Bank Manager Sentiment, Loan Growth and Bank Risk*

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Abstract

We build a textual score measuring the tone of bank earnings press release documents. We use this measure to define bank manager sentiment as the variation in the textual tone score which is orthogonal to bank-specific and macroeconomic fundamentals. Using this definition of sentiment, we present evidence on how bank managers' systematic over-optimism affects the amount of credit that they supply to the real sector. Our empirical evidence suggests that decisions on the volume of new loans partially depend on past realizations of economic fundamentals, implying that loan growth and contemporaneous economic fundamentals might be systematically disconnected. Furthermore, we show that over-optimism on the part of bank managers spills over to their equity investors, who seem to perceive banks with high bank manager sentiment as having a lower systemic risk.

Keywords: sentiment, text data, extrapolation, loan growth, systemic risk

JEL classification: G00, G10, G21, G41

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1 Introduction

The financial crisis of 2007–2009 has sparked a renewed interest in the underlying drivers of credit booms and busts. New evidence from novel datasets suggests that bank credit growth is a strong predictor of financial crisis (Schularick and Taylor, 2012; Aikman et al., 2014) and poor bank performance (Foos et al., 2010; Baron and Xiong, 2017; Fahlenbrach et al., 2017). A prominent rational explanation for why credit growth is associated with financial fragility is the existence of dynamic financial frictions (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Gertler and Kiyotaki, 2010). In these models, financial frictions imply that exogenous shocks to firms' net worth become amplified and are highly persistent, which in turn affects the firms' ability to access external funding (Brunnermeier et al., 2012). While a large positive shock can initiate a series of periods with increasing net worths and leverage, i.e. a credit boom, a large negative shock can have the opposite effect, i.e. a credit bust.[1] In contrast, more recent contributions argue that credit cycles can be traced back to behavioral factors (Greenwood and Hanson, 2013; Greenwood et al., 2016; López-Salido et al., 2017; Bordalo et al., 2018). In line with Minsky (1977) and Kindleberger (1978), this strand of the literature takes the view that a credit crisis arises when banks and bank investors suddenly realize that their expectations of economic fundamentals have been too high and adjust their expectations accordingly. Consistent with this view, Greenwood and Hanson (2013), Baron and Xiong (2017) and Fahlenbrach et al. (2017) present empirical evidence for the prevalence of systematic over-optimism on the part of banks, equity analysts and investors in equities and corporate bonds.

Against this background, this paper aims to provide evidence on how systematic over-optimism on the part of banks may affect the amount of credit that they supply to the real sector. We proceed in three steps. First, we extract a measure of the tone of bank earnings press release documents using textual analysis methods: the textual tone score. Our analysis focuses on medium-sized and large European banks at the banking group level, from the first quarter of 2006 to the second quarter of 2019. To check the validity of the textual tone score, we study its distribution over time and compare it with the one we would have obtained using a machine learning approach. We find similar distributions. We then explore the relationship of the textual tone score with bank-specific and macroeconomic variables. The results of these analyses strongly suggest that the textual tone scores contain information about the fundamentals of banks, i.e. their performance, business models and the economic environments in which they operate. More specifically, over the sample period, the textual tone score is on average positively associated with GDP growth rates and interbank interest rates and negatively associated with bank-level impairments on loans, the term spread and the OIS spread. Furthermore, we find that banks that rely more on retail deposits and that are less reliant on interest income show higher levels of textual tone score on average. Importantly, the textual tone score captures both bank-specific and macroeconomic fundamentals, bank managers' subjective opinions (Jiang et al., 2019), or their expectations about future firm outcomes (Li, 2010; Davis et al., 2012). Since we are interested in the informational content of the earnings press release documents orthogonal to the bank-specific and macroeconomic fundamentals, we control for the bank-specific and macroeconomic variables and include fixed effects in all our subsequent regressions. We define the variation in textual tone score orthogonal to fundamentals, as bank manager sentiment.

Second, we explore whether bank manager sentiment has an extrapolative structure, i.e. whether it is associated with past realizations of economic fundamentals.[2] Expectations with

[1] The predictions of these models motivate the empirical analysis of the relationship between financial crisis and preceding rapid buildups of leverage (López-Salido et al., 2017).

[2] The existence of extrapolative expectation formation rules is well documented in the finance literature. Extrapolative expectations are, for example, prevalent in survey data on stock return expectations (Greenwood and

an extrapolative structure imply over-optimism: if expectations depend on past realizations of economic fundamentals, the logical implication is that expectations will not be fully in line with current fundamentals. Thus, relative to current fundamentals, expectations will be too high, i.e. excessively optimistic, or too low, i.e. excessively pessimistic (Greenwood et al., 2016).[3] When forming their expectations, bank managers might, for example, extrapolate recent news on impairments in their loan portfolios (see e.g. Greenwood et al., 2016) or on macroeconomic developments (see e.g. Bordalo et al., 2018) into the future. In our empirical investigation, we find two pieces of evidence that suggest that bank managers' expectations are partially backward looking. First, we document that GDP growth rates have incremental predictive power for future values of bank manager sentiment. Second, we find that bank manager sentiment is auto-correlated, implying that innovations in variables that were found to be correlated with bank manager sentiment are also associated with its subsequent realizations.

Third, we study whether bank manager sentiment is associated with the investment decisions of banks and their equity investors. On the part of banks, we explore whether bank manager sentiment has incremental predictive power for loan growth. We do this for two reasons. First, evidence of a relationship between the two variables strengthens our case that bank manager sentiment reflects information about the expectations of bank managers. Second, a positive relationship between bank manager sentiment and loan growth is a necessary condition for the existence of a link between excessively optimistic expectations of bank managers and high loan growth rates. In our empirical analysis, we find that bank manager sentiment has incremental but weak predictive power for loan growth over the subsequent six months. When we replace bank manager sentiment by its components, we find that the predictive power of bank manager sentiment is mainly driven by the share of negative words that managers use in their press releases.

On the part of bank equity investors, we explore whether bank manager sentiment influences how bank investors perceive the risk associated with loan growth. The perceived riskiness of a bank is an important determinant of its cost of capital, which in turn is an important determinant of the bank's investments in loans. Empirical evidence suggests that equity market participants sometimes seem to be too optimistic when judging the risk associated with high bank loan growth (see e.g. Baron and Xiong, 2017; Fahlenbrach et al., 2017). Therefore, we hypothesize that bank manager sentiment is related to the perceived risk associated with bank loan growth and that this perceived risk is lower when bank managers are more optimistic.[4] Using *SRISK* (Brownlees and Engle, 2016) as our measure for the risk perception of market participants, we find that a higher bank manager sentiment is indeed associated with a lower perceived risk, and that the association between loan growth and risk decreases in bank manager sentiment, even though the latter is not significant.

The paper proceeds as follows. Section 2 summarizes the related literature and explains how this paper extends the respective strands of research. Section 3 introduces the textual tone score and other variables used throughout the paper. Section 4 studies the development of textual tone scores over time and their relationships with important bank-specific and macroeconomic variables. Section 5 defines bank manager sentiment and explores whether it is extrapolative in past fundamentals. Section 6 examines whether bank manager sentiment is predictive for

Shleifer, 2014), survey data on the expectations of CFOs with respect to macroeconomic developments and the future profitability of their own firms (Gennaioli et al., 2016) and forecasts of credit spreads (Bordalo et al., 2018).

[3]The implicit assumption here is that only the current state of the economy matters for decision making, which is a widely used assumption in economics and finance.

[4]Baron and Xiong (2017) find that rapid credit expansions on the country level predict low and sometimes negative aggregate bank equity returns, suggesting that investors sometimes underestimate the risk associated with bank loan growth. Fahlenbrach et al. (2017) show that equity analysts' forecasts of profitability and growth for high loan growth banks are often too optimistic and are subsequently revised downwards.

subsequent loan growth rates and whether the perceived risk associated with bank loan growth by bank equity investors differs when bank managers are over-optimistic versus when they are over-pessimistic. Finally, Section 7 summarizes and discusses the results.

2 Literature Overview

Our paper contributes to three strands of research. First, our paper contributes to the growing finance and accounting literature that studies the informational content of the textual sentiment of voluntary corporate disclosures. Within this literature, researchers study different text sources (e.g. annual reports, press releases, conference call transcripts), use different approaches to classify the content of these text sources (e.g. dictionary-based and machine learning approaches) and use different ways to calculate an aggregate textual tone [5] score from the classified text contents (Kearney and Liu, 2014). Overall, the empirical evidence suggests that the textual tone of corporate disclosures contains incremental informational content about the future performance of the reporting firms and that market participants respond to textual tone. For example, Li (2010) applies a machine-learning approach to the forward-looking statements in the Management Discussion and Analysis section of 10-K and 10-Q filings to study the incremental predictive power of textual tone for future earnings. He finds that textual tone is positively correlated with future return on assets up to three quarters ahead. Loughran and McDonald (2011) demonstrate that general dictionaries wrongly classify many words as negative that do not have a negative connotation in a financial context and introduce new word lists that are better suited to capture the textual tone in financial texts. They find that the proportion of negative words, as identified by their new word list, is negatively associated with 10-K filing returns. Davis et al. (2012) study a large sample of earnings press release documents published between 1998 and 2003. They find that textual tone is a predictor of future returns on assets and that the unexpected portion of their measure has incremental and positive predictive power for cumulative abnormal returns over a three day window centered around the earnings press release date. Huang et al. (2013) study earnings press releases published between 1997 and 2007 and present evidence for strategic firm behavior. They find that textual tone is more positive if firms have strong incentives to bias investor expectations upward and that higher tone is associated with a larger stock price response to the announcement. They also find that the initial increases in stock prices are accompanied with subsequent return reversals. Gandhi et al. (2019) specifically look at annual reports of US banks and find that the proportion of negative words is positively related to different measures of financial distress. Jiang et al. (2019) construct an aggregate manager sentiment score from firm-level textual tone and by controlling for macroeconomic fundamentals. They find that aggregate manager sentiment is negatively associated with stock returns on the market level and in the cross-section and that it has predictive power for aggregate investment. Using a new sample of European banks, we extend the literature by extracting a textual tone score of earnings press release documents thanks to dictionary and machine learning approaches [6]. Most importantly, by focusing on the part of the textual tone score which is orthogonal to the macroeconomic and bank-specific fundamentals, we are able to identify bank manager sentiment and study its characteristics and influence.

Second, it is related to the literature that links credit cycles to behavioral factors, which

[5] What we call "textual tone" is sometimes called "textual sentiment" in the existing literature. Given that we introduce the notion of "bank manager sentiment" later on, we prefer to use the term "textual tone" to avoid any confusion for the reader.

