture key theoretical prerequisites of liquidity indicators.

Unlike Dombret *et al* (2019), which examines both macro- and micro- level liquidity, this study focuses solely on liquidity at the aggregate or macroeconomic level and the CEB and MM liquidity measures of the ESRB both capture macro-level liquidity. According to Dombret *et al* (2019), while the CEB liquidity indicator focuses on instruments which mature in the medium and long term, the MM liquidity indicator refers to instruments maturing in the short term. The CEB and MM indicators of the ESRB were designed to capture different aspects of financial market liquidity in the sense that, the money market, on the one hand, tends to be dominated by financial institutions and banks while the currency, equity and bond markets, as captured by the CEB liquidity, are served by a broader variety of market players. Dombret *et al* (2019) also notes that countries with a short-term fixation on loans might be more exposed to liquidity in the money market (as measured by the MM liquidity indicator) than to liquidity in the bond market (as measured by the CEB liquidity indicator).

The CEB liquidity indicator is comprised of eight (8) components. The components of the CEB liquidity index are bid ask spreads for i) exchange rates (EUR with USD, JPY and GBP) ii) stocks (Dow Jones EURO STOXX 50 components) and iii) interest rates (EONIA 1M and 3M swap rates are used). In addition, return to turnover ratios of iv) stocks (Dow Jones EURO STOXX 50 Components), (v) bonds (euro bond markets) and vi) options (equity option market) are also included within the CEB liquidity indicator. Liquidity premia included within the CEB liquidity measure are taken from (vii) bonds (euro area high yield corporate bonds which are corrected for credit risk by subtracting Moody's expected default frequencies (EDFs) and viii) deposits (euro area spreads between interbank deposit and repo interest rates). The composite CEB indicator is then computed as an unweighted index of these aforementioned 8 measures. Combining these components of liquidity to derive the CEB indicator reflects the fact that financial market liquidity is inherently a multi-dimensional concept and, as such, duly requires the inclusion of several components in order to arrive at a measure which adequately captures liquidity conditions and is a concept that extends well beyond changes in liquidity premia.

Higher values of both the CEB and MM liquidity indicators indicate greater levels of liquidity within financial markets.

Prior studies exploring the impact of central bank sentiment shocks on other financial market variables adopt an event-study methodology, making use of intra-day data, typically collected within an event window surrounding the ECB governing council statement, or in the case of other central banks, the communication of the specified central bank. Hubert and Lebondance (2021) and Lee et al (2016), both exemplify this approach. Unfortunately, a general intraday measure of liquidity with sufficient coverage, is simply not available for financial markets within the European Monetary Union. One potentially promising source of such data is the Euro – Area Monetary Policy Event Database (see Altavila et al, 2019), but this dataset does not yet contain a measure of liquidity which encompasses tightness, depth or resilience and liquidity premiums; which are key, desirable definitional concepts. Moreover, the CEB and MM liquidity indicators, while satisfying this criterion, also provide broad liquidity measures across multiple financial markets as has been explained previously. Therefore, having identified the measures of aggregate or macroeconomic liquidity within the European Monetary Union which will be employed within the present study, the procedure employed to extract the sentiments from the ECB Governing Council statements will now be explained.

A critical step in quantifying the sentiments of ECB's Governing Council statements is to classify all sentences pronounced within the statements. This paper adopts the approach taken by Picault and Renault (2017) which involves the manual classification of all sentences contained within the ECB Governing Council's statements into seven (7) categories. Under the Picault and Renault schema, the categories, which correspond to monetary policy inclinations, are: i) monetary policy "hawkish" ii) monetary policy "neutral" iii) monetary policy "dovish" iv) economic outlook "positive" v) economic outlook "neutral" vi) economic outlook "negative" and finally vii) none. Then, for each word (or group of words - *n*-grams hereafter) appearing in at least two ECB introductory statements, the authors compute the probability that the *n*-gram belongs to one of the 7 aforementioned categories. Lastly, the tone of each ECB statement is computed by summing the *n*-gram probabilities, using a term-weighting approach.

Picault and Renault (2017) use standard natural language processing techniques in the preparation of the corpus. In particular, i) all words were converted to lower case, removing numbers and punctuations ii) Porter's (1980) algorithm was then used to "stem" the words in order to reduce inflected words to their roots (e.g., "unemployment" to "unemploy" etc..) iii) a set of 32 stop words (such as: “a”, “the”, “an”, “of”, “to” ... etc) were removed from the text. The *n-grams* derived from the, corpus which have been converted to lower-case, stemmed and from which stop words have been removed, were then used as the basis for quantifying the sentiments within a given text.

A key strength of the Picault and Renault (2017) approach is that it quantifies both i) monetary policy and ii) economic outlook sentiments of the European Central Bank Governing Council. One implication of the multidimensionality of the index is that, between any two (2) periods of interest, each index may move independently of the other over time, thereby creating interesting dynamics while, at the same time, capturing the nuances of central bank tone. For example, given that monetary policy sentiments and economic outlook sentiments are quantified separately under the Picault and Renault (2017) method, it is theoretically possible for monetary policy sentiment to grow more “hawkish” while economic outlook could become more “negative” within a given time interval. It is also important to make explicit here the clear distinction between neutral monetary policy sentiments and neutral economic outlook sentiments within this framework. Neutral economic outlook statements pertain to the ECB Governing Council’s statements pertaining to its economic outlook which can neither be described as “positive” or “negative” while neutral monetary policy statements pertain to monetary policy but can neither be described as expressing a “hawkish” or “dovish” sentiment.

Statements making reference to past monetary policy decisions are *not* considered during the classification process since, intuitively, textual references to past monetary policy decisions do not represent new information to market participants. Monetary policy (MP) sentiments also include references to the short- and medium-term views of the Governing Council. On the other hand, economic sentiments (EC) “focus on policy makers’ descriptions of the current economic situation and their views about the future economic outlook”. The last category – “none” - groups sentences not directly relevant to either monetary policy decisions or the Governing Council’s economic outlook. In addition, the “none” category also includes sentences presenting data that have already been released prior to the date of the ECB statement. This includes past information on the Harmonized Index of Consumer Prices (HICP) inflation, real Gross Domestic Product (GDP) growth and other monetary aggregates. Statements falling within the “none” category therefore, do not contain any forward-looking statements or any additional information for that matter.

The next step in deriving the desired quantitative measure of sentiments from central bank statements is an aggregation step. At this stage, the frequency of occurrence of each n-gram, *n,* (from 1-gram to 10-grams) appearing at least twice within each statement and classified within each of the previously-defined seven categories is derived and the probability that the n-gram belongs to category *c* (monetary policy-MP or economic outlook-EC) with inclination *i* (dovish, neutral, hawkish for MP – positive, negative, neutral for EC) is computed. The computed Picault-Renault (2017) probabilities for each *n* can be written as:

$$P_n^{c,i} = \frac{number\ of\ occurences_n^{c,i}}{total\ number\ of\ occurrences_n} \tag{1}$$

In Equation 1, $P_n^{c,i}$ represents the probability of an *n*-gram falling in the category *c* (MP or EC) with the inclination *i* (dovish, neutral, hawkish for MP – positive, negative, neutral for EC). The denominator of Equation 1 measures the total frequency of a given *n*-gram within the lexicon defined for the entire corpus of ECB speeches for the review period. The numerator on the other hand measures the frequency of occurrence of the given *n*-gram within each of the 6 categories corresponding to the specific inclinations of monetary policy (MP) and economic outlook (EC) into which the sentence containing the *n*-gram has been categorized. Using the computed values of $P_n^{c,i}$, the size of the central bank communication specific lexicon of n-grams is further reduced by considering only n-grams with a probability of over 0.5 in one of the six classes of interest; those relating to monetary policy- MP: i) hawkish ii) neutral iii) dovish – and economic outlook - EC: i) positive ii) neutral iii) negative). Thus, the final, reduced set of n-grams generated using this procedure defines the final field specific lexicon which is denoted by n'.

In the next stage, probabilities from contiguous groups of words (or *n*-grams) are combined to develop a sentiment score for each statement of the ECB Governing Council. For a given introductory statement *s,* all words and groups of words (*n*-grams) pronounced by the ECB President are analysed and a probability of classification within one of the six (6) inclinations of interest computed. A term-weighted approach is employed, making use of the final, field-specific lexicon. More precisely, the probability of a given statement being classified in category *c* with inclination *i* is defined as:

$$P_s^{c,i} = \frac{\sum_{n'=1}^{l} P_{n's}^{c,i} * Occurrence_{n',s}}{\sum_{n'=1}^{l} P_{n's}^{c} * Occurrence_{n',s}} \tag{2}$$

Equation 2 above introduces a few new terms. The term $P_{n's}^{c,i}$ is the probability of the ECB Governing Council's statement falling into one of the six (6) categories using the reduced lexicon, n'. Following naturally from this definition, each ECB Governing Council statement will therefore generate 6 values. The term $Occurrence_{n',s}$ is a binary indicator variable that switches to one (1) if the n-gram is present within the text. For a set of related n-grams, the binary indicator is "switched on" only for the longest n-gram within the group. Similarly, the term $P_{n's}^{c}$ captures the total probability of a given n-gram being classified within a given category such as economic outlook (EC) or monetary policy (MP), irrespective of the inclination, i. For the version of the Picault-Renault (2017) dictionary used in this study the value of the *l,* or the size of the updated lexicon of n-grams is 61,660[5]. As pointed out by Picault and Renault (2017), a direct result of the manner in which the probabilities are defined in equation 2 is that, in a given Governing Council statement, *s*, for *c* = MP, for all *i* = (hawkish, dovish, neutral) $\sum_{c=1}^{3} P_s^{MP,c} = 1$. Similarly, for *c* = EC, for all *i* = (positive, neutral, negative) $\sum_{c=1}^{3} P_s^{EC,c} = 1$.