[6] By construction, the textual tone score could be related to either bank-specific and macroeconomic fundamentals, or bank managers' subjective opinions (Jiang et al., 2019), or their expectations about future firm outcomes (Li, 2010; Davis et al., 2012) or a combination of both.

was initiated by Minsky (1977). In this literature, a positive association between credit growth and financial fragility is explained by overly optimistic or extrapolative expectations. Recent theoretical contributions to this literature are Greenwood et al. (2016) and Bordalo et al. (2018). Greenwood et al. (2016) present a model in which lenders extrapolate past realizations of credit defaults. The extrapolative expectation formation rules imply that credit cycles in the model are more persistent than the cycles in the underlying fundamentals. Bordalo et al. (2018) present a model in which credit cycles are driven by what they label diagnostic expectations of agents. Under the assumption of diagnostic expectations, agents assign too high probabilities to future outcomes that become more likely relative to the observed current state. Diagnostic expectations imply that agents have extrapolative expectations and neglect risk. In contrast to the model of Greenwood et al. (2016), the model of Bordalo et al. (2018) predicts that a crisis can be triggered by changing expectations without a corresponding decrease in fundamentals. Empirical evidence for excessive optimism in credit markets is presented in Greenwood and Hanson (2013), Greenwood et al. (2016), López-Salido et al. (2017), Fahlenbrach et al. (2017) and Bordalo et al. (2018). Greenwood and Hanson (2013) study the relationship between the average credit quality of new corporate bond issues and excess corporate bond returns. They find that lower average debt issuer quality predicts low excess corporate bond returns, where the latter also turn negative. One explanation for this relationship given by Greenwood and Hanson (2013) is that corporate bond investors over-extrapolate past low corporate bond default rates, causing them to demand risk premia that are too low. By showing that measures of sentiment in the credit market depend on past realization of defaults, Greenwood et al. (2016) provide additional empirical evidence for extrapolative expectations in credit markets. López-Salido et al. (2017) use the expected excess return for bearing credit risk as a proxy of credit market sentiment and present evidence that high credit market sentiment predicts low real GDP growth and a decrease of net debt issuance relative to net equity issuance. Fahlenbrach et al. (2017) present bank-level evidence that is consistent with excessively optimistic bank managers and equity analysts. They show that high loan growth banks do not provision more for loan losses than low loan growth banks and that equity analysts expect that high loan growth banks have higher future loan and earnings growth rates relative to low loan growth banks. Lastly, Bordalo et al. (2018) document that analysts expect credit spreads to be more persistent than they actually are and that analysts' forecast revisions are negatively associated with past credit spreads. We contribute to this strand of literature by providing bank-level evidence of the extrapolative structure of bank manager sentiment, and by showing that bank manager sentiment is related to future loan growth.

Third, our paper contributes to the empirical literature concerned with the relationship between credit growth and bank stability. Country-level evidence (e.g. Schularick and Taylor, 2012; Aikman et al., 2014; Baron and Xiong, 2017) as well as firm-level evidence (e.g. Foos et al., 2010; Fahlenbrach et al., 2017) suggest that high bank loan growth is positively associated with financial fragility and negatively associated with subsequent bank performance. Schularick and Taylor (2012) introduce a new dataset that covers 12 developed countries over the period 1870–2008. The evidence from this dataset suggests that the occurrence of a financial crisis is more likely if there has been a credit boom in the preceding five years (Schularick and Taylor, 2012), that the severity of recessions increased in the build-up of bank credit during the preceding boom (Jordà et al., 2013) and that credit booms predict the occurrence of banking crises (Aikman et al., 2014). Deploying a different panel dataset which covers 20 developed countries over the period 1920–2012, Baron and Xiong (2017) document that large increases in bank lending predict an increase in bank equity crash risk and that holders of bank equity have not been compensated for this crash risk in terms of higher bank equity returns. On the bank level, Foos et al. (2010) and Fahlenbrach et al. (2017) find that high loan growth predicts high subsequent loan loss provisions and lower returns on assets. Moreover, Fahlenbrach et al. (2017) show that high loan growth banks significantly underperform low loan growth banks in terms of their stock market returns. We contribute to this strand of literature by showing that higher bank manager sentiment is associated with a lower risk of the banks as perceived by the financial markets.

3 Data

This section introduces the textual tone score as well as bank-specific and macroeconomic control variables used in our analyses.

3.1 Textual Tone Score

Our textual tone score is based on the bank earnings press release documents. Our sample comprises all English language press releases of banks from developed European markets that are available in the database of data provider S&P Global Market Intelligence (SNL, hereafter).[7] Bank earnings press releases in the SNL database are available starting from the first quarter of the year 2005. Our sample ends in the second quarter of the year 2019.

It takes three steps to transform earnings press release documents into final textual tone scores. The first step is to calculate textual tone scores for all earnings press release documents. To process the documents, we use the bag-of-words approach, i.e. for each document, we create a list of all words contained in the document and count how often they appear.[8] Based on the document-specific word lists, we then classify the words as having a positive connotation, having a negative connotation, or as being neutral. The classification is done via the financial dictionary of Loughran and McDonald (2011). As demonstrated by Loughran and McDonald (2011), their financial dictionary is more appropriate for financial texts than standard dictionaries like the widely used Harvard Dictionary. We follow Davis et al. (2012), Huang et al. (2013) and Jiang et al. (2019) and calculate the textual tone score, $tone_{i,p,d}$, of the earnings press release document d of bank i for the reporting period p as the difference between the share of words that have a positive connotation, $pos_{i,p,d}$, and the share of words that have a negative connotation, $neg_{i,p,d}$, i.e.

$$tone_{i,p,d} = pos_{i,p,d} - neg_{i,p,d}, \quad \text{with} \quad pos_{i,p,d} = \frac{N^{pos}_{i,p,d}}{N_{i,p,d}} \quad \text{and} \quad neg_{i,p,d} = \frac{N^{neg}_{i,p,d}}{N_{i,p,d}}. \tag{1}$$

The variables $N^{pos}_{i,p,d}$, $N^{neg}_{i,p,d}$ and $N_{i,p,d}$ count the occurrences of words with a positive connotation, the occurrences of words with negative connotation and the total number of words in document d, respectively. The reporting period p thereby refers to a quarter. If the bank's reporting frequency is semi-annually, press textual tone scores are only available for the second and fourth quarter of any year. In addition, we take negations into account by following Das and Chen (2007) and Renganathan and Low (2010): In the presence of negations (“no”, “not”, “none”,...), we invert the polarity of the sentence (ex: “not good” would be considered as negative). To take care of complex negations, we identify conjunctions (and“, “or“, “but”) and use the following rule: whenever there is a negation in a sentence, we check all the words following this negation, until there is either a punctuation mark or a conjunction. For the words between a negation and a punctuation mark or a conjunction, we then reverse the polarity of any word identified as positive or negative by the financial dictionary of Loughran and McDonald (2011). Even by doing so, the dictionary approach still has some limitations (not only to take negations into account, but also

[7] The Developed Europe category in the S&P Global Market Intelligence database comprises Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom.

[8] See e.g. Gentzkow et al. (2019) for a description of the bag-of-words approach.

complex sentences formulations, conjunctions, irony, etc). To tackle this issue, we do a robustness check by using a machine learning approach as an alternative method to compute our textual tone score (denoted $tone\_ML$). In contrast to our previous approach, in which we had to specify ourselves the rules for the handling of negations and long-range connections between words, machine learning algorithms are able to learn these rules from large amounts of existing text data. Among those models, we use FinBERT, a financial domain specific BERT (Bidirectional Encoder Representation from Transformers) model [9] created by Yang et al. (2020). In practice, both BERT and FinBERT require a high memory and computational power for the pre-training step. Because of these costs and because the financial sentiment classification task we would like to perform is similar to the one of Yang et al. (2020), we do not fine-tune FinBERT to our earnings press release documents. Instead, we use the pre-trained and fine-tuned version provided by Yang et al. (2020) to predict the tone of each of the financial statements in our dataset. In order to match the level of analysis of the fine-tuning, we predict the tone of our sample of financial press releases at the sentence level, aggregate the sentences' tone at the document level, and adjust by the number of sentences in each document.

The second step is to deal with the existence of multiple, possibly differing earnings press release documents from the same bank and for the same reporting period. For simplicity, we solve this issue by combining all textual tone scores by calculating the average, i.e.

$$S_{i,p} = D_{i,p}^{-1} \sum_{d=1}^{D_{i,p}} S_{i,p,d}, \tag{2}$$

where S refers to *tone*, *pos* or *neg* and $D_{i,p}$ is the number of earnings press release documents released by bank i at the end of reporting period p.

The third and final step is to align the frequency of all bank-level textual tone score time-series. About one third of the banks in the sample report their earnings on a semi-annual frequency, the remaining banks in the sample report quarterly. We therefore transform all time-series with a quarterly frequency into time-series with a semi-annual frequency. As in the second step, we combine the textual tone scores of banks with a quarterly reporting frequency by calculating a simple average, i.e. $S_{i,t} = 0.5(S_{i,p1} + S_{i,p2})$, where t refers to the first or second half of a given year (e.g. 2006H1), S refers to *tone*, *pos* or *neg* and $p1$ and $p2$ refer to the first and second quarter, respectively, within t. A detailed analysis of the final textual tone scores is presented in Section 4.

Our approach to extract textual tone scores from earnings press release documents has one weakness. We are currently not able to determine to which reporting period a specific part of an earnings press release document relates to. As the main purpose of the document is to inform about the performance of the bank during the last reporting period, we treat the whole document as if it relates only to the reporting period that ends at time t. However, earnings press release documents usually also contain forward looking passages and might also contain passages that relate to previous reporting periods. If the latter is the case, the document's textual tone score will be correlated with past fundamentals, which could be a problem for our analysis in Section 7. More specifically, our result that the GDP growth rate has incremental predictive power for subsequent realizations of bank manager sentiment could be partially or fully driven by occurrences of passages relating to past reporting periods. Section 7 outlines how this weakness could be addressed in order to increase the robustness of our results.

[9] More details on BERT can be found in Devlin et al. (2018).

3.2 Accounting Data

We merge the textual tone score dataset with a dataset containing semi-annual accounting data of European banks from SNL.[10] To ensure that the accounting data aligns with the content of the press releases documents, we download all variables as they have been originally reported at the end of the respective reporting period. However, if the originally reported values are not available, we use restated accounting values, i.e. accounting values that were changed retrospectively by the bank. The accounting data is available for the reporting periods 2006H1 to 2019H2. Some banks only report key balance sheet variables at the end of the fiscal year. To avoid losing those interim observations in our empirical analysis, we impute these missing values with the average of the value reported at the end of the previous year and the value reported in the same year. The dummy variable *imputed*, which indicates whether the value of at least one variable was imputed, is included in all regressions. Table 1 gives an overview over the accounting variables used in this paper.

Table 2 reports summary statistics for the intersection of the textual tone score dataset and the accounting dataset as well as for the banks, for which no textual tone scores are available. The summary statistics provided in columns 2–7 of Panel A of Table 2 show a considerable variation in the size of the banks in the intersection of the two datasets. Our sample includes both very small (the fifth percentile is €1.45 billion) and also very large banks (the ninety-fifth percentile is €1,275.13 billion), as measured by their total assets (*totalassets*).[11] The average bank has assets of 228.26 billion, invests the majority of its assets in loans (*loans*), funds about half of its balance sheet via deposits (*deposits*) and is highly reliant on interest income (*interestincome*)[12]. With an average of 2.32 % and a standard deviation of 13.06 %, semi-annual loan growth rates (*loangrowth*) have been on average positive but extremely volatile. The relatively high standard deviation statistic of *loangrowth* indicates the presence of outliers. An inspection of the distribution of *loangrowth* over the sample period depicted in Figure 1 confirms this. To limit the effect that these outliers have on our regression results, we winsorize *loangrowth* by replacing its values below the 5th percentile by the its 5th percentile and values above the 95th percentile by its 95th percentile. The percentiles are thereby calculated from the distribution of *loangrowth* specific to period t, i.e. only the distribution of *loangrowth* observed in period t is used to winsorize the observations from period t. We choose the 5th and the 95th percentiles because these quantiles are both very stable over the sample period and have a sensible magnitude. Finally, bank profitability has been particularly weak during the sample period, which includes the financial crisis of 2007–2009 and the European debt crisis of 2010–2012. On average, operating income (*operatingincome*) was barely sufficient to cover operating expenses (*operatingexpenses*) and impairments on loans and securities (*impairments*).

Columns 8–13 in Panel A of Table 2 reveal that banks that release earnings press release documents systematically differ from banks that do not. The former are on average larger, invest less in loans and are therefore less reliant on interest income and have lower equity ratios (see also column 14). Our results thus may not necessarily generalize to all European banks. However, since the banks in our textual tone score sample account for a large majority of outstanding loans, our results may nevertheless contribute to our understanding of aggregate credit cycles.

[10] Accounting data with a semi-annual frequency is readily available in SNL. No transformations were necessary on our side.

[11] In our analysis, we only use the log of *totalassets*, which we refer to as *logta*.

[12] We have winsorized the variable *interestincome* so that it lies between 0 and 1. Trading losses, which are a component of net operating income, can lead to values below 0 or above 1, which we set to 0 and 1, respectively.

Table 1: List of macroeconomic and financial covariates

Variable	Abbreviation	Source	Comments
Total assets	*totalassets*	SNL	SNL Code: 132264
Net loans to total assets	*loans*	SNL	SNL Codes: 132214 (loans), 132264 (total assets)
Cash to total assets	*cash*	SNL	SNL Codes: 246025 (cash), 132264 (total assets)
Total securities to total assets	*securities*	SNL	SNL Codes: 132191 (cash), 132264 (total assets)
Deposits to total assets	*deposits*	SNL	SNL Codes: 132288 (deposits), 132264 (total assets)
Equity to total assets	*equity*	SNL	SNL Codes: 132385 (equity), 132264 (total assets)
Total debt	*debt*	SNL	SNL Codes: 132319 (total debt), 132264 (total assets)
Operating income to total assets	*operatingincome*	SNL	SNL Codes: 225155 (operating income), 132264 (total assets)
Net interest income to net operating income	*interestincome*	SNL	SNL Codes: 132553 (net interest income), 225155 (operating income)
Operating expenses to total assets	*operatingexpenses*	SNL	SNL Codes: 225159 (operating expenses), 132264 (total assets)
Total impairments to total assets	*impairments*	SNL	SNL Codes: 225181 (impairments), 132264 (total assets)
Loan loss reserves to total assets	*reserves*	SNL	SNL Codes: 248860
GDP growth	*gdp*	Eikon Datastream	nominal, seasonally adjusted
Consumer price inflation	*inflation*	Eikon Datastream	–
Three month interbank rate	*interbank*	Eikon Datastream	EURIBOR for Eurozone countries, country-specific LIBOR rates for non-Eurozone countries
Term spread	*term*	Eikon Datastream	yield on benchmark 10-year government bonds - 3-month interbank rates
OIS spread	*ois*	Eikon Datastream	3-month interbank rates - OIS rates
Market capitalization	W	Eikon Datastream	–
Bank stock returns	R_i	Eikon Datastream	total return
Market return	R_m	Eikon Datastream	Return on the MSCI Europe Index

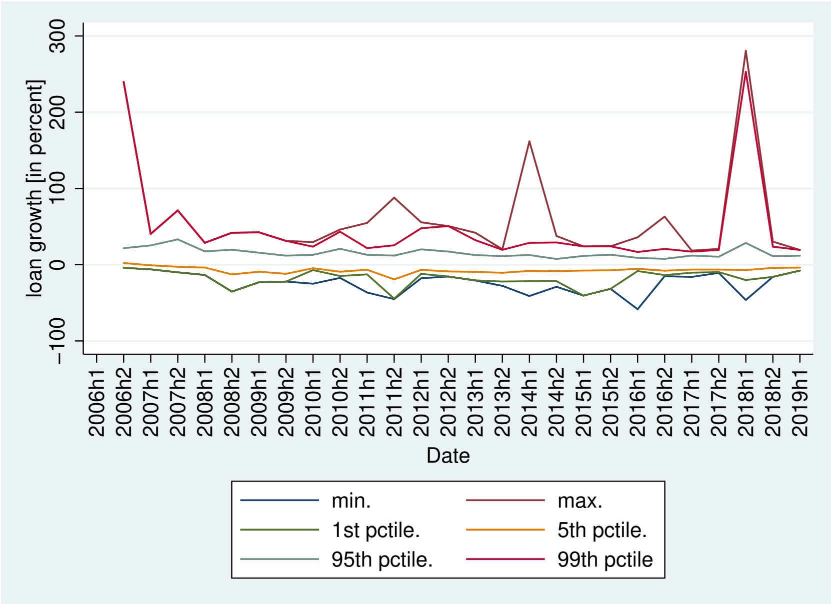
Table 2: Summary statistics

Panel A: Bank-level variables	textual tone score sample						No textual tone score available						
Variable	N	mean	std	p5	p50	p95	N	mean	std	p5	p50	p95	$\Delta mean$
Balance sheet and income variables													
totalassets (in billion Euros)	3,033	228.26	428.94	1.45	45.33	1275.13	3,922	48.06	155.43	0.37	10.71	176.67	180.20***
loans (in %)	3,022	59.38	18.21	23.71	62.03	84.17	3,896	65.22	20.11	19.44	69.80	87.40	-5.84***
cash (in %)	3,027	4.45	5.59	0.09	2.35	15.391	3,841	5.41	9.54	0.13	1.92	18.71	-0.97*
securities (in %)	3,006	22.29	14.15	4.93	19.33	51.40	3,867	17.70	13.48	1.24	14.88	40.73	4.59***
deposits (in%)	3,021	51.16	19.39	18.55	51.84	81.96	3,892	50.72	24.16	0.00	55.95	82.27	0.44
equity (in %)	3,031	7.05	3.89	2.60	6.46	14.08	3,908	6 8.53	6.15	2.12	7.71	16.47	-1.47***
interestincome (in %)	3,033	60.54	21.96	21.14	60.42	100.00	3,922	66.44	21.10	27.03	67.58	100.00	-5.90***
loangrowth (in %)	2,792	2.32	13.06	-7.82	1.39	15.19	3,393	2.63	16.79	-8.22	1.65	13.47	-0.31
Profitability variables													
operatingincome (in %)	3,016	1.33	0.88	0.34	1.23	2.64	3,815	1.45	1.44	0.15	1.19	3.21	-0.12
operatingexpenses (in %)	3,020	0.85	0.55	0.21	0.76	1.71	3,812	0.92	1.20	0.07	0.70	2.06	-0.07
impairments (in %)	3,006	0.30	0.75	-0.02	0.11	1.15	3,839	0.27	0.67	-0.04	0.11	1.04	0.02

Panel B: Macro-level variables	textual tone score sample						No textual tone score available						
Variable	N	mean	std	p5	p50	p95	N	mean	std	p5	p50	p95	$\Delta mean$
gdp (in %)	3,033	1.22	1.92	-2.08	1.33	3.77	3,886	1.28	1.93	-2.04	1.39	3.82	-0,06
inflation (in %)	3,033	0.71	0.80	-0.40	0.61	2.08	3,886	0.75	0.79	-0.39	0.65	2.21	-0.04
interbank (in %)	3,033	1.07	1.65	-0.33	0.53	4.67	3,886	1.05	1.61	-0.50	0.52	4.67	0.02
term (in %)	3,031	1.71	2.22	-0.46	1.18	4.96	3,884	1.30	1.66	-0.37	0.92	4.08	0.40***
ois (in %)	2,852	0.26	0.30	0.02	0.14	0.76	3,753	0.27	0.30	0.01	0.20	0.84	-0.01

Note: This table presents summary statistics for the bank-specfic and macroeconomic variables used throughout this paper. The summary statistics are reported for two samples. The summary statistics for the research sample, i.e. banks, for which textual tone score is available, are reported in columns 2–7. Columns 8–13 report the summary statistics for European banks, for which no textual tone scores are available. Column 14 reports the differences in means between both samples, as well as whether the differences are statistically significant at the 10%(*), 5%(**) or 1%(***) level, respectively. The statistical tests are based on standard errors clustered on the bank level.

Figure 1: The distribution of loan growth rates over the sample period



3.3 Macroeconomic Data

We merge macro-level variables downloaded from Refinitiv Datastream and the website of the European Central Bank to the dataset containing the textual tone scores and accounting data. All macro-level variables are country-specific and relate to the same reporting period as the textual tone score and the accounting data.[13] The macro-level variables are GDP growth (nominal, seasonally adjusted; *gdp*), the consumer price inflation rate (*inflation*), the three month interbank rate (*interbank*), the OIS swap rate (*ois*) and the term spread (*term*) (see Table 1). The variables *gdp* and *inflation* have publication lags of between 1 and 2 months, i.e. the values of their realizations for period t become only known in the first half of period $t+1$. However, we do not account for publication lags in our main analyses, because we consider these variables as proxies for the economic conditions observed by bank managers during period t.[14] All interest rate variables are semi-annual averages calculated from daily data. The OIS spread is a proxy for the degree of counterparty risk in the interbank market and is calculated as the difference between the three month interbank rate and the three month OIS swap rate (see e.g. Gorton and Metrick, 2012). The term spread is the difference between the ten years government bond yield and the three months interbank rate and proxies for the slope of the yield curve. Given that our sample contains the periods of the European Sovereign Debt Crisis, *term* also captures stress in sovereign debt markets.