This study focuses on the potential effects of central bank sentiments on financial market liquidity. In order to achieve this objective, use is made of aggregate indicators to capture the "net sentiment" on monetary policy (MP) and economic outlook (EC). Two variables I_s^{MP} and I_s^{EC} are defined in order to capture the concept of the European Governing Council's "net sentiment" regarding monetary policy and economic outlook for each speech, respectively. Concretely, the variables are defined as:

$$(I_s^{MP}, I_s^{EC}) = \begin{cases} I_s^{MP} = P_s^{MP,hawk} - P_s^{MP,dovi.}, I_s^{MP} \in [-1,1] \\ I_s^{EC} = P_s^{EC,posi.} - P_s^{EC,nega.}, I_s^{EC} \in [-1,1] \end{cases} \quad (3)$$

In Expression 3, the final "net" monetary policy "sentiment, I_s^{MP} is derived by simply subtracting the "dovish" monetary policy sentiment score $P_s^{MP,dovi.}$ for a given statement (or speech) from the "hawkish" sentiment score or probability for a given statement. Similarly, to quantify the "net" economic outlook sentiment indicator the negative economic outlook probability score for a given speech $P_s^{EC,nega.}$ is subtracted from the corresponding positive

[5] The lexicon used to construct the Picault- Renault (2017) sentiment indices was accessed on the 24th of November, 2019 and consists of 61660 n-grams. The authors provide the actual computed sentiment indices on their websites at http://www.cbcomindex.com. On the other hand, the size of the lexicon of n-grams in the original paper Picault and Renault (2017) is 34,052.

probability $P_s^{EC,posi.}$. The derived I_s^{MP} and I_s^{EC} resulting from these intuitive transformations are the used as key explanatory variables within the empirical analysis to follow.

For the sake of robustness, this paper also provides empirical results using an alternative quantitative measure of sentiment or "tone". Namely, the Loughran and McDonald (2011, 2015) lexicon is also used to quantify the degree of "net" negativity or "positivity" of the textual content of each statement pronounced by the European Central Bank's Governing Council. The widely used Loughran and McDonald (LM) index contrasts with the Picault and Renault (2017) methodology, in that under the LM approach, which exemplifies the traditional "bag of words" methodology, each statement of the ECB's Governing Council is classified as representing a "positive" or "negative" sentiment based on a list of positive and negative single words (unigrams). The actual words within the lexicon are provided in the, periodically updated, LM lexicon which has been provided by way of "open-source" access to researchers by the authors (Loughran and McDonald; 2011, 2015). Within this study, use is made of the most recently updated master LM dictionary. Recall that while the LM lexicon is specific to finance and is therefore field-specific in that sense, but the Picault and Renault (2017) lexicon is even more narrowly specific to central bank communications. In fact, unlike other lexica which are specific to central bank communications such as those due to Apel and Blix-Grimaldi (2012) and Bennani and Neuenkirch (2017), the Picault and Renault (2017) approach does not rely solely on unigrams (single words) in extracting sentiments from the European Governing Council's statements. By using n-grams instead of unigrams, the context of certain key words included within the statements can be more effectively inferred. This feature, added to the fact that the Picault and Renault (2017) quantifier captures a range of sentiments and inclinations found within central bank communication, makes it an ideal choice for the current study.

3.2 Sentiments and Liquidity within the EMU

Having quantified the ECB Governing Council's sentiments using the Picault and Renault (2017) measure, this section explores the degree of relatedness between the evolution of ECB's sentiments and the level of financial market liquidity within the European Monetary Union (EMU) over time. Figure 1 depicts four (4) time series panels relating the quantified ECB's sentiments on economic outlook and monetary policy to the CEB and MM liquidity indicators over the review period. Note that for the time series depicted, the scale of the liquidity indices is represented on the left-most vertical axes while the right-most vertical axes are used to represent the value of the sentiment indices. Recall that the CEB liquidity index is a relatively broad measure of liquidity across key financial markets, as its name suggests, while the MM index measures liquidity within, more narrowly defined, money markets. The top half of Figure 1, shows the relationship between CEB liquidity and the two key sentiment indices for economic outlook (I_t^{EC}) and monetary policy (I_t^{MP}). The topmost panels also reveal a general pattern of co-movement between CEB liquidity and both i) ECB economic outlook sentiment and ii) monetary policy sentiment indicators over the sample period. Figure 1 reveals a relatively closer co-movement between the economic outlook sentiment index and the indicator of CEB liquidity over the period. On the other hand, a divergence between the CEB liquidity index and ECB's sentiments on monetary policy becomes apparent toward the end of the sample period. Another interesting feature of the topmost panels is that both liquidity indicators register a sharp decline during the global financial crisis (GFC) within the 2007 to 2009 timeframe. Subsequently, the CEB liquidity index, economic outlook sentiment and monetary policy sentiment both recovered during the post-crisis period.

[Figure 1 here]

Examining the lower half of the panel reveals an additional period of significantly lower MM liquidity within the context of European financial markets. In particular, the MM liquidity indicator shows a noticeable negative spike in the 2010 – 2012 timeframe corresponding to the European sovereign debt crisis. In fact, Dombret *et al* (2019) states that this significant decline in MM liquidity ends after Mario Draghi's "whatever it takes speech" delivered toward the end of July 2012. While the European sovereign debt crisis does not appear to have affected the CEB liquidity indicator in the graphs presented in the upper half of the figure, the crisis does appear to have had a discernible impact on the economic outlook sentiment of the ECB's Governing Council. This finding again, underlines the fact that CEB and MM liquidity indices capture distinctly different aspects of financial market liquidity within the EU.

The degree of co-movement in the time series relationships observed in the lower half of Figure 1 relating MM liquidity to ECB sentiments appears less pronounced than the co-movement observed in the upper-half of the panel relating ECB sentiments to the CEB liquidity indicator. Dombret *et al* (2019) also points out that the differences in the patterns of evolution of the CEB and MM indicator confirms that each of the liquidity indicators captures distinct elements of financial market liquidity.

Another interesting pattern which is directly observable from the rightmost panels of Figure 1, is the divergence between both liquidity indicators and monetary policy sentiments towards the end of the sample period. This trend coincides with a period in which the main refinancing operations rate tended towards the zero-lower bound and when the sentiments of the ECB Governing Council became relatively more "dovish" when compared to the pre-2012 time period.

[Figure 2 here]

[Figure 3 here]

Figure 2 depicts the time series relationship between the CEB liquidity index and the Loughran – McDonald (LM) sentiment indicator. The pattern observed in Figure 2 mirrors closely the earlier patterns observed in Figure 1 which features the, relatively more specialized, Picault-Renault (2017) sentiment indicator. The similarity is observed despite the fact that the LM indicator differs significantly from the Picault-Renault (2017) index in that, *inter alia* i) it does not distinguish between sentiments on economic outlook and monetary policy ii) does not use a probability weighted, n-gram approach for sentiment classification and iii) the lexicon is not specific to central bank communication. Despite these differences, Figure 2 reveals that quantifying ECB sentiment using the simpler "bag of words" approach employed by the LM index is also closely related to the CEB liquidity variable over the entire review period.

Figure 3 presents the analogous time series plot of the LM index and the money market (MM) liquidity indicator. Although the figure implies a relationship between the MM liquidity series and the LM sentiment indicator, the relationship is not as strong as can be observed in Figure 2. This pattern mirrors that found earlier with the Picault-Renault (2017) monetary policy sentiment indicator. In general, therefore the observed relationship between financial market liquidity and ECB sentiments are generally consistent across both the Picault and Renault (2017) and the LM indices. Moreover, the observation of a noticeable divergence between the various measures of ECB sentiment and financial market liquidity toward the end of the sample period is a strikingly consistent pattern across Figures 1 and 3. This divergence is particularly apparent in graphs showing the relationship between both the sentiment indices (LM or Picault and Renault, 2017) and the money market (MM) liquidity index. This divergence possibly implies a breakdown in the relationship between the two especially towards the end of the period as the main policy rate tended toward the zero-lower bound.

[Table 1 here]

Finally, Table 1 depicts the pairwise correlations between all financial market liquidity and ECB sentiment indicators used within the current study. The table reveals that the strongest pairwise, linear associations can be observed between the Picault and Renault (PR) economic outlook indicator and the CEB liquidity indicator; confirming the findings from a visual inspection of Figure 1.

The table also reveals statistically significant, strong pairwise linear correlations between the LM sentiment index and ECB sentiments on economic policy. The relatively low correlation between the liquidity variables also confirms our earlier observations that both liquidity variables capture separate aspects of market liquidity. Although, judging from the pairwise correlations, there appears to be a relatively strong relationship between the ECB sentiments on economic outlook and its sentiments on monetary policy, the magnitude of the estimate is low enough to suggest that both variables capture separate dimensions of ECB sentiment.

3.3 Empirical Model

To investigate the effects of central bank sentiments on liquidity within the European Monetary Union (EMU), this paper follows the framework outlined by Hubert and Lebondance (2017, 2021). Applying their approach involves estimating regressions involving i) the indices quantifying various elements of central bank sentiment and ii) the financial market liquidity indicators. Recall that the two liquidity indices i) CEB and ii) MM liquidity, provided by the ESRB, capture different aspects of financial market liquidity with CEB liquidity representing a relatively broader measure of liquidity since it measures liquidity in financial markets serving a wider array of market participants (currency, equity and bond markets). Moreover, CEB liquidity differs from MM liquidity in the sense that it pertains to instruments maturing in the medium to long term. On the other hand, the MM liquidity index, is a relatively more narrow and short-term measure of liquidity, which focusses on money market activity; including the activities of banks and other similar financial institutions (Dombret et al, 2019).

$$Tone_t = \beta_0 + \beta_1 Tone_{t-1} + \beta_2 \Delta MP_t + \beta_3 X_{t-1} + \beta_4 Z_t + Sent\_Shock'_t \quad (4)$$

$$Sent\_Shock'_t = \beta_5 + \beta_6 Sent\_Shock'_{t-1} + Sent\_Shock_t \quad (5)$$

Although the relationship between liquidity and ECB Governing council tone is of primary interest within the present study, Hubert and Labondance (2017, 2021) and Cannon (2015) suggest estimating the auxiliary Equations 4 and 5 in the first stage, due to endogeneity concerns. In Equation 4, $Tone_t$, (either I_s^{MP} or I_s^{EC} from Equation 3), is the dependent variable which is derived from ECB Governing Council statements using the Picault and Renault (2017) methodology. It should be noted that in Equation 4, $Tone_t$ is explained, in part, by its own lagged value. Such dynamic effects have been emphasized in the previous literature by Hubert and Maule (2021), Hanson and Stein (2015) and Hansen et al (2020).