Panel B of Table 2 provides summary statistics for these variables. The sample period includes both boom periods and recessions, as well as periods with very low, even negative interest rates. As column 14 reveals, *term* is on average higher in our research sample than in the sample, for

[13]Given that earnings press release documents and the accounting data are published 1–2 months after the end of a reporting period, at the time of the release, bank managers already have partial information about the macroeconomic environment during the next period. The textual tone score for period t might thus also be related to the realizations of macroeconomic variables between the end of t and the release of the press release document.

[14]Not accounting for publication lags does not seem to pose a problem. Robustness checks (available from the authors upon request), in which we account for these publication lags, yield very similar results.

which textual tone scores are not available. This is the result of an over-representation of banks from countries that were affected by the sovereign debt crisis in our textual tone score sample.

3.4 Systemic Risk

For the listed banks in our sample, we calculate the systemic risk measure *SRISK* introduced in Brownlees and Engle (2016). *SRISK* is the dependent variable in Section 6.2. It is the conditional expectation of the capital shortfall of the bank under a systemic event. The capital shortfall is defined as the difference between required market equity, e.g. due to microprudential regulations, and actual market equity. The systemic event is defined as a multi-period return of the total equity market that is smaller than a threshold value c. The formula for *SRISK* (Brownlees and Engle, 2016, p. 52) is

$$SRISK_{i,t} = W_{i,t}\left[kLVG_{i,t} + (1-k)LRMES_{i,t} - 1\right], \tag{3}$$

where $W_{i,t}$, $LVG_{i,t}$ and $LRMES_{i,t}$ are the market value of equity, the market leverage ratio (market equity plus the book value of debt (*debt*, hereafter) over market equity) and the Long Run Marginal Expected Shortfall (LRMES), respectively, of bank i in period t. The parameter k represents the leverage ratio requirement. While $W_{i,t}$ and $LRMES_{i,t}$ can in principal be observed daily on the stock market, $LVG_{i,t}$ depends on *debt*, which can only be observed quarterly or semi-annualy.[15] Since the frequency chosen in this paper is semi-annual, $SRISK_{i,t}$ also has a semi-annual frequency. Given that the accounting data used in this study either relates to the six months ending in June or December of a given year, we use market values from the end of June and December, respectively, for all variables that are based on market prices, i.e. $W_{i,t}$ and $LRMES_{i,t}$. LRMES is defined as (Brownlees and Engle, 2016, p. 53)

$$LRMES_{i,t} = -E_t\left(R_{i,t+1:t+h} | R_{m,t+1:t+h} < c\right). \tag{4}$$

The variables $R_{i,t+1:t+h}$ and $R_{m,t+1:t+h}$ are the multi-period returns of bank i and the stock market, respectively, where the parameter h defines the horizon over which the returns are calculated. To obtain $W_{i,t}$ and $LVG_{i,t}$, we download market values from Datastream and *debt* from SNL. We use Datastream to obtain bank stock returns and the return on the stock market, which are the inputs to the calculation of the LRMES. As a proxy for the European stock market, we use the MSCI Europe Index.

To calculate the LRMES of a bank, we assume that its stock return and that of the market are generated by a bivariate normal distribution with mean zero. The bivariate normal model has the advantage that it has an (approximate) closed-form solution (Brownlees and Engle, 2016). The parameters to be estimated are the standard deviation of the market return ($\sigma_{m,t}$), the standard deviation of the stock return of the bank ($\sigma_{i,t}$) and their coefficient of correlation ($\rho_{i,t}$). Given $\sigma_{i,t}$, $\sigma_{m,t}$ and $\rho_{i,t}$, the LRMES of bank i at time t can be approximated by (Brownlees and Engle, 2016, p. 55)

$$LRMES_{i,t} \approx \sqrt{h}\rho_{i,t}\sigma_{i,t}\frac{\phi(\frac{c}{\sigma_{m,t}})}{\Phi(\frac{c}{\sigma_{m,t}})}, \tag{5}$$

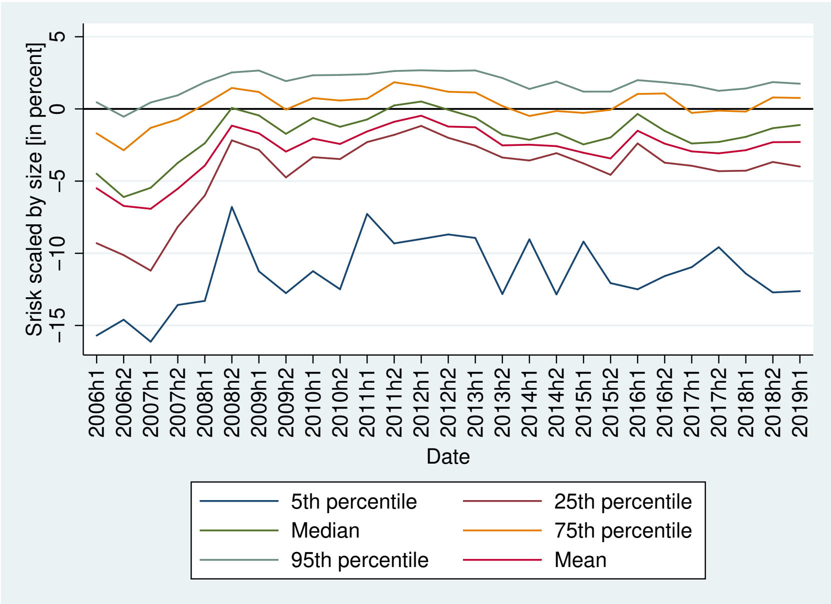
where $\phi(\cdot)$ and $\Phi(\cdot)$ are the normal distributions' density and distribution function, respectively. Since these values are likely to be dynamic, we estimate $\sigma_{i,t}$, $\sigma_{m,t}$ and $\rho_{i,t}$ with a rolling window of 60 months of stock return data, i.e. each parameter is estimated with the monthly returns between $t-59$ and t. With regard to the parameters h and c, we adopt the values chosen

[15] Due to the publication lag of *debt*, the realization of $LVG_{i,t}$ becomes known only after the end of period t. We implicitly assume that the market participants can forecast *debt*.

by Brownlees and Engle (2016) and set them to 1 month and 10 %, respectively. We set the parameter k to 3 %, which corresponds to the current Basel III leverage ratio requirement. Since it is measured in Euros, we scale *SRISK* by the enterprise value of the bank, i.e. we divide it by the sum of its market equity and the book value of its debt ($W_{i,t} + debt_{i,t}$).[16]

Figure 2 depicts the distribution of scaled *SRISK* over the sample period. *SRISK* has been negative on average in the large majority of periods, meaning that the banks in our sample had capital surpluses on average. Periods with particular high levels of risk have been the second half of 2008 (the global financial crisis), the first half of 2012 (the European sovereign debt crisis) and the first half of 2016 (the Brexit referendum). In the cross-section, the dispersion between banks remains relatively stable over time. While the 25 % most risky banks had a conditional expected capital shortfall in the majority of periods, the 25 % least risky banks had conditional expected capital surpluses. With the exception of the year 2012, median *SRISK* has been negative over the sample period.

Figure 2: The distribution of SRISK over the sample period



4 The Properties of Textual Tone Scores

The aim of this section is to verify the validity of our textual tone scores. We first study the developments of the textual tone scores and the shares of positive and negative words, respectively, over time from the dictionary approach. We also compare the textual tone score using the dictionary approach with the one obtained using the machine learning approach. We then explore the relationship between the textual tone score obtained from the dictionary approach and its two components (i.e. *tone*, *pos* and *neg*) and important bank-specific and macroeconomic variables.

[16]We scale by enterprise value and not by the size of the balance sheet, because *SRISK* is based on market equity.

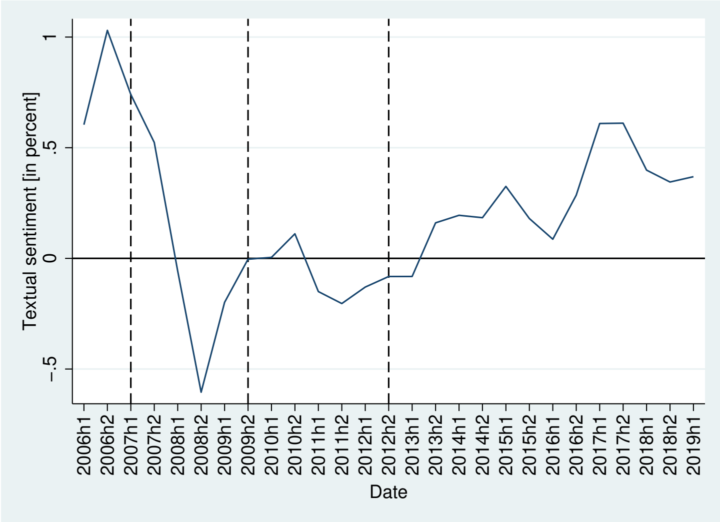
4.1 Textual Tone Scores over Time

Figures 3a and 3b depict the textual tone score using the dictionary approach over the sample period. As shown by Figure 3a, the average textual tone score is pro-cyclical. Consistent with global events, the average of *tone* is negative in the crisis years 2008 and 2009 (i.e. during the global financial crisis) and 2011 to 2013 (i.e. during the European sovereign debt crisis) and positive in boom periods, i.e. before the year 2008 and after the year 2013. Average *tone* starts to decrease in 2007, remains around zero between the end of 2009 and 2013 and recovers afterwards. As shown by Figure 3b, this pro-cyclicality is an aspect which is consistent across the distribution of banks. Figure 3c reveals that the decrease in average *tone* before the financial crisis is predominantly driven by an increase in the average of *neg*. While the average of *neg* doubles between 2007H1 and 2008H2 (from 0.98 % to 1.99 %), the average of *pos* only decreases by about 19.17 % (from 1.71 % to 1.39 %). The upward trend in the average of *tone*, which has its start in the year 2013, is driven by opposing trends in *pos* and *neg*.

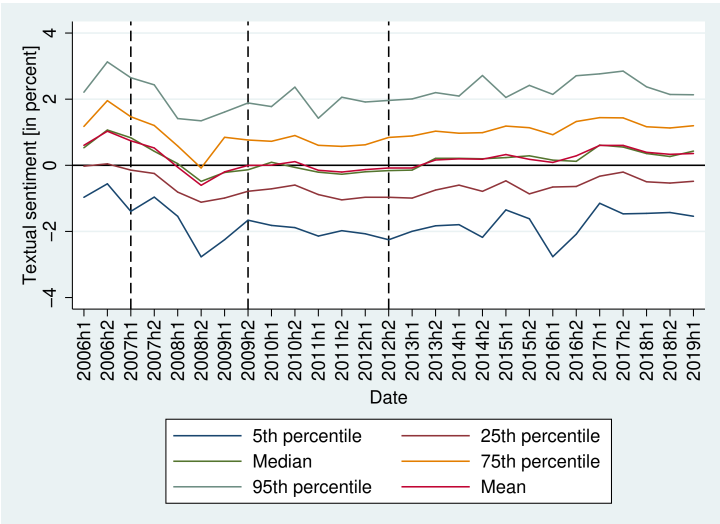
As a robustness check, we then compute the textual tone score for each press release obtained by using a machine learning approach (FinBERT). We refer to the textual tone score obtained from the machine learning approach as $tone\_ML$. As FinBERT is fine-tuned at the sentence level, we compute a textual tone score for each sentence of our press releases. We then aggregate those scores at the press release level by summing the sentences' scores and by dividing this sum by the number of sentences in the press release. The average textual tone score over time and its distribution across banks are shown in Figures 4a and 4b. The evolution of both the average textual tone score and of its distribution are very similar to the ones we obtained in the dictionary approach. The levels are however very different, due to the different approaches used. In order to check that both approaches are also similar at the micro level, we compute two additional exercises. First, we regress the textual tone score obtained from the machine learning approach ($tone\_ML$) on the textual tone score obtained from the dictionary approach (*tone*) at the bank-time level. Including bank fixed effects has the advantage of taking into account the specificity of each bank when computing our textual tone score. However, if the rank of the textual tone score is different between the two approaches, this would also be captured by the bank fixed effect. Similarly, time fixed effects would allow to take into account the influence of being in a specific time period. But on the other hand, any change of relationship between the textual tone score of the two approaches due to this time period would also be captured by the time fixed effect. For this reason, we estimate the regression both with and without bank and time fixed effects. The results are presented in Table 3. The textual tone scores obtained from each approach have a strong and positive relation, with or without fixed effects. As a further check, we also compute the Spearman's rank correlation between the textual tone scores obtained from each approach. We implement this exercise both for the full sample period (2006H1-2019H1) and for each semester to check that the correlation is stable over the business cycle. The results are presented in Table 4. The Spearman's rank correlation is strongly positive and significant at the 1% level, not only for the full sample period (0.72), but also for each semester taken separately, independently of the economic environment.

Given the similarities of the textual tone scores obtained from both approaches, we choose to focus on the textual tone score obtained from the dictionary approach (*tone*) in the rest of the paper.

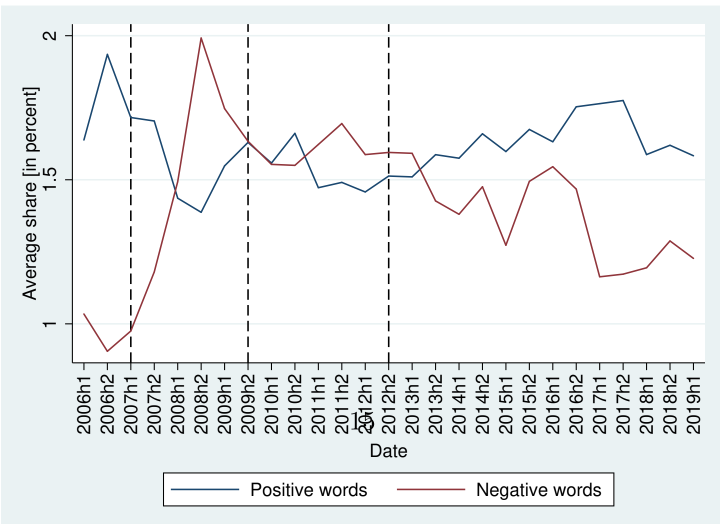
Figure 3: Textual tone score (dictionary approach)



(a) Average textual tone score over time



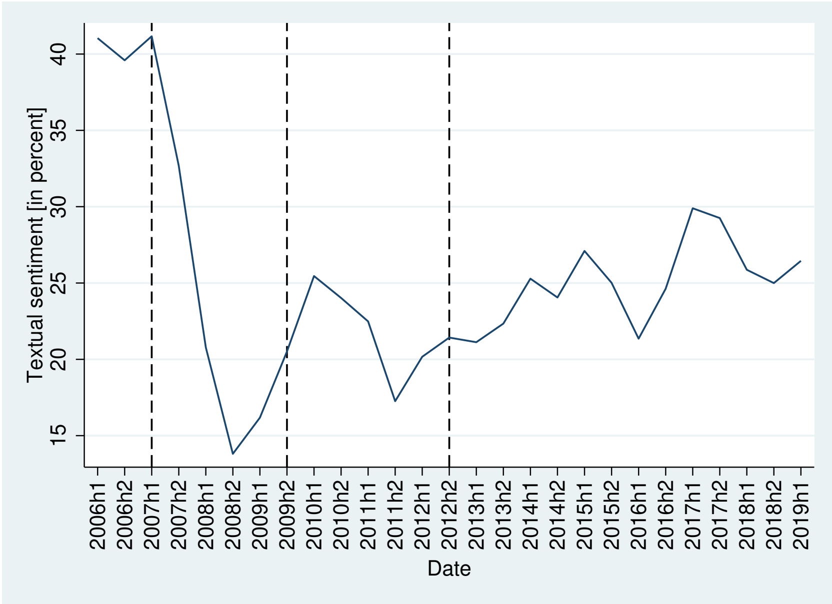
(b) The distribution of the textual tone score over time



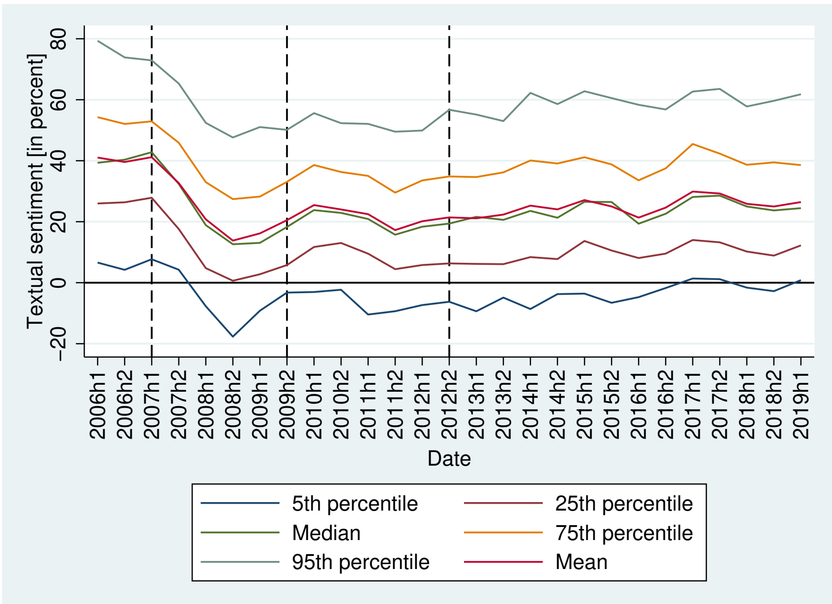
(c) The averages of *pos* and *neg*

Note: These figures plot properties of the average textual tone score using the dictionary approach (Figure 3a), the distributions of *tone* (Figure 3b), *pos* and *neg* (Figure 3c) over the sample period. The vertical lines indicate the start of the global financial crisis, the end of the global financial crisis and the end of the European sovereign debt crisis, respectively.

Figure 4: Textual tone score (machine learning approach)



(a) Average textual tone score over time



(b) The distribution of the textual tone score over time

Note: These figures plot properties of the average textual tone score using the machine learning approach (Figure 4a) and the distributions of $tone\_ML$ (Figure 4b) over the sample period. The vertical lines indicate the start of the global financial crisis, the end of the global financial crisis and the end of the European sovereign debt crisis, respectively.

Table 3: Regression of the textual tone score from the machine learning approach ($tone\_ML_{i,t}$) on the textual tone score from the dictionary approach ($tone_{i,t}$)

	$tone\_ML_{i,t}$	$tone\_ML_{i,t}$	$tone\_ML_{i,t}$
$tone_{i,t}$	11.19***	10.23***	8.96***
	(0.20)	(0.24)	(0.25)
Constant	0.23***	0.38***	0.53***
	(0.00)	(0.09)	(0.09)
Bank fixed effects	No	Yes	Yes
Time fixed effects	No	No	Yes
N	3316	3316	3316
R^2	0.50	0.64	0.67
Adjusted R^2	0.49	0.61	0.64

Note: The standard errors are reported in parentheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

Table 4: Spearman's rank correlation (ρ) between the textual tone score of the dictionary approach ($tone_{i,t}$) and the textual tone score of the machine learning approach ($tone\_ML_{i,t}$)

Time window	ρ	N
Full period	0.7242***	3316
2006h1	0.5971***	83
2006h2	0.7447***	97
2007h1	0.6444***	101
2007h2	0.7465***	112
2008h1	0.6541***	112
2008h2	0.6613***	123
2009h1	0.7641***	122
2009h2	0.6742***	141
2010h1	0.5848***	127
2010h2	0.7345***	144
2011h1	0.6301***	133
2011h2	0.6090***	142
2012h1	0.6964***	117
2012h2	0.7228***	129
2013h1	0.6862***	127
2013h2	0.7281***	137
2014h1	0.7713***	131
2014h2	0.7510***	131
2015h1	0.6739***	114
2015h2	0.6948***	131
2016h1	0.7757***	127
2016h2	0.7454***	123
2017h1	0.7781***	128
2017h2	0.7124***	129
2018h1	0.7077***	129
2018h2	0.8184***	115
2019h1	0.6265***	109

Note: ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

4.2 Textual Tone Scores at the Bank Level

To shed some light on the informational content of the textual tone scores, we run separate regressions of *tone*, *pos* and *neg* on a set of bank characteristics, macroeconomic state variables, country fixed effects and bank fixed effects. The bank-specific and country-specific variables come from three categories: profitability measures, bank business model indicators and macroeconomic state variables. The profitability variables are *operatingincome*, *operatingexpenses* and *impairments*. Given that textual tone scores are extracted from earnings press release documents, we expect that the profitability variables are directly related to *tone*. The business model indicators include *loans*, *deposits*, *equity*, *interestincome* and the logarithm of *totalassets*. The motivation for the inclusion of the business model proxy variables is that some bank business models may have been more successful than others since 2006, which we expect to be reflected in *tone*. Finally, the set of country-specific macroeconomic state variables encompasses *gdp*, *inflation*, *interbank*, *term* and *ois*. Since a more favorable macroeconomic environment, i.e. high values of *gdp* and *term* and low values of *ois*, is positive for the business of banks, we expect the first two variables to be positively associated with *tone* and *ois* to be negatively associated with *tone*.