Also, in Equation 4, the subscript *t* represents the time frequency used within the current study. Equations 4 and 5 are estimated using data recorded at a monthly frequency. A monthly frequency was chosen for the empirical analysis although for 8 months during the review period (January 2006 to April, 2016), ECB Governing Council statements were delivered more than once per month. This implies that the overwhelming majority of ECB governing council statements over the review period were delivered at a monthly frequency. Furthermore, the other control variables within X_{t-1} and Z_t were available at varying time frequencies, details of which are provided in Table 3. In order to minimize the need for data interpolation and imputation, daily values of regressors available at frequencies higher than one month (e.g., variables available at a daily frequency) are exactly matched with sentiments extracted at each ECB Governing Council statement date, before averaging to monthly frequencies. For variables available at lower frequencies than one month on the other hand, following Hubert and Labondance (2021), the value of the variable nearest to months *t* and *t-1* is matched with the quantified sentiment of the ECB's Governing council for that month. Therefore, variables expressed in differences reflect changes over a one-month period in this study, unless otherwise specified. This approach has both benefits and disadvantages. As mentioned earlier, the benefit of the approach of using a monthly frequency for the analysis is that the need for the use of interpolation and imputation methods is minimized. On the other hand, the disadvantage of this approach is that for the 8 months within the sample in which there were more than one ECB Governing Council statements, some variation within the sentiment shock variable is lost (Hubert and Lebondance, 2021).

Among the regressors used to model the predictable components of $Tone_t$ is the variable ΔMP_t which represents the change in the monetary policy stance of the ECB's monetary policy stance since the last statement. The information contained in ΔMP_t is not solely related to changes in the policy rate itself but to a broad suite of monetary policy tools as captured by the Wu-Xia (2016) shadow rate. The matrix Z_t captures the set of control variables which affect $Tone_t$ contemporaneously and consists of the composite indicator of systemic stress (CISS) and the EURO STOXX50 returns between the last statement date and the day prior to the current statement date. The rationale for the inclusion of these variables is that they are potential factors affecting the dependent variable; the tone expressed in ECB Governing Council statements. The variables included within X_{t-1} capture information from lagged financial and economic variables which affect or drive ECB Governing Council's tone. In particular, included within X_{t-1} is the European Commission's economic sentiment indicator and a variable capturing changes in oil prices which are a major driver of inflation and their expectations. The X_{t-1} matrix also includes estimates of the output and the inflation gap, which are key areas of concern for the ECB and which, likely, also affect the tone of statements of the Governing Council. Moreover, additional variables included within X_{t-1} are inflation forecasts of the ECB and the changes in the volatility of international financial markets. Note, too, that the specification of the X_{t-1} and Z_t matrices mirrors very closely the specification employed by Hubert and Lebondance (2022). Moreover, as in Hubert and Labondance (2017), Equation 5 is also estimated in order to remove its autoregressive (AR) contribution. Inclusion of the autoregressive term takes into account i) observations from the information frictions literature and ii) the intuition that the estimated sentiment shock for the current period ($Sent\_Shock_t'$) is likely to be a combination of current and past sentiment shocks. Estimates of the error term in Equation 5, $Sent\_Shock_t$, therefore, reflect exogenous shocks to the tone variable and can be interpreted under this formulation as the sentiment shock series.

Having derived the component of tone which is orthogonal to key economic and financial variables which are likely to affect ECB tone during a given period, the following equation is then estimated (as in Hubert and Labondance; 2017, 2021), with the derived sentiment shock, $Sent\_Shock_t$ variable, included as a key regressor of interest:

$$\Delta Liq_t = \alpha + \beta_0 \Delta Liq_{t-1} + \sum_{i=1}^{4} \beta_{1i} \Delta Sent\_Shock_{t+1-i}^{EC} + \sum_{i=1}^{4} \beta_{2i} \Delta Sent\_Shock_{t+1-i}^{MP} + \gamma_1 X_{t-1}' + \epsilon_t \quad (6)$$

In Equation 6, the dependent variable, ΔLiq_t is regressed on its lag and other regressor variables, as in Dombret *et al's* (2019) study which studied the determinants of Euro-Area liquidity. In addition, the two (2) differenced sentiment shock variables derived from the estimated residuals of Equation 5 are also included among the regressor variables in Equation 6. The sentiment shock variable $\Delta Sent\_Shock_t^{MP}$ represents the differenced estimated residuals from ECB Governing Council monetary policy sentiments and the other term, $\Delta Sent\_Shock_t^{EC}$ is similarly derived from the ECB's sentiments on economic outlook. Various specifications of Equation 6 are estimated, each containing varying numbers of lags of the differenced sentiment shock variables. This approach is adopted since the theory does not explicitly state the lags at which sentiment shocks are able to affect liquidity. Overall, it is expected that positive economic outlook sentiment shocks ($\Delta Sent\_Shock_t^{EC}$) would tend to reduce uncertainty in markets and increase liquidity, while negative economic sentiment shocks would have the opposite effect on liquidity. On the other hand, "hawkish" sentiments expressed by the ECB governing council on monetary policy over time are expected to reduce liquidity, since, over and above the effect of such a tone shock on expectations, private agents can reasonably expect a credible central banker to intervene through monetary policy to reduce liquidity. Using a similar rationale, the opposite effect on liquidity is expected for "dovish" monetary policy sentiment shocks. The use of the *i* index in the specification of Equation 6 ensures that contemporaneous as well as lagged effects of both types of sentiment shocks (in particular, $\Delta Sent\_Shock_t^{EC}$ and $\Delta Sent\_Shock_t^{MP}$) are included within the specification of Equation 6 which explains the evolution of liquidity.

The matrix of variables, X_{t-1}', in Equation 6 consists of factors which affect financial market liquidity within the European Monetary Union (EMU). Since liquidity is such a central prerequisite for the proper functioning of financial markets (Dombret et al, 2019), and therefore naturally a major concern of monetary policy, it should come as no surprise that there is significant overlap between the determinants of liquidity across financial markets and central bank tone as modelled in Equation 4 above. The exact specification of the variables affecting liquidity are is reflected in the specification of the X_{t-1}' matrix. In particular X_{t-1}' contains the lagged inflation gap $(\pi_{t-1} - \pi^*)$, which is defined as the difference between the current level of inflation as measured by the euro area Harmonized Index of Consumer Prices (HICP) available at the time of the statement, minus the ECB target rate of inflation ($\pi^* = 2\%$). The 12-month ahead inflation forecast from the ECB Quarterly Survey to Professional Forecasters (SPF) is used as a proxy for inflationary expectations π_{t-1}^e. Equation 6 also controls for the state of the real economy since the relationship between liquidity and economic growth, albeit a complex one, has been established in the economic literature (see for example the recent study by Chu and Chu; 2019). The output gap, $(y_{t-1} - y^*)$, is measured by the difference between the euro area industrial production (excluding construction)[6] and potential output, $y*$. Potential output is proxied as the trend of the Hodrick-Prescott filter of the industrial production series[7]. The European Commission's Economic Sentiment Indicator (ESI) minus its long-term trend is used as a proxy for the output gap expectations y_t^e, following Sauer and Sturm (2007). The Wu-Xia (2016) shadow rate is also included among the regressors since it contains information on the ECB's policy stance even as the policy rate tended towards the zero lower bound variable, as was the case in Equation 4 (Carpinelli and Crosignani, 2021).

Changes in oil prices and the EURO STOXX 50 returns since the last ECB Governing Council statement are also included among the regressors in X'_{t-1} as possible determinants of market liquidity (see for example, Zhang and Boon; 2022 and Tarun et al, 2001). Following the example of Hubert and Lebondance (2021), the Chicago Board Options Exchange's volatility index (VIX) is also included as a proxy for uncertainty in global financial markets (ΔVIX_t) in Equation 6, as it was in the first stage regression - Equation 4. The volatility index (ΔVIX_t) is included given empirical evidence suggesting that financial uncertainty in US markets (as measured by the VIX) plays a "pivotal" role in global uncertainty and across multiple major financial markets within the euro-area (Smales, 2022). In general, the expected relationship between financial market uncertainty and financial market liquidity, broadly defined, is that uncertainty varies negatively with financial market liquidity (Rehse, Riordan, Rottke, Zietz; 2019).

$$\Delta Liq_t = \alpha + \beta_0 \Delta Liq_{t-1} + \sum_{i=1}^{4} \beta_{1i} \Delta Sent\_Shock_{t+1-i}^{LM} + \gamma_1 X'_{t-1} + \epsilon_t \qquad (7)$$

Equation 7 represents the final variant of the regression model to be estimated. This specification differs from the earlier specification of Equation 6 in only one respect: the ECB-specific sentiment indicators due to Picault and Renault (2017) - $\Delta Sent\_Shock_{t+1-i}^{EC}$ and $Sent\_Shock_{t+1-i}^{MP}$- are replaced by the, more generic, sentiment shock indicator derived from the Loughran -McDonald (2011, 2015) sentiment quantifier. Recall from the earlier discussion that the LM lexicon from which the Loughran-McDonald (2011, 2015) index was designed for use in quantifying the sentiments in generic financial text and not specifically designed for quantifying sentiments in the ECB Governing Council Statements per se. Despite this drawback of the LM sentiment indicator, it has proven to be a useful tool in the empirical finance literature

[6] Picault and Renault (2017) and Gerlach (2007) employ a similar measure.
[7] Following Picault and Renault (2017), the smoothing parameter used for the analysis was set to 14,400.

to measure and compare the “positivity” or “negativity” of sentiments within a given financial text. Equation 7 is specified to include lags 1 to 3 of the Loughran -McDonald sentiment indicator in an attempt to capture dynamic effects and, as such, serves as a useful robustness check of the results obtained from the specifications using the, more specialized, Picault and Renault (2017) sentiment quantifier.

[Table 2 here]

Table 2 depicts the Augmented Dickey Fuller test statistics for the key variables included within the regression model. The table confirms that the key economic time series included within the model are integrated of order one. In particular, column 2 of the table depicts the test statistics generated from the Augmented Dickey Fuller test, performed on differenced versions of both dependent variables –the CEB and MM liquidity indices – and regressors included in equations 3 and 4. Comparing the computed test statistics in column 2 of the table to the critical values in columns 3 – 5 of the table reveals that, in all cases, the null hypothesis of a unit root in the differenced series is strongly rejected.

Table 3 presents descriptions, sources, time frequencies and selected descriptive statistics for the key variables used within the estimation of Equations 4–7. Both CEB and MM liquidity indicators are sourced from the ESRB and the range and other descriptive statistics of these indicators are consistent with summary statistics presented in the prior literature (see for example, Dombret *et al*, 2019 in which statistical summaries for these two variables are also presented). The specialized European Central Bank Governing Council sentiment indicator was obtained from Picault and Renault (2017)[8] while the Loughran and McDonald financial sentiment lexicon with an updated and refined word lists were obtained from Loughran and McDonald (2011, 2015)[9]. In general, the summary statistics computed for both sentiment indicators used within this study are consistent with values obtained from prior studies.

[Table 3 here]

[8] The Picault and Renault (2017) word and n-gram lists in addition to an updated version of the indices are available at http://www.cbcomindex.com (accessed on the November 24th, 2019)

[9] The data and python code can be found at https://sraf.nd.edu/textual-analysis/code/ (accessed on August 06th, 2021)

The ECB staff projections for the inflation gap, and the Composite Indicator of Systemic Stress (CISS) were all sourced from the ECB database. The 12-month ahead inflation forecast, obtained from the ECB Quarterly Survey to Professional Forecasters (SPF) was used as a proxy for expected inflation. The European Commission Sentiment indicator (ESI) was sourced from EUROSTAT and provides a measure of economic sentiment for the region. The economic sentiment indicator is constructed using a weighted average of the responses to selected questions addressed to consumers and firms from five (5) major sectors[10] covered by the EU Business and Consumer Surveys. Data on West Texas Intermediate Crude Oil prices, and the volatility index (VIX) were obtained from the Federal Reserve Economic Dataset (FRED). The EURO STOXX50 return data was downloaded from Yahoo Finance. The EURO STOXX50 return data are computed between the date of the previous Governing Council's statement and the day before the current ECB Governing Council statement date.

Studies exploring the effects of monetary policy on other economic variables typically include the main refinancing operations rate of the ECB as it is generally informative about the monetary policy stance of the ECB. However, as stated earlier, the tendency of this variable toward the zero- lower-bound (ZLB) has created a need for a more ideal measure of monetary policy which is also able to capture the range of unconventional monetary policy tools which have been employed by the ECB over time, in the conduct of monetary policy. For this reason, this study, like numerous others in the recent literature (see for example Sahuc and Mouhabbi, 2019; Dell'Ariccia, Rabata and Sandri, 2018), makes use of estimates of the shadow rate to capture the "effective" signal rate containing information about the ECB's monetary policy stance even at the ZLB. The shadow rate takes into account both conventional and non-conventional monetary policy measures. However, the shadow rate is identical to the policy rate in normal periods when the policy rate does not approach the ZLB. Wu and Xia's (2016) estimate of the shadow rate for the EU was used in this study, however an alternative estimate of the shadow rate provided by Krippner (2013) provides qualitatively identical results to the results presented in this paper.

Table 3 also highlights the fact, mentioned earlier, that the variables are available at varying frequencies. For example, the sentiment variables correspond to the dates of the Governing

[10] The sentiment indicator covers responses from i) industry ii) services iii) consumer iv) retail and v) construction. The dataset can be found at https://ec.europa.eu/eurostat/web/main/home (accessed on August 06th, 2021).

Council statements while data on Euro area industrial production are made available at a monthly frequency. The Wu-Xia (2016) shadow rate estimates and sentiment indicator data are also provided at a monthly frequency and the data for these variables are matched with the speech date which is closest in proximity. Data made available at a quarterly frequency such as forecasted GDP growth rate and expected inflation are matched with sentiments quantified from ECB statements within that specific quarter, as alluded to earlier. Daily data, on the other hand, are matched to the exact date of the speeches unless otherwise specified in Table 3.

[Table 4 here]

Table 4 contains pairwise Pearson correlation coefficients for all variables included within the regressions. The table reveals a positive but relatively weak relationship between the differenced liquidity indicators. Table 4 also reveals that although there is a positive relationship between the output and inflation gaps the correlations are, again, relatively weak and thus should not pose a multicollinearity concern within the linear regression estimation framework. The table also generally reveals positive and statistically significant relationships between changes in the liquidity proxies and changes in the sentiment variables. Interestingly also, Table 4 reveals a positive relationship between the i) the economic outlook indicator ii) the monetary policy sentiment index and iii) the LM sentiment index. However, although the table provides some evidence of a positive relationship between (differenced) sentiment indicators the relationship cannot be described as particularly strong on the basis of the pairwise correlations. The correlations also accord with expectations, as can be observed by the negative relationship between changes in financial market volatility as captured by changes in the VIX and the liquidity measures. In general, therefore, on the basis of the findings from Table 4, the pairwise correlations do not suggest a potential multicollinearity problem.

4. Empirical Results

Table 5 contains estimation results for Equations 4 and 5. The names of the variables used in the estimation are displayed in column 1 of the table and the estimated coefficients with their associated robust standard errors are displayed in the corresponding rows of Table 5. Columns 2–4 of Table 5 depict the estimated coefficients and robust standard errors under alternative specifications of the model.

The R-squared for each regression reveals that the included explanatory variables across the various specifications of the model explain a significant proportion of the variation in the dependent variable, however defined. In particular, column 2 of Table 5 reveals that the model explains 80% of the variation in the ECB Governing Council's sentiments on economic outlook whereas the model explains an even greater share of the variation in the sentiments on monetary policy. On the other hand, the model explains 69% of the variation in the Loughran – McDonald (2011, 2015) sentiment index. Across all specifications of the model displayed in columns 2-4, the coefficient on the lagged dependent variable is highly statistically significant, revealing significant inertia in the sentiments expressed within ECB Governing Council statements, however measured, over time.

The results depicted in Table 5 show that the fluctuations of inflation around its target level is a statistically significant determinant of ECB Governing Council's economic sentiments. This result likely reflects the importance of price stability as a key objective of the ECB. The opposite signs of the coefficients on the inflation gap variable across columns 2 and 3 of Table 5 reflect differences in the effect of the inflation gap on ECB Governing Council's sentiments on economic outlook and monetary policy. Column 2 also confirms that increased uncertainty in global financial markets, as captured by ΔVIX_t and its lags, is statistically significant and negatively related to the "positivity" of sentiments on economic outlook expressed by the ECB Governing Council.

[Table 5 here]

The estimation results displayed in column 3 of Table 5 expose even more determinants of ECB Governing Council's monetary policy sentiments. Firstly, an increase in the economic sentiment indicator (meaning, an increase in the positive sentiments regarding economic outlook expressed by manufacturers, service providers, consumers, retailers and constructors, ΔESI_{t-1}), in turn, drives "hawkish" monetary policy sentiment from the ECB, albeit at a 10% level of significance. On the other hand, an increase in systemic stress ($\Delta CISS_{t-1}$) eventually leads to a more "dovish" monetary policy tone. The coefficient on the inflation forecast variable from column 3 suggests that an increase in inflationary expectations has a positive and statistically significant effect on the future monetary policy tone of the ECB Governing council. In particular, an increase in inflationary expectations leads to increased hawkishness in the ECB Governing Council's sentiments on monetary policy in the subsequent period. Column 4 of Table 5, may hint at the inability of the Loughran-McDonald sentiment indicator to differentiate between economic policy and monetary policy sentiments. An increase in the shadow rate, for example, increases the "positivity" of LM sentiment as does positive changes in the economic sentiment indicator. At the same time, column 4 reveals a positive and statistically significant coefficient on lagged changes in volatility, implying that changes in volatility in the preceding month may lead to positive LM sentiment in the current period; a result which is slightly ambiguous. Table 5 also provides some evidence that the autoregression of order one AR (1) which is used to remove the autocorrelation component from sentiment shocks as suggested by Hubert and Lebondance (2017, 2021), has significant explanatory power in explaining both the i) economic and ii) monetary policy dimensions of Picault and Renault (2017) sentiments.

Table 6 shows the estimation results for Equation 6 with the change in currency, equity and bond (CEB) liquidity as the dependent variable. The first column of the table contains variable names of explanatory variables used within each specification. Columns 2 – 5 of Table 6 contain the estimated coefficients and corresponding standard deviation estimates, with each of the columns of the table displaying estimation results for an alternative specification of the model. Note also that specifications in columns 2-5 of the table differ with respect to the number of lags of the Picault and Renault (2017)-based sentiment shock variables included within the specification of the model. Higher-numbered columns include additional lagged sentiment shock variables and column 2 contains only contemporaneous values of the sentiment shock variables. Robust standard errors are reported for all estimated results.

[Table 6 here]

The lagged dependent variable is statistically significant and negatively signed across all specifications of the model represented in column 2-5 of Table 6. The coefficient on expected economic activity as captured by the economic sentiment indicator (Δy^e_{t-1}) and the inflationary expectations ($\Delta \pi^e_{t-1}$) variables are both highly significant across all specifications of the model. This highly robust finding implies that the expectations of financial market agents of economic activity and inflation are statistically significant determinants of CEB liquidity. Across all specifications of the model, higher expectations of economic activity imply increased CEB liquidity in the subsequent period, while the opposite relationship exists for inflationary expectations; with a greater marginal effect observed in the case of the latter variable. It is worth noting that the expectations of agents in a given period say *t-1*, can have implications for liquidity in subsequent periods as long as market frictions exist (such as transaction costs, information asymmetries and so on). Changes in expectations of inflation or economic activity can therefore cause market participants in general, and the most well-informed participants in the first instance, to adjust their portfolio allocations in line with revised expectations. Such adjustments, over time, potentially impact liquidity in subsequent periods. This finding is consistent with key themes from the portfolio frictions literature (see for example, Bacchetta, Davenport and van Wincoop; 2022).