4.2.1 Country-Specific and Bank-Specific Differences in Textual Tone Scores

Differences in culture and communication styles across countries and banks may have a significant impact on textual tone scores. Under the assumption that these differences are constant over time, we first attempt to quantify the incremental explanatory power of country and bank fixed effects. Adjusted R^2 statistics from separate regressions of *tone*, *pos* and *neg* on profitability, business model, macroeconomic, country dummy and bank dummy variables are documented in Table 5. The first column reports the results from our baseline regression model, which only includes the profitability, business model and macroeconomic variables. The adjusted R^2 statistics range from 8.50 % for *pos* to 18.50 % for *neg*. The majority of the variation in the textual tone score and its components thus remains unaccounted for. Next, we include country dummy variables to measure the incremental explanatory power of country fixed effects. The second column of Table 5 reveals that country fixed effects have sizable explanatory power for both the textual tone score and its two components. With an increase of approximately 138 %, *pos* sees the highest relative increase, suggesting that country-specific factors are an especially important determinant of the occurrence of words with a positive connotation in earnings press release documents. Finally, we replace the country dummy variables by bank dummy variables, which produces the highest increases in adjusted R^2. As the third column of Table 5 shows, bank fixed effects account for over 50 % of the variation in the dependent variables. The incremental explanatory power of bank fixed effects relative to the baseline specifications ranges from 35.40 to 42.40 percentage points. These results indicate that bank fixed effects are the most important determinant of *tone*, *pos* and *neg*. They also highlight the necessity to control for bank fixed effects in the following investigations.

4.2.2 The Textual Tone Score, Bank Characteristics and the Macroeconomic Environment

Next, we study the relationships between the three textual tone score variables (*tone*, *pos* and *neg*) and the profitability, business model and macroeconomic state variables in detail. The empirical model is

$$S_{i,t} = \alpha + \mathbf{X}_{i,t}^{profit}\boldsymbol{\beta}^{profit} + \mathbf{X}_{i,t}^{bm}\boldsymbol{\beta}^{bm} + \mathbf{X}_{c,t}^{macro}\boldsymbol{\beta}^{macro} + u_i + v_h + \epsilon_{i,t}, \quad (6)$$

Table 5: Country-specific and bank-specific differences in textual tone scores

	(1)	(2)	(3)
Adjusted R^2 (in %)	I (baseline)	II	III
tone	16.80	29.70	55.70
pos	8.50	20.20	51.10
neg	18.50	31.80	53.90

Note: This table reports adjusted R^2 statistics from separate regressions of *tone*, *pos* and *neg* on bank-specific and country-specific macroeconomic variables, country fixed effects and bank fixed effects. The baseline model (I) only includes the profitability, business model and macroeconomic variables. The second model (II) is augmented by country fixed effects. In the third model (III), country fixed effects are replaced by bank fixed effects.

where i indexes banks, t indexes time (e.g. 2006H1), c indexes countries and h indicates whether t relates to the first or second half of the year. The variable $S_{i,t}$ refers to $tone_{i,t}$, $pos_{i,t}$ or $neg_{i,t}$ of bank i in period t. The vectors $\mathbf{X}_{i,t}^{profit}$, $\mathbf{X}_{i,t}^{bm}$ and $\mathbf{X}_{i,t}^{macro}$ hold the profitability, business model and macroeconomic variables, respectively. We further include bank fixed effects u_i and season dummies (i.e. half-year fixed effects) v_h to control for time-invariant unobservables specific to each bank and to seasonal effects, respectively.[17]

The regression results are reported in Table 6. The variable *impairments* is the profitability variable in the regression of *tone* having the highest statistical significance (column 1). On average, higher impairments are associated with a decrease in *pos* (column 2), an increase in *neg* (column 3) and consequently a decrease in *tone*. While the variable *operatingincome* has a positive and statistically significant relationship with *tone* and *pos*, the variable *operatingexpenses* is statistically insignificant in all three regressions.

Of the business model variables, *interestincome* is statistically significant at the 1 % level while *deposits* and *equity* are statistically significant at the 5 % level. A more stable funding structure, i.e. higher ratios of deposits and equity to total assets, is on average associated with higher levels of *tone*. In terms of economic significance, *deposits* is the most important variable in the regression. Lastly, a larger dependence on interest income is associated with lower textual tone score on average, whereby larger values of *interestincome* coincide with lower values of *pos* and higher values of *neg* on average.

Of the macroeconomic variables, all variables with exception of *inflation* are statistically significant at the 1 % or at the 5 % level. While *gdp* and *interbank* are on average positively associated with *tone*, the variables *term* and *ois* are on average negatively associated with *tone*. All four variables are thereby only associated with *neg*. The negative coefficient on *termspread* is unexpected, given that banks typically engage in maturity transformation, which is more profitable when the spread between long-term and short-term rates is larger. However, since the European sovereign debt crisis falls within the sample period, *term* might also measure sovereign risk, which we expect to be negatively associated with our textual tone score.

To summarize, the results of the analyses carried out in this section strongly suggest that the textual tone score captures relevant information about the fundamentals of the bank. The development of the textual tone score over the sample period is consistent with global events. Moreover, the textual tone score and its components co-vary with important profitability, busi-

[17] Time and country-time fixed effects are not included because they would absorb a large fraction of the variation in bank-specific and macroeconomic variables.

Table 6: Textual tone score, bank characteristics and the macroeconomic environment.

	(1) $tone_t$	(2) pos_t	(3) neg_t
$impairments_t$	-0.12***	-0.07***	0.11***
	(0.02)	(0.02)	(0.03)
$operatingincome_t$	0.10*	0.09**	-0.06
	(0.06)	(0.04)	(0.05)
$operatingexpenses_t$	-0.02	0.02	0.05
	(0.06)	(0.06)	(0.05)
$logta_t$	0.29	0.23	-0.21
	(0.26)	(0.28)	(0.23)
$loans_t$	0.05	-0.07	-0.15**
	(0.07)	(0.07)	(0.08)
$deposits_t$	0.22**	0.22***	-0.12
	(0.09)	(0.08)	(0.09)
$equity_t$	0.10**	0.05	-0.10**
	(0.05)	(0.04)	(0.05)
$interestincome_t$	-0.12***	-0.07**	0.12***
	(0.03)	(0.03)	(0.03)
gdp_t	0.07***	0.02	-0.09***
	(0.02)	(0.02)	(0.02)
$inflation_t$	-0.00	0.00	0.00
	(0.02)	(0.02)	(0.02)
$interbank_t$	0.13***	0.04	-0.17***
	(0.04)	(0.04)	(0.04)
$term_t$	-0.08**	-0.02	0.10***
	(0.03)	(0.03)	(0.04)
ois_t	-0.14***	-0.02	0.19***
	(0.02)	(0.02)	(0.03)
$imputed$	0.05	0.06	-0.01
	(0.06)	(0.06)	(0.06)
Constant	0.98***	0.58***	-0.93***
	(0.10)	(0.10)	(0.10)
Bank fixed effects	Yes	Yes	Yes
Season fixed effects	Yes	Yes	Yes
N	2,805	2,805	2,805
R^2	0.59	0.55	0.58
Adj. R^2	0.56	0.51	0.54

Note: This table documents the results of separate regressions of *tone*, *pos* and *neg* on bank-specific and macroeconomic variables. All variables are standardized. The variable *imputed* indicates whether missing values for an observation have been estimated via interpolation. The standard errors are clustered on the bank level and are reported in parentheses. Bank fixed effects are included as dummy variables. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

ness model and macroeconomic variables, whereas the directions of these relationships are, with the exception of the term spread, as expected.

5 Do Bank Managers Extrapolate Past Fundamentals?

Starting from this section, we introduce the notion of bank manager sentiment. We define bank manager sentiment as the variation in the textual tone score orthogonal to contemporaneous realizations of economic and bank-specific fundamentals. As we are interested in bank manager sentiment rather than the textual tone score, we control for the contemporaneous realizations of economic and bank-specific variables and fixed effects in all the subsequent regressions, so that we can interpret the coefficients of interest as the influence of bank manager sentiment. In this specific section, we explore whether bank manager sentiment score has an extrapolative structure, i.e. whether it is associated with past realizations of economic and financial fundamentals. We therefore estimate the model

$$S_{i,t} = \alpha + \sum_{l=1}^{2} \beta_l S_{i,t-l} + \sum_{l=0}^{2} \gamma_l \mathbf{X}_{i,t-l} + \sum_{l=0}^{2} \boldsymbol{\eta}_l X^{bm}_{i,t-l} + v_h + u_i + \epsilon_{i,t} \tag{7}$$

where the variable $S_{i,t}$ represents either $tone_{i,t}$, $pos_{i,t}$ or $neg_{i,t}$, respectively. The bank-specific and macroeconomic state variables are represented by $\mathbf{X} = \left(X^{profit}_{i,t}, X^{macro}_{i,t}\right)$, while the business model variables are contained in $X^{bm}_{i,t}$. The variables u_i and v_h hold for bank and seasonal fixed effects to control for unobserved time-invariant bank heterogeneity and seasonal effects, respectively. Importantly, controlling for the contemporaneous realizations of the bank-specific, macroeconomic and business-model variables, and for the bank and seasonal fixed effects allows us to interpret the coefficients on the variables of interest ($\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_2$, i.e. the coefficients on $\mathbf{X}_{i,t-1}$ and $\mathbf{X}_{i,t-2}$, the bank-specific and macroeconomic state variables lagged by one and two semesters, respectively) as the relation between past bank-specific and macroeconomic state variables on the one hand, and contemporaneous bank manager sentiment on the other hand. We also control for lagged business model variables ($X^{bm}_{i,t-1}$ and $X^{bm}_{i,t-2}$) and lagged bank textual tone scores variables ($S_{i,t-1}$ and $S_{i,t-2}$) to control for autocorrelation.