Across all specifications, both contemporaneous and lagged values of the variables capturing lagged changes in volatility (ΔVIX_t), which proxy global financial market uncertainty, are also statistically significant determinants of CEB liquidity. In fact, the signs and statistical significance of the coefficients on all the volatility variables (ΔVIX_t) are consistently returned across all specifications of the model in Table 6, confirming the robustness of this result. In addition, Table 6 depicts the statistically significant effect of monetary policy sentiment shocks on liquidity. This is also a relatively robust finding despite the relatively low level of significance across most specifications. This result implies that increasingly "hawkish" monetary policy sentiment shocks imply significantly lower levels of CEB liquidity, in a statistical sense, in the subsequent period.

[Table 7 here]

Table 7 presents analogous results to those presented in Table 6, however the dependent variable in the case of Table 7 is money market (MM) liquidity. Across all specifications of the model, the coefficient estimates reveal a statistically significant role played by international global financial market uncertainty, as captured by the variable capturing changes in volatility (ΔVIX_t) and its lag. Interestingly, only the contemporaneous and one period lagged values of ΔVIX_t are highly statistically significant, which differs from the earlier findings in the Table 6 which revealed statistically significant coefficients on even higher lags of the ΔVIX_t variable. All considered, the results corroborate earlier findings that uncertainty in global financial markets has a statistically significant, negative effect on MM liquidity.

Turning the attention to the estimated coefficients on the sentiment shock variables reveals that the ECB Governing Council's lagged sentiment shocks on economic conditions are generally statistically significant determinants of MM liquidity across most specifications of the model. In particular, Table 7 reveals that ECB Governing council sentiment shocks expressing a positive economic outlook can have a, fairly robust, statistically significant, positive effect on MM liquidity. The results from Table 7 therefore indicate that, changes in economic outlook sentiments expressed within the ECB's Governing Council statements above and beyond that implied by financial and economic information available at the time, produces a relatively greater impact on MM liquidity in financial markets than its statements on monetary policy.

One possible explanation for this interesting finding is that, during a period in which the overall monetary policy stance is highly predictable and consistent, changes in the ECB Governing Council's economic outlook sentiments may be an excellent forward indicator of potential changes in the policy stance or actions of the central bank. Under these circumstances, the economic outlook of the ECB Governing Council could provide key information for market agents regarding their asset allocations. Under such conditions, therefore, the ECB Governing Council's views on economic conditions may provide greater insight into how the central bank perceives market and economic conditions in the foreseeable future, which is ultimately a very important signal to market participants on whether the bank is likely to change or maintain its current monetary policy stance.

[Table 8 here]

The results obtained from the estimation of the empirical model using sentiments based on the Picault-Renault (2017) sentiment quantifier can be compared to those obtained using sentiment shocks derived from using the, more generic, Loughran-McDonald (2011, 2015) sentiment quantifier. Results obtained after replacing the Picault and Renault (2017) sentiment shocks with Loughran-McDonald (2011, 2015) sentiment shocks as explanatory variables are displayed in Table 8. The dependent variable used in order to obtain the estimation results presented in Table 8 is CEB liquidity. The general format of Table 8 is identical to that of Tables 6 and 7.

The results from Table 8 corroborate the earlier findings from Table 6. The lagged dependent CEB liquidity variable is negatively signed and statistically significant across all specifications as was the case in Table 6. Yet another point of similarity between the estimations in Tables 8 and Table 6, is that Table 8 corroborates the earlier findings regarding the European Commission sentiment variable (Δy_{t-1}^{e}), inflationary expectations ($\Delta \pi_{t-1}^{e}$) and contemporaneous and lagged ΔVIX_t variables. In particular, the robustly returned signs and high levels of statistical significance of the coefficient estimates, emphasize once more the important role played by inflationary and output expectations and uncertainty within global financial markets in determining broad CEB liquidity conditions.

In Table 8, the coefficients on the variables capturing the effects of LM sentiment shocks are not statistically significant across columns 2-5 of the table. Table 8, therefore, shows that when only the "positivity" or "negativity" of ECB Governing Council tone shocks are measured using the LM indicator the effects of central bank tone on CEB liquidity can be understated.

[Table 9 here]

Table 9, explores whether there is empirical evidence to support the hypothesis that Loughran and McDonald sentiment shocks are an important determinant of money market (MM) liquidity. Columns 3-5 of Table 9 show that the coefficient on both the contemporaneous and one-period lagged sentiment shock variables are statistically significant across most specifications of the model. Interestingly, this finding mirrors earlier findings from Table 7 in which both contemporaneous and lagged values of ECB sentiment shocks on economic outlook also proved to be statistically significant determinants of money market (MM) liquidity. The result from Table 9 implies that positive LM sentiment shocks by the ECB governing council also produce a statistically significant effect on MM liquidity. All the statistically significant coefficients on the LM sentiment shock variables are also similarly signed, again mirroring the findings in Table 7. Overall, therefore, the results from the empirical model suggest that sentiment shocks appear to have a relatively greater impact on the, more narrowly defined, money market (MM) liquidity measure. The impact of ECB Governing Council sentiment shocks is more likely to be robustly observed in the liquidity of markets dominated by banks and other financial institutions (MM liquidity), rather than in the more broadly defined CEB liquidity. Importantly however, the empirical results show that global financial market uncertainty has, by far, more robust, statistical effects on both CEB and MM liquidity across all specifications of the model.

5. Conclusions

This study explores the effects of central bank communication on financial market liquidity within the European Monetary Union (EMU). The focus on financial market liquidity is of key importance since the lack of or "drying up" of market liquidity, has been a common thread of multiple, recent financial crises (Brunnermeier and Pedersen, 2009). Although the previous economic literature has acknowledged the importance of central bank communications as a key policy tool which aids greater transparency among market participants, the literature on quantifying central bank communication which explores, more deeply, its relationship to key economic variables is still in its nascent stages. This study follows the example of prior studies such as Hansen and McMahon (2015), Picault and Renault (2017) and Hubert and Lebondance (2021) which use computational linguistic tools to quantify central bank sentiments and then relate the quantified sentiments to economic phenomena. Unlike all these prior studies, however, this paper explores the issue of whether central bank sentiments have consequential effects on financial market liquidity.

To achieve its objectives, sentiments contained in ECB's Governing Council statements over the period January, 2006 to April 2016, are quantified using a field- and ECB-specific lexicon contributed by Picault and Renault (2017). The study then goes on to compare the findings obtained using the Picault and Renault (2017) lexicon with the results obtained after applying the more traditional and generic, dictionary-based sentiment quantifier of Loughran and McDonald (2013, 2015). Unlike the Picault and Renault (2017) methodology which offers a more nuanced measure of sentiments by separately quantifying monetary policy sentiments and economic outlook sentiments expressed within the statements, the LM sentiment quantifier only assesses the "positivity" or "negativity" of sentiments contained within a given speech or text. On the other hand, Picault and Renault (2017) measure the "hawkishness" or "dovishness" of the monetary policy tone of the ECB Governing Council's statements in addition to the "positivity" or "negativity" of the ECB Governing Council's tone on economic outlook. Another unique aspect of the Picault and Renault (2017) method is that it employs a term weighting methodology to a dictionary of *n*-grams in in order to reflect the relative importance of certain phrases. The use of "*n*-grams" (contiguous multi-word combinations) as opposed to unigrams (single words), as is traditionally used within the natural language processing literature, better captures the context and other nuances in the meanings of phrases within the corpus. Over the review period, the evolution of the time series of quantified sentiments on both i) economic outlook and ii) monetary policy evolve with a similar pattern to that observed in the financial market liquidity series, however measured. This is especially the case for CEB liquidity. A similar relationship between liquidity and ECB Governing Council sentiments was observed when sentiments are quantified using the LM sentiment quantifier.

In order to control for possible endogeneity, the empirical approach chosen in this paper focuses on the component of central bank sentiments which is orthogonal to central bank current policy and to other key financial and macroeconomic information available at the time of the statement. Changes in this orthogonal component, over time, is referred to within the literature as a series of "sentiment shocks". The paper then investigates whether changes in these sentiment shocks affect financial market liquidity. Although the empirical analysis within this paper, reveals relatively robust evidence that sentiment shocks affect currency, equity and bond (CEB) liquidity, there is relatively stronger statistical evidence in support of contemporaneous and one-period lagged effects of sentiment shocks on money market (MM) liquidity; a liquidity measure which is more narrowly defined. The effects of sentiment shocks were also found to be highly intuitive, in that, relatively more "hawkish" monetary policy sentiment shocks lead to reduced CEB liquidity, while positive economic outlook shocks have the opposite effect on money market liquidity. In general, global uncertainty and risk, as proxied by the VIX, proved to be more consequential for determining liquidity outcomes and was found to robustly produce a negative and statistically significant effect on both types of liquidity (Breitenlechner et al, 2021).

The results obtained from conducting a similar analysis with the alternative Loughran and McDonald (2015) sentiment quantifier generally corroborate the findings obtained using the relatively more sophisticated sentiment quantifier of Picault and Renault (2017). In particular, the results obtained using the Loughran and McDonald (2015) sentiment quantifier support the hypothesis that LM sentiment shocks are likely to have a statistically significant, transitory impact on liquidity. The statistically significant effects of the LM sentiment shocks were, however, only evident on MM liquidity. Relatively robust contemporaneous and lagged effects of LM sentiment shocks on MM liquidity were observed across most specifications of the model. One key finding of the current study is that when sentiments are classified into the two major categories: i) sentiments on monetary policy ii) sentiments on economic outlook, as is provided for under the Picault and Renault (2017) approach, richer inferences can be drawn regarding the specific elements of central bank tone which tend to drive financial market liquidity outcomes. This ability to differentiate between the effects of "hawkish" or "dovish" monetary policy sentiment shocks on market liquidity on the one hand and "positivity" or "negativity" of ECB Governing Council sentiments on economic outlook on the other, improves the quality of the inferences which can be drawn from the empirical analysis.

Finally, three (3) potentially promising avenues for future research which would build on the research carried out in the current study are: i) further research to identify specific financial markets which are relatively more sensitive to ECB Governing council sentiment shocks than others. This research could potentially make use of intra-day data, since the use of indices measuring MM and CEB liquidity does not illuminate the specific effects of sentiment in specific markets (e.g. stock, foreign exchange or bond markets), ii) to investigate further the role of central bank sentiments in emerging or developing economies and iii) to detect and explore the effects of possible coordination in the sentiments expressed by major central banks on global economic phenomena using computational linguistic tools.

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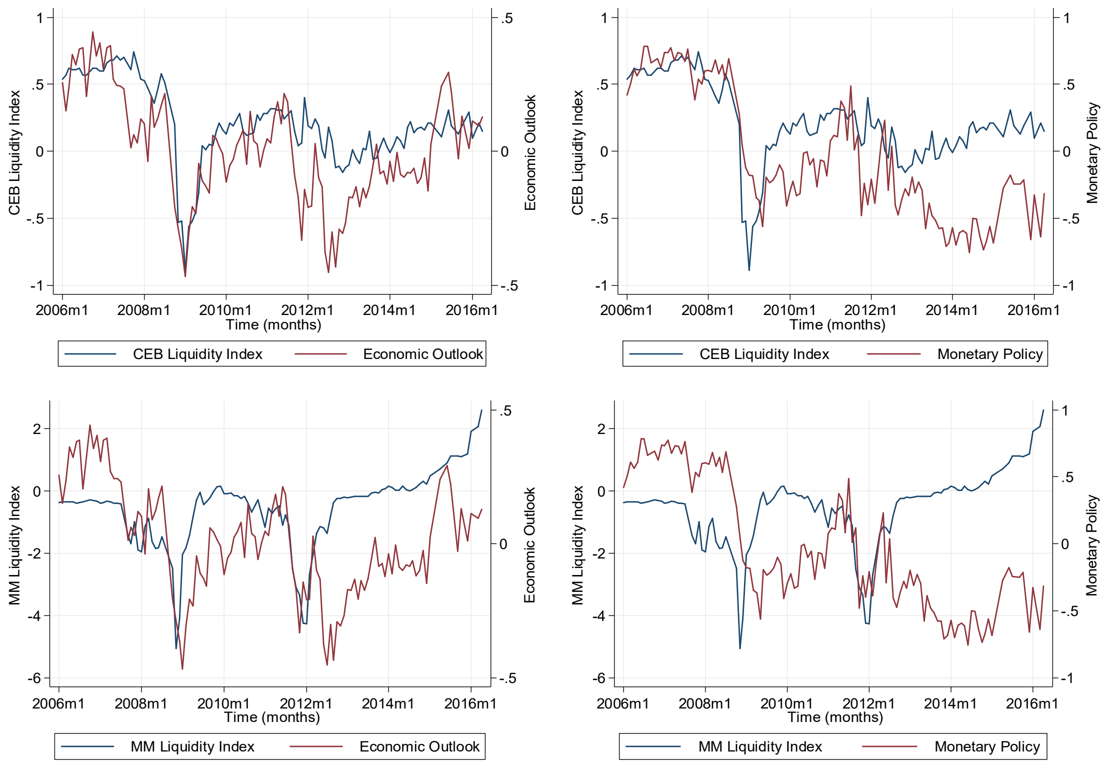

Figure 1: Figure showing the relationship between liquidity and sentiments of the ECB's Governing Council over the period January, 2006 to April, 2016. The top half of the figure shows a close relationship between CEB liquidity and sentiments on economic outlook over time. On the other hand, the bottom half of the figure reveals that the relationship between ECB's monetary policy sentiment and money market liquidity, while apparent in certain periods is not as strong. Both figures show the effect of the global financial crisis but the effects of the European sovereign debt crisis are more apparent in the MM liquidity index.

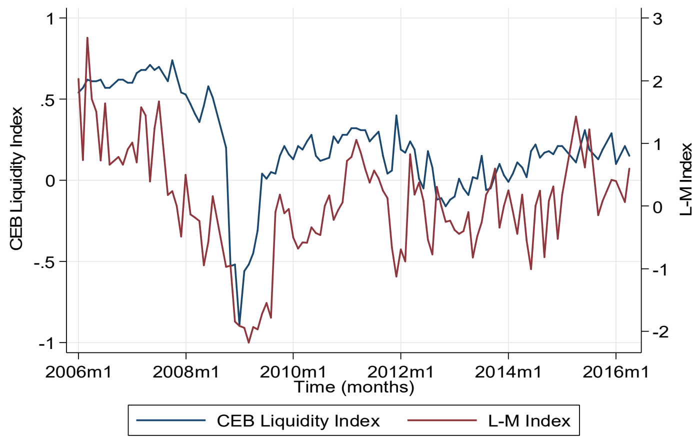

Figure 2: Figure 2 shows the relationship, over time, between the currency, equity and bonds (CEB) liquidity indicator and the Loughran and McDonald ECB sentiment the period January, 2006 to April, 2016. The figure reveals a close relationship between the CEB liquidity index and the L-M sentiment indicator.

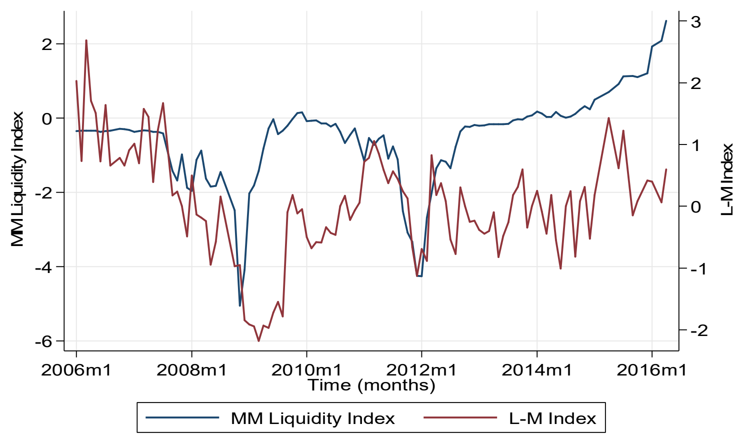

Figure 3: Figure 3 shows the relationship over time between the money market (MM) liquidity indicator and e Loughran and McDonald ECB sentiment for the period January, 2006 to April, 2016. The figure reveals a less close relationship between the MM liquidity index and the L-M sentiment indicator than was observed for the CEB indicator in **Figure 2**.

Level Variables	ceb	mmt	I_t^{ec}	I_t^{mp}	LM_t
ceb	1				
mmt	0.2199**	1			
I_t^{ec}	0.7971***	0.3254***	1		
I_t^{mp}	0.6534***	-0.243**	0.6562***	1	
LM_t	0.7146***	0.2571***	0.7236***	0.5040***	1

Table 1: Table 1 contains the pairwise correlations between all sentiment and aggregate financial market liquidity indicators during the time period January, 2006 to April, 2016.

*** means the null hypothesis of zero value for the correlation coefficient is rejected at the 1% level of significance.
** means the null hypothesis of zero value for the correlation coefficient is rejected at the 5% level of significance.
* means the null hypothesis of a zero value for the correlation coefficient is rejected at the 10% level of significance.

Variables (1)	Augmented Dickey Fuller Test t- statistic (2)	1% Critical Value (3)	5% Critical Value (4)	10 % Critical Value (5)
Δceb_t	-13.142***	-4.058	-3.458	-3.155
Δmmt_t	-9.578***	-4.058	-3.458	-3.155
$\Delta(y_t - y^*)$	-14.161***	-4.058	-3.458	-3.155
$\Delta(\pi_t - \pi^*)$	-14.224***	-4.058	-3.458	-3.155
Δy_t^e	-6.351***	-4.058	-3.458	-3.155
$\Delta \pi_t^e$	-9.687***	-4.058	-3.458	-3.155
ΔSR_t	-7.523***	-4.058	-3.458	-3.155
$\Delta Tone_t^{ec}$	-13.53***	-4.058	-3.458	-3.155
$\Delta Tone_t^{mp}$	-14.81***	-4.058	-3.458	-3.155
ΔLM_t	-14.79***	-4.058	-3.458	-3.155
ΔVIX_t	-14.96***	-4.058	-3.458	-3.155

Table 2: Results from the Augmented Dickey Fuller Unit Root Tests for key variables used within estimation of the model.

*** means the null hypothesis of unit root is rejected at the 1% level of significance.
** means the null hypothesis of unit root is rejected at the 5% level of significance.
* means the null hypothesis of unit root is rejected at the 10% level of significance.