Table 7 documents the regression results. We begin by estimating Equation (7) without controlling for auto-correlation, i.e. we drop $S_{i,t-1}$ and $S_{i,t-2}$. The results of these regressions are shown in columns 1 to 3. These columns reveal that there is a statistically significant relationship between the first lag of *gdp* and the one of *ois* on the one hand and *tone* on the other hand (column 1), as well as both components of the latter, except between *neg* and *ois* (columns 2 and 3), while controlling for contemporaneous bank-specific and economic fundamentals. A one standard deviation increase in the first lag of *gdp* is associated with an average increase in bank manager sentiment of approximately 0.08 standard deviation. While lagged *gdp* is positively associated with *pos*, it is negatively associated with *neg*. Conversely, a one standard deviation increase in the first lag of *ois* is associated with an average decrease in *tone* of approximately 0.11 standard deviation. Lagged *ois* is negatively associated with *pos*, and positively associated with *neg* (even though coefficient on the latter is not statistically significant). When focusing on the second lags of *gdp* and *ois*, the significance of the association with bank manager sentiment and its components fades out.

Next, we estimate Equation (7), i.e. we do not drop the lagged textual tone score variables. Columns 4 to 6 of Table 7 document the regression results. The coefficients on the first and second lagged values of *tone* (i.e. β_1 and β_2, respectively) are all positive and statistically significant at the 1% level, suggesting a strong and persistent autocorrelation of those variables. With respect to *gdp*, controlling for lagged sentiment has virtually no impact on the interpretation of its coefficients in the regressions of *tone*, *pos* and *neg*, but reduces their significance. In contrast, *ois* is now not significant anymore albeit the sign of the coefficients stays the same. The interpretation of the results for the second lag of *gdp* and of *ois* are the same as without controlling for autocorrelation, i.e. the coefficients are insignificant. The result that bank managers seem to extrapolate past realizations of *gdp* remains valid when we use the Arellano–Bover/Blundell–Bond system estimator to estimate Equation (7) (columns 7–9 of Table 7).[18] The result is significant for the first lag of *gdp* at the 1% level for both *tone* and *pos*, but insignificant for *neg*. As in the previous specifications, the second lag of *gdp* is insignificant for both *tone*, *pos* and *neg*. The strong autocorrelation is also still present in this last specification where both first and second lags of *tone* and its components are positive and significant at the 1% or at the 5% level (with the exception of the first lag of *pos*).

In summary, the evidence reported in Table 7 is consistent with the hypothesis that bank managers extrapolate economic fundamentals into the future. Past realizations of *gdp* have incremental predictive power for subsequent realizations of bank manager sentiment. Furthermore, the results suggest that bank manager sentiment is strongly auto-correlated, implying that innovations in variables that were found to be correlated with *tone* are also associated with subsequent realizations of *tone*, even after controlling for contemporaneous realizations of bank-specific and macroeconomic fundamentals.

[18]The Arellano–Bover/Blundell–Bond system estimator produces consistent estimates of the coefficients of interest in a dynamic panel setting (Arellano and Bond, 1991; Blundell and Bond, 1998). In a dynamic panel setting, a bias may arise because the first lag of the dependent variable and the error term are correlated (see e.g. Baltagi, 2008). Although this bias decreases with the number of periods (Nickell, 1981), Judson and Owen (1999) show that it can be still quite large when the panel length is as large as 30.

Table 7: Is bank manager sentiment extrapolative in economic fundamentals?

	(1) $tone_{i,t}$	(2) $pos_{i,t}$	(3) $neg_{i,t}$	(4) $tone_{i,t}$	(5) $pos_{i,t}$	(6) $neg_{i,t}$	(7) $tone_{i,t}$	(8) $pos_{i,t}$	(9) $neg_{i,t}$
$impairments_{i,t}$	-0.15***	-0.09***	0.14***	-0.14***	-0.08***	0.14***	-0.14***	-0.05**	0.15***
	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)	(0.04)	(0.04)	(0.03)	(0.05)
$operatingincome_{i,t}$	0.24***	0.22***	-0.16**	0.24***	0.22***	-0.16**	0.22***	0.18**	-0.12
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.08)	(0.08)	(0.08)
$operatingexpenses_{i,t}$	-0.03	-0.04	0.01	-0.06	-0.05	0.05	-0.21**	-0.11	0.16
	(0.08)	(0.07)	(0.09)	(0.08)	(0.07)	(0.09)	(0.09)	(0.08)	(0.10)
gdp_t	0.08***	0.02	-0.11***	0.07**	0.01	-0.11***	0.06**	-0.00	-0.11***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$interbank_t$	-0.22**	-0.19*	0.15	-0.23***	-0.18*	0.19*	-0.22**	-0.09	0.30**
	(0.09)	(0.10)	(0.11)	(0.09)	(0.09)	(0.11)	(0.11)	(0.12)	(0.14)
$term_t$	0.12*	0.09	-0.10	0.15**	0.10	-0.13**	0.14**	0.14**	-0.11*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
ois_t	-0.08**	0.04	0.16***	-0.09**	0.01	0.15***	-0.14***	-0.02	0.21***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
$impairments_{i,t-1}$	-0.01	-0.01	0.00	0.01	-0.01	-0.03	0.00	0.00	-0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
$operatingincome_{i,t-1}$	-0.01	-0.02	-0.01	-0.02	-0.03	-0.01	-0.06	-0.04	0.02
	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.04)	(0.05)	(0.03)	(0.07)
$operatingexpenses_{i,t-1}$	0.02	0.09	0.05	-0.00	0.07	0.07	-0.04	0.09	0.18**
	(0.08)	(0.09)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)	(0.09)	(0.08)
gdp_{t-1}	0.08***	0.06*	-0.07***	0.07**	0.04	-0.06**	0.09***	0.09***	-0.04
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
$interbank_{t-1}$	0.33***	0.21	-0.30**	0.30**	0.20	-0.28*	0.33***	0.11	-0.48***
	(0.12)	(0.14)	(0.14)	(0.12)	(0.14)	(0.15)	(0.12)	(0.13)	(0.17)
$term_{t-1}$	-0.06	-0.02	0.08	-0.10	-0.03	0.11	-0.03	0.01	0.04
	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.09)	(0.09)
ois_{t-1}	-0.11**	-0.10*	0.07	-0.08	-0.09	0.04	-0.09	-0.06	0.11
	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)
$tone_{i,t-1}$				0.17***			0.10**		
				(0.03)			(0.05)		
$pos_{i,t-1}$					0.08**			0.02	
					(0.03)			(0.04)	
$neg_{i,t-1}$						0.21***			0.15***
						(0.03)			(0.04)
$impairments_{i,t-2}$	-0.06***	-0.04*	0.06*	-0.04**	-0.03	0.04	-0.03**	-0.01	0.04
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
$operatingincome_{i,t-2}$	0.08	0.05	-0.08	0.06	0.03	-0.07	0.04	0.01	-0.06
	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
$operatingexpenses_{i,t-2}$	-0.07	-0.06	0.06	-0.05	-0.06	0.01	-0.06	-0.05	0.07
	(0.06)	(0.06)	(0.08)	(0.05)	(0.06)	(0.08)	(0.07)	(0.08)	(0.08)
gdp_{t-2}	0.03	0.00	-0.04*	0.01	0.01	-0.02	0.04	0.04	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
$interbank_{t-2}$	0.00	0.01	0.01	-0.01	0.01	0.04	-0.04	0.12	0.07
	(0.11)	(0.10)	(0.12)	(0.10)	(0.10)	(0.12)	(0.11)	(0.10)	(0.14)
$term_{t-2}$	0.04	0.02	-0.05	0.06	0.02	-0.07	0.02	0.02	-0.03
	(0.05)	(0.04)	(0.06)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
ois_{t-2}	0.02	0.03	0.00	0.03	0.03	-0.02	0.05	0.05	-0.03
	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)	(0.03)
$tone_{i,t-2}$				0.19***			0.13***		
				(0.04)			(0.04)		
$pos_{i,t-2}$					0.22***			0.18***	
					(0.04)			(0.05)	
$neg_{i,t-2}$						0.14***			0.10**
						(0.04)			(0.04)
Constant	0.92***	0.50***	-0.93***	0.52***	0.21*	-0.61***	-0.05	-0.12	0.04
	(0.14)	(0.13)	(0.14)	(0.12)	(0.11)	(0.11)	(0.07)	(0.09)	(0.07)
N	1933	1933	1933	1933	1933	1933	1933	1933	1933
R^2	0.65	0.59	0.64	0.68	0.61	0.67	NA	NA	NA
Adj. R^2	0.61	0.54	0.59	0.64	0.56	0.63	NA	NA	NA

Note: This table documents the results of separate regressions of *tone*, *pos* and *neg* on lagged bank-specific and macroeconomic variables. All specifications include the lagged version of the business model variables specified in Section 4.2 as control variables. All specifications also include the variable *imputed*, which indicates whether missing values for an observation have been estimated via interpolation. All variables are standardized. Specifications 1–3 and 4–6 are estimated with the fixed effects estimator. The standard errors are clustered on the bank level and are reported in parentheses. Specifications 7–9 are estimated with the Arellano–Bover/Blundell–Bond system estimator with robust standard errors. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

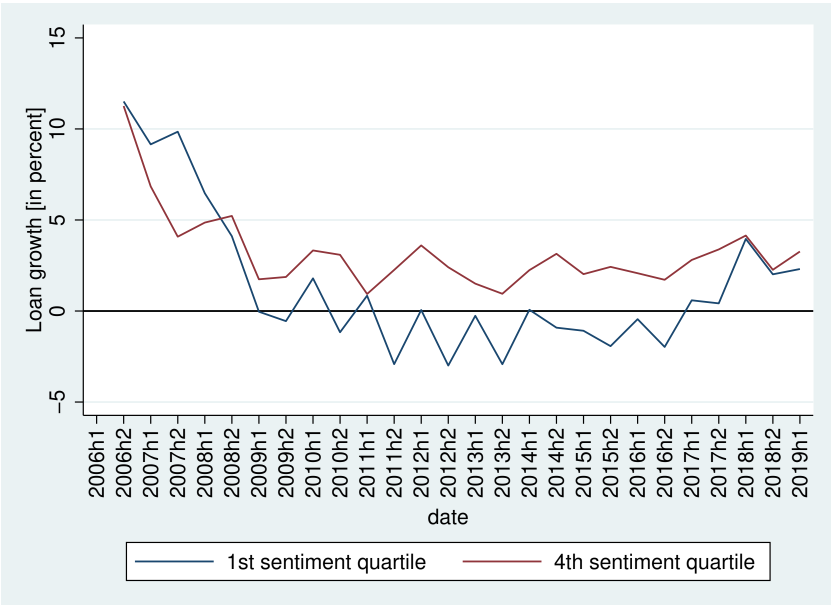
6 Bank Manager Sentiment and the Investment Decisions of Banks and their Investors

In this section, we study whether bank manager sentiment is associated with the investment decisions of banks and their equity investors. In Section 6.1, we explore whether bank manager sentiment has incremental predictive power for the bank's loan growth over the subsequent six months. In Section 6.2, we study whether the sentiment of bank managers influences how bank investors perceive the risk associated with loan growth.