Variable (1)	Source (2)	Unit of Measurement (3)	Mean (4)	Standard Deviation (5)	Min. (6)	Max. (7)
Δceb	European Systemic Risk Board (speech date)	Index units	-0.004	0.123	-0.883	0.37
Δmmt	European Systemic Risk Board (speech date)	Index units	0.037	0.477	-2.98	1.46
$\Delta(y_t - y^*)$	European Central Bank (ECB) (monthly)	Euro area industrial production (*less construction*) minus potential output	0.0252	0.855	-2.386	2.29
$\Delta(\pi_t - \pi^*)$	European Central Bank (ECB) (quarterly)	Harmonized Index of Consumer Prices (HICP) – 2% target rate	-0.0142	0.664	-4.1	3.9
Δy_t^e	European Commission's Sentiment Indicator minus its long-term average -Eurostat (monthly)	Index units	0.0333	2.076	-9.4	4.9
$\Delta \pi_t^e$	ECB Quarterly Survey to Professional Forecasters (SPF) (quarterly)	Expected inflation forecast	-0.0057	0.109	-0.5	0.3
ΔSR_t	Shadow rate estimate (ECB)-Wu and Xia (monthly)	Rate (per cent)	-0.0435	0.3456	-2.325	0.699
$\Delta Tone_t^{ec}$	Picault and Renault (2017) estimates Economic Conditions (speech date)	Index units	-0.004	0.116	-0.423	0.244
$\Delta Tone_t^{mp}$	Picault and Renault (2017) estimates Monetary Policy (speech date)	Index units	-0.008	0.186	-0.596	0.409
ΔLM_t[11]	Author's own estimates using Loughran and McDonald (2015) (speech date)_	Index units	-0.024	0.628	-1.492	1.954
ΔVIX_t	Chicago Board of Exchange Volatility Index (daily)	Index units	0.247	5.199	-10.23	36.85
$CISS_t$	Composite Systemic Stress Indicator (weekly)	Index Units	0.267	0.2070	0.0362	0.7942
$Eurostoxx\_ret_t$	EURO STOXX 50 Index (daily)	Returns between previous ECB statement and the day before current statement date	0.0018	0.0542	-0.132	0.153
$GDP\_gro\_e_t$	Expected GDP growth Rate (quarterly)	ECB staff projections	0.0162	0.0116	-0.006	0.046
ΔOil_t	Change in oil price (year-on-year)	Percentage change	0.0863	0.456	-0.528	1.594

[11] The estimates were directly generated by the software provided by the Loughran and McDonald on the website https://sraf.nd.edu/textual-analysis/code/ (accessed on the November 24th, 2019)

	(daily)					

Table 3: Table containing the variable names, sources and summary statistics for all the variables used within this study. The sample covers the time period January, 2006 to April, 2016. There are 112 observations within the sample.

Variables	Δceb	Δmmt	$\Delta(y_t - y^*)$	$\Delta(\pi_t - \pi^*)$	Δy_t^e	$\Delta\pi_t^e$	ΔSR_t
Δceb_t	1						
Δmmt_t	0.3987***	1					
$\Delta(y_t - y^*)$	0.0505	0.1624*	1				
$\Delta(\pi_t - \pi^*)$	0.1120	0.0253	0.123	1			
Δy_t^e	0.5180***	0.2701**	0.006	0.1816*	1		
$\Delta\pi_t^e$	0.3186***	0.2153**	-0.087	0.130	0.208**	1	
ΔSR_t	0.1126***	0.0508	-0.121	0.0767	0.3349***	0.1423	1
$\Delta Tone_t^{ec}$	0.3812***	0.3735***	0.0958	-0.0550	0.3322***	0.212**	0.134
$\Delta Tone_t^{mp}$	0.1723**	0.262***	0.166*	0.083	0.192*	0.334***	0.037
ΔLM_t	0.130	0.200**	0.227**	-0.2049**	0.159	0.102	0.10
ΔVIX_t	-0.551***	-0.591***	0.008	-0.053	-0.428***	-0.229**	-0.07
$CISS_t$	-0.128	-0.0095	0.040	-0.0323	-0.31***	-0.157	-0.341
$Eurostoxx\_ret_t$	-0.341***	0.1472	-0.045	-0.091	-0.504***	0.022	-0.297***
ΔOil_t	-0.011	0.266***	0.119	-0.159	0.059	-0.245**	-0.34***

Table 4: Table containing the pairwise correlations between variables used within the estimation.

Variables	$\Delta Tone_t^{ec}$	$\Delta Tone_t^{mp}$	ΔLM_t	ΔVIX_t	$CISS_t$	$\Delta Eurostoxx\_ret_t$	ΔOil_t
$\Delta Tone_t^{ec}$	1						
$\Delta Tone_t^{mp}$	0.30***	1					
ΔLM_t	0.418***	0.241**	1				
ΔVIX_t	-0.361***	-0.1711*	-0.1642*	1			
$CISS_t$	-0.160	-0.218**	-0.066	-0.142	1		
$Eurostoxx\_ret_t$	-0.20**	-0.1313	-0.1124	0.4198***	-0.171*	1	
ΔOil_t	0.077	-0.058	0.046	-0.188*	0.275***	0.007	1

Table 4 continued: Table containing the remaining pairwise correlations between variables used within the estimation.

*** means the null hypothesis of zero value for the correlation coefficient is rejected at the 1% level of significance
** means the null hypothesis of zero value for the correlation coefficient is rejected at the 5% level of significance
* means the null hypothesis of a zero value for the correlation coefficient is rejected at the 10% level of significance

Variables (1)	Tone_t^{EC} (2)	Tone_t^{MP} (3)	LM_t (4)
Lagged dependent variable	0.847*** (0.066)	0.939*** (0.036)	0.681*** (0.065)
ΔSR_t	0.066* (0.036)	0.012 (0.070)	0.357* (0.192)
$\Delta CISS_t$	-0.108 (0.146)	-0.730*** (0.218)	-0.331 (0.757)
$Eurostoxx\_ret_t$	0.051 (0.262)	0.0314 (0.409)	0.066 (1.363)
ΔESI_{t-1}	0.002 (0.009)	0.0221* (0.0122)	0.070** (0.031)
$\Delta(\pi_t - \pi^*)_{t-1}$	0.0199** (0.009)	-0.024* (0.0145)	0.109 (0.078)
$\Delta(y_t - y^*)_{t-1}$	0.011 (0.01)	-0.0209 (0.0132)	-0.021 (0.04)
ΔOil_{t-1}	0.01 (0.027)	0.005 (0.042)	-0.068 (0.151)
$\Delta\pi_{t-1}^e$	0.103 (0.113)	0.455** (0.173)	0.600 (0.632)
ΔVIX_t	-0.0052* (0.003)	-0.0005 (0.004)	-0.006 (0.014)
ΔVIX_{t-1}	0.0023 (0.002)	0.0023 (0.0034)	0.029** (0.115)
ΔVIX_{t-2}	-0.006*** (0.002)	-0.0065** (0.003)	-0.0129 (0.010)
ΔVIX_{t-3}	0.0009 (0.003)	0.0022 (0.004)	0.009 (0.013)
$constant$	-0.0007 (0.010)	-0.0107 (0.017)	-0.007 (0.054)
R Squared: F-Stat :	0.80 33.17***	0.89 90.59***	0.69 32.93***
Sample size :	102	102	102
AR (1) Coefficient	-0.379***	-0.412***	-0.129
AR(1) Wald Chi-squared	18.68***	17.31***	1.08

Table 5: Results from estimation of sentiment shocks with AR filter of the residual terms

*** means significant at the 1% level
** means statistically significant at the 5% level
* means statistically significant at the 10% level

Dependent Variable = Change in CEB Liquidity Index				
Variables **(1)**	**Lags of sentiment: (t)** **(2)**	**Lags of sentiment: (t – 1)** **(3)**	**Lags of sentiment: (t - 2)** **(4)**	**Lags of sentiment: (t - 3)** **(5)**
Δceb_{t-1}	-0.222* (0.118)	-0.199* (0.118)	-0.208* (0.117)	-0.203* (0.117)
$\Delta(y_t - y^*)_{t-1}$	-0.0109 (0.010)	-0.007 (0.010)	-0.007 (0.010)	-0.009 (0.0109)
$\Delta(\pi_t - \pi^*)_{t-1}$	-0.005 (0.008)	-0.005 (0.009)	-0.007 (0.010)	-0.007 (0.01)
Δy^e_{t-1}	0.013** (0.006)	0.0142** (0.006)	0.014** (0.006)	0.0145** (0.006)
$\Delta \pi^e_{t-1}$	-0.345*** (0.129)	-0.357*** (0.128)	-0.354*** (0.130)	-0.352**** (0.128)
$Eurostoxx\_ret_t$	0.166 (0.239)	0.210 (0.245)	0.223 (0.245)	0.247 (0.252)
ΔOil_{t-1}	0.015 (0.027)	0.008 (0.028)	0.006 (0.029)	0.008 (0.029)
ΔSR_t	0.024 (0.047)	0.013 (0.043)	0.012 (0.043)	-0.010 (0.042)
$\Delta Sent\_shock^{ec}_t$	0.025 (0.065)	0.004 (0.075)	-0.0143 (0.082)	0.013 (0.093)
$\Delta Sent\_shock^{mp}_t$	0.030 (0.053)	-0.0208 (0.0527)	-0.018 (0.060)	-0.026 (0.067)
$\Delta Sent\_shock^{ec}_{t-1}$	-	-0.054 (0.095)	-0.060 (0.101)	-0.034 (0.139)
$\Delta Sent\_shock^{mp}_{t-1}$	-	-0.112* (0.056)	-0.119* (0.070)	-0.149* (0.089)
$\Delta Sent\_shock^{ec}_{t-2}$	-	-	-0.060 (0.101)	0.036 (0.135)
$\Delta Sent\_shock^{mp}_{t-2}$	-	-	-0.011 (0.070)	-0.042 (0.066)
$\Delta Sent\_shock^{ec}_{t-3}$	-	-	-	0.127 (0.107)
$\Delta Sent\_shock^{mp}_{t-3}$	-	-	-	-0.035 (0.059)
ΔVIX_t	-0.0122** (0.005)	-0.013* (0.005)	-0.013** (0.005)	-0.0132** (0.005)
ΔVIX_{t-1}	-0.007*** (0.003)	-0.007*** (0.0025)	-0.007*** (0.003)	-0.0076*** (0.003)
ΔVIX_{t-2}	-0.006*** (0.002)	-0.007*** (0.0025)	-0.007*** (0.003)	-0.006*** (0.002)
ΔVIX_{t-3}	-0.004* (0.002)	-0.004** (0.002)	-0.004** (0.002)	-0.0043** (0.002)
$constant$	-0.006 (0.008)	-0.007 (0.007)	-0.007** (0.008)	-0.007 0.008
R Squared: F-Stat :	0.592 4.99***	0.6121 5.42***	0.62 4.63***	0.63 4.25***
Sample size :	101	100	99	98

Table 6: Estimation results from various specifications of the linear model. Lags 1- 3 of the sentiment indicator variables are included among the explanatory variables. The dependent variable used for all specifications is the CEB liquidity indicator.

*** means significant at the 1% level
** means statistically significant at the 5% level
* means statistically significant at the 10% level

Dependent Variable = Change in MM Liquidity Index				
Variables **(1)**	**Lags of sentiment: (t) (2)**	**Lags of sentiment: (t – 1) (3)**	**Lags of sentiment: (t - 2) (4)**	**Lags of sentiment: (t - 3) (5)**
Δmmt_{t-1}	0.124 (0.133)	0.113 (0.130)	0.101 (0.129)	0.077 (0.130)
$\Delta(y_t - y^*)_{t-1}$	-0.064 (0.042)	-0.074* (0.040)	-0.074* (0.041)	-0.080* (0.041)
$\Delta(\pi_t - \pi^*)_{t-1}$	0.016 (0.031)	0.027 (0.026)	0.028 (0.028)	0.038 (0.032)
Δy^e_{t-1}	-0.035* (0.024)	-0.042* (0.022)	-0.041* (0.023)	-0.042* (0.022)
$\Delta \pi^e_{t-1}$	0.108 (0.401)	0.311 (0.403)	0.324 (0.423)	0.367 (0.409)
$Eurostoxx\_ret_t$	1.827* (1.011)	1.571 (1.07)	1.640 (1.114)	1.741 (1.106)
ΔOil_{t-1}	0.107 (0.090)	0.129 (0.099)	0.142 (0.101)	0.164 (0.105)
ΔSR_t	-0.036) (0.148)	-0.099 (0.169)	-0.086 (0.176)	-0.095 (0.175)
$\Delta Sent\_shock^{ec}_t$	0.413 (0.354)	0.847** (0.411)	0.973** (0.443)	1.134** (0.466)
$\Delta Sent\_shock^{mp}_t$	0.263 (0.204)	0.256 (0.264)	0.260 (0.267)	0.277 (0.274)
$\Delta Sent\_shock^{ec}_{t-1}$	-	0.921** (0.448)	1.101** (0.480)	1.446** (0.564)
$\Delta Sent\_shock^{mp}_{t-1}$	-	-0.045 (0.264)	-0.0532 (0.259)	-0.073 (0.291)
$\Delta Sent\_shock^{ec}_{t-2}$	-	-	0.296 (0.372)	0.746 (0.534)
$\Delta Sent\_shock^{mp}_{t-2}$	-	-	0.122 (0.253)	0.063 (0.304)
$\Delta Sent\_shock^{ec}_{t-3}$	-	-	-	0.644 (0.464)
$\Delta Sent\_shock^{mp}_{t-3}$	-	-	-	-0.053 (0.230)
ΔVIX_t	-0.065*** (0.015)	-0.065*** (0.015)	-0.064*** (0.015)	-0.066*** (0.015)
ΔVIX_{t-1}	-0.026* (0.012)	-0.026** (0.011)	-0.025** (0.011)	-0.027** (0.011)
ΔVIX_{t-2}	-0.007 (0.009)	-0.009 (0.008)	-0.009 (0.008)	-0.008 (0.009)
ΔVIX_{t-3}	-0.006 (0.009)	-0.007 (0.009)	-0.006 (0.008)	-0.007 (0.008)
$constant$	0.045 (0.037)	0.035 (0.037)	0.0344 (0.038)	0.034 (0.039)
Adjusted R Squared: F-Stat :	0.523 4.59**	0.55 5.19***	0.56 5.42***	0.57 4.81***
Sample size :	101	100	99	98

Table 7: Estimation results from various specifications of the linear model. Lags 1- 3 of the sentiment indicator variables are included among the explanatory variables. The dependent variable used for all specifications is the MM liquidity indicator.

*** means significant at the 1% level
** means statistically significant at the 5% level
* means statistically significant at the 10% level

Dependent Variable = Change in CEB Liquidity Index				
Variables **(1)**	**Lags of sentiment: (t)** **(2)**	**Lags of sentiment: (t – 1)** **(3)**	**Lags of sentiment: (t - 2)** **(4)**	**Lags of sentiment: (t - 3)** **(5)**
Δceb_{t-1}	-0.205* (0.111)	-0.217* (0.109)	-0.215* (0.109)	-0.194* (0.112)
$\Delta(y_t - y^*)_{t-1}$	-0.013 (0.010)	-0.010 (0.011)	-0.011 (0.011)	-0.012 (0.011)
$\Delta(\pi_t - \pi^*)_{t-1}$	-0.004 (0.008)	-0.008 (0.009)	-0.008 (0.009)	-0.010 (0.008)
Δy^e_{t-1}	0.0127** (0.006)	0.015** (0.006)	0.0142** (0.006)	0.0140** (0.006)
$\Delta \pi^e_{t-1}$	-0.354*** (0.125)	-0.378*** (0.124)	-0.382*** (0.124)	-0.407*** (0.130)
$Eurostoxx\_ret_t$	0.148 0.239	0.180 (0.238)	0.165 (0.241)	0.125 (0.241)
ΔOil_{t-1}	0.014 (0.239)	0.012 (0.026)	0.012 (0.267)	0.125 (0.026)
ΔSR_t	0.021 (0.045)	0.024 (0.044)	0.0264 (0.044)	0.036 (0.042)
$\Delta Sent\_shock^{LM}_t$	-0.009 (0.011)	-0.020 (0.013)	-0.0141 (0.0135)	-0.023 (0.016)
$\Delta Sent\_shock^{LM}_{t-1}$	-	-0.023 (0.015)	-0.012 (0.018)	-0.030 (0.025)
$\Delta Sent\_shock^{LM}_{t-2}$	-	-	0.014 (0.013)	-0.010 (0.021)
$\Delta Sent\_shock^{LM}_{t-3}$	-	-	-	-0.027 (0.020)
ΔVIX_t	-0.012** (0.005)	-0.012** (0.005)	-0.012** (0.005)	-0.012** (0.005)
ΔVIX_{t-1}	-0.007*** (0.003)	-0.007** (0.003)	-0.007** (0.003)	-0.006** (0.003)
ΔVIX_{t-2}	-0.006*** (0.002)	-0.006*** (0.002)	-0.006*** (0.0018)	-0.006*** (0.002)
ΔVIX_{t-3}	-0.004* (0.002)	-0.0039* (0.002)	-0.004* (0.002)	-0.003* (0.002)
Constant	-0.006 (0.008)	-0.006 (0.008)	-0.007 (0.008)	-0.006 (0.008)
R Squared: F-Stat :	0.5869 5.24***	0.60 5.21***	0.61 4.96***	0.62 4.89***
Sample size :	101	100	99	98

Table 8: Estimation results from various specifications of the linear model. Lags 1- 3 of the L-M sentiment variable are included among the explanatory variables. The dependent variable is the CEB liquidity index.

*** means significant at the 1% level
** means statistically significant at the 5% level
* means statistically significant at the 10% level

Dependent Variable = Change in MM Liquidity Index				
Variables **(1)**	**Lags of sentiment:** **(t)** **(2)**	**Lags of sentiment:** **(t – 1)** **(3)**	**Lags of sentiment:** **(t - 2)** **(4)**	**Lags of sentiment:** **(t - 3)** **(5)**
Δmmt_{t-1}	0.140 (0.126)	0.139 (0.118)	0.139 (0.116)	0.128 (0.116)
$\Delta(y_t - y^*)_{t-1}$	-0.075* (0.041)	-0.093* (0.041)	-0.095** (0.041)	-0.096** (0.043)
$\Delta(\pi_t - \pi^*)_{t-1}$	0.013 (0.030)	0.0365 (0.030)	0.040 (0.030)	0.036 (0.027)
Δy^e_{t-1}	-0.033 (0.024)	-0.044* (0.024)	-0.045* (0.024)	-0.044* (0.024)
$\Delta \pi^e_{t-1}$	0.084 (0.377)	0.250 (0.387)	0.242 (0.396)	0.313 (0.409)
$Eurostoxx\_ret_t$	1.868* (1.066)	1.630 (1.06)	1.580 (1.058)	1.674 (1.073)
ΔOil_{t-1}	0.105 (0.091)	0.127 (0.083)	0.130 (0.086)	0.126 (0.087)
ΔSR_t	-0.051 (0.150)	-0.064 (0.154)	-0.054 (0.165)	-0.073 (0.174)
$\Delta Sent\_shock^{LM}_t$	0.055 (0.061)	0.122* (0.066)	0.141* (0.083)	0.168** (0.095)
$\Delta Sent\_shock^{LM}_{t-1}$	-	0.130* (0.067)	0.162* (0.088)	0.227** (0.103)
$\Delta Sent\_shock^{LM}_{t-2}$	-	-	0.039 (0.091)	0.117 (0.119)
$\Delta Sent\_shock^{LM}_{t-3}$	-	-	-	0.083 (0.077)
ΔVIX_t	-0.065*** (0.016)	-0.066*** (0.016)	-0.066*** (0.016)	-0.068*** (0.016)
ΔVIX_{t-1}	-0.026** (0.011)	-0.025** (0.0108)	-0.024** (0.011)	-0.027** (0.0106)
ΔVIX_{t-2}	0.007 (0.098)	-0.0086 (0.009)	-0.009 (0.010)	-0.008 (0.009)
ΔVIX_{t-3}	-0.006 (0.008)	-0.007 (0.008)	-0.007 (0.008)	-0.007 (0.009)
Constant	0.036 (0.038)	0.033 (0.038)	0.034 (0.038)	0.036 (0.038)
Adjusted R Squared: F-Stat :	0.51 5.20***	0.53 5.68**	0.531 5.60***	0.54 5.32**
Sample size :	101	100	99	98

Table 9: Estimation results from various specifications of the linear model. Lags 1- 3 of the L-M sentiment variable are included among the explanatory variables. The dependent variable is the MM liquidity index.

*** means significant at the 1% level
** means statistically significant at the 5% level
* means statistically significant at the 10% level