6.1 Is Bank Manager Sentiment Predictive for Loan Growth?

A first look at the average loan growth rates of the banks with the highest textual tone score and the banks with the lowest textual tone score (Figure 5) suggests that the textual tone score is positively associated with loan growth rates.

Figure 5: Average loan growth rates for high and low textual tone score banks



Note: This figure compares the development of loan growth rates for high textual tone score banks and low textual tone score banks. It has been constructed as follows: every six months, banks have been sorted into quartiles based on the textual tone score. The depicted loan growth rates are then calculated as the average of the seasonally-adjusted growth rates over the next six months within the quartiles. Loan growth rates are winsorized at the 5th and 95th percentile.

To test whether there is indeed a difference between the loan growth rates of the two groups, we run regressions of loan growth rates on *tone* and control variables. As we are interested in the component of the textual tone score orthogonal to bank-specific and economic fundamentals, we include the contemporaneous realizations of the bank-specific and macroeconomic controls defined previously. Therefore, we estimate the following model:

$$loan\ growth_{i,t+1} = \alpha + \beta S_{i,t} + \boldsymbol{\gamma} \mathbf{X}_{i,t} + \boldsymbol{\eta} X^{bm}_{i,t} + \boldsymbol{\lambda} X^{bk}_{i,t} + u_i + w_{c,t} + \epsilon_{i,t} \qquad (8)$$

where $\mathbf{X}_{i,t}^{b}k$ is a vector holding for the control variables *cash*, *securities* and *reserves*. The variables u_i and $w_{c,t}$ capture bank and country-time fixed effects, respectively. The coefficient of interest is β. As we control for $X_{i,t}$, $X_{i,t}^{bm}$, $X_{i,t}^{bk}$, u_i and $w_{c,t}$, we can interpret the remaining variation in textual tone score, which identifies β, as bank manager sentiment. All variables are standardized, which enables a better assessment of economic significance.

We first estimate model (8) without $X_{i,t}^{bk}$ and without country-time fixed effects. The regression results documented in the first column of Table 8 suggest that bank manager sentiment on its own is predictive of subsequent loan growth, with a statistical significance at the 1% level. A one standard deviation increase in bank manager sentiment is associated with an average increase in the loan growth rate of 0.16 standard deviations. When distinguishing between the positive and the negative components of *tone*, most of the variation in loan growth rates seems to be driven by *neg*. While both coefficients on *pos* and *neg* are significant at the 1% level, the magnitude of the coefficient of *neg* is three times larger than the one of *pos* (column 2 and 3 of Table 8).

As robustness tests, we include additional control variables and estimate model (8) with country-time fixed effects. When we include the control variables contained in the vector $X_{i,t}^{bk}$ into the model, we find that the coefficients on *tone* and *neg* (columns 4 and 6 of Table 8) are smaller in magnitude than those from the model without those variables (columns 1 and 3), but remain statistically significant at the 1% level. The value of the coefficient on *pos* is mostly unchanged and now only statistically significant at the 5% level. The introduction of country-time fixed effects further reduces the magnitude of the coefficients on *tone* and *neg*, the former being statistically significant at the 5% level as a result (columns 7 and 9). Compared with the previous estimations, the coefficient on *pos* in column 8 of Table 8 is still positive but has a much lower value and is not significant anymore. Even if bank manager sentiment on its own is predictive of subsequent loan growth (given the significance at the 1% level of the coefficient of *tone*), it has only weak incremental explanatory power. When we run the same model, but without the textual tone score or each of its components as regressor [19], we indeed find an adjusted R^2 of 0.305, compared to an adjusted R^2 of 0.307 for the fully specified model (column 7), where most of the variation seems to be driven by the negative component with an adjusted R-squared of 0.309 (column 9).

In summary, our empirical results suggest that bank manager sentiment is significantly and positively associated with subsequent loan growth. However, bank manager sentiment overall has limited explanatory power that is derived from its component *neg*.

[19]The results are available from the authors upon request.

Table 8: Is bank manager sentiment predictive of loan growth?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$
$tone^*_{t-1}$	0.1569***			0.1321***			0.0803**		
	(0.0330)			(0.0312)			(0.0319)		
pos^*_{t-1}		0.0591***			0 .0570**			0.0179	
		(0.0279)			(0. 0272)			(0.0294)	
neg^*_{t-1}			-0.1724***			-0.1375***			-0.0995***
			(0.0336)			(0.0330)			(0.0340)
imputed	0.1572*	0.1324	0.1520*	0.0555	0 .0439	0.0502	-0.0315	-0.0397	-0.0311
	(0.0813)	(0.0815)	(0.0799)	(0.0755)	(0. 0750)	(0.0755)	(0.0845)	(0.0840)	(0.0841)
Constant	-0.0204***	-0.0136*	-0.0203***	0.2047***	0 .2078***	0.2063***	-5.0900	-4.1922	-5.0283
	(0.0077)	(0.0076)	(0.0075)	(0.0425)	(0. 0435)	(0.0427)	(9.0336)	(9.1226)	(8.7695)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
N	2417	2417	2417	2208	2208	2208	2208	2208	2208
R^2	0.0419	0.0072	0.0550	0.1991	0 .1922	0.2002	0.4508	0.4488	0.4521
Adj. R^2	0.0411	0.0064	0.0543	0.1925	0 .1855	0.1936	0.3070	0.3045	0.3086

Note: This table reports the results of separate regressions of loan growth on *tone*, *pos*, *neg*. All variables are standardized. The controls include *impairments*, *operatingincome*, *operatingexpenses*, *logta*, *loans*, *deposits*, *equity*, *interestincome*, *gdp*, *inflation*, *interbank*, *term*, *ois*. The additional controls refer to the vector $X^{bk}_{i,t}$ and hence include *cash*, *securities*, and *reserves*. The variable *imputed* indicates whether missing values for an observation have been estimated via interpolation. The standard errors are clustered on the bank level and are reported in parentheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

6.2 Bank Manager Sentiment and the Risk Associated with Loan Growth

In the previous section, we have studied the influence of bank manager sentiment on bank behavior, i.e. lending decisions. Now, we turn to the question of whether bank manager sentiment spills over to their equity investors. As has been shown empirically, equity investors and analysts are sometimes too optimistic when assessing the risk–return profile of high growth banks (see e.g. Baron and Xiong, 2017; Fahlenbrach et al., 2017). Fahlenbrach et al. (2017), in particular, show that equity analysts systematically underestimate the risk associated with high loan growth rates.

Motivated by this empirical evidence, we ask whether equity investors' assessments of the risk associated with bank loan growth is influenced by the sentiment of bank managers. More specifically, we explore whether bank equity investors interpret the combination of a high loan growth rate and high bank manager sentiment as a signal for "healthy" loan growth, i.e. loan growth that creates value for the bank and its investors. We measure the equity market participants' assessment of bank risk by *SRISK* scaled by the enterprise value of the respective banks (see Section 3.4). Since it is based on equity market prices, *SRISK* is a forward-looking measure that is driven by market participants' assessments for the outlooks for cash flows and exposures to equity market risk. This leads us to the following predictions: Investors interpret high bank manager sentiment as a positive signal for the risk associated with bank loan growth. Higher values of bank manager sentiment are negatively associated with the relationship between $SRISK$ and loan growth. To test these predictions, we estimate the following model:

$$\begin{aligned} SRISK_{i,t} &= \alpha + SRISK_{i,t-1} + \beta_1 \times loangrowth_{i,t-1} \\ &\quad + \beta_2 \times tone_{i,t-1} + \beta_3 \times tone_{i,t-1} \times loangrowth_{i,t-1} \\ &\quad + \boldsymbol{\gamma}\mathbf{X}_{i,t-1} + u_i + w_{c,t} + \epsilon_{i,t} \end{aligned} \tag{9}$$

where the vector $\mathbf{X}_{i,t} = \left(X_{i,t}^{profit}, X_{i,t}^{bm}\right)$ holds the bank-specific control variables used in the previous regressions and the variables u_i and $w_{c,t}$ are bank and country-time fixed effects, respectively. Using the same logic as before, as we control for contemporaneous bank-specific and macroeconomic fundamentals, the coefficient of interest, β_3, can be interpreted as how the relationship between $SRISK$ and loan growth depends on bank manager sentiment.

We lag the explanatory variables by one period for two reasons. First, financial results and the corresponding press releases are typically released a few weeks after the end of the reporting period. Because the book value of total debt is an input in the calculation of *SRISK*, $SRISK_{i,t}$ is thus also observable only after the release of the financial statement. Second, to avoid that our results suffer from both hindsight bias and endogeneity problems, we use the next observable realization, $SRISK_{i,t+1}$ as our dependent variable. We also include the first lag of $SRISK$ as a control variable, given that it is highly persistent.

The regression results are documented in Table 9. All variables are standardized. Columns 1 and 2 of Table 9 report the results from nested versions of the model specified in Equation (9). These nested versions only include $loangrowth_{t-1}$ (column 1) and $loangrowth_{t-1}$ and $tone_{t-1}$ (column 2), respectively. The results reported in both columns suggest that the two variables are negatively associated with $SRISK$, but the relationship is not significant. When we distinguish by bank manager sentiment (column 3), we are also able to detect a negative but statistically insignificant relationship between bank loan growth and bank risk for banks with the most optimistic bank managers.

Since we include the first lag of the dependent variable as a control variable in our regressions, a concern with the results in columns 1–3 is dynamic panel bias (see also Section 5). To increase the robustness of our results, we re-estimate the specifications in columns 1–3 using the Arellano–Bover/Blundell–Bond system estimator. The results are reported in columns 4–6 of Table 9 and suggest that dynamic panel bias is an issue with the OLS results. Notable differences between the results from the Arellano–Bover/Blundell–Bond system estimator and that from the OLS estimator are that the coefficient on $tone_{t-1}$ in column 5 is statistically significant at the 5% level. The results in column 5 suggest that a one standard deviation increase in $tone_{t-1}$ is on average associated with an 0.0272 standard deviations decrease in $SRISK_t$. The results in column 6 suggest that the Arellano–Bover/Blundell–Bond system only changes the statistical significance of the coefficient of $tone_{t-1}$ (at the 10% level) but not its economic interpretation and does not change the conclusion for the coefficient of the interaction between $tone_{t-1}$ and $loangrowth_{t-1}$ (still negative but insignificant).

In summary, the results documented in columns 3 and 6 of Table 9 support that the sentiment of bank managers has a negative influence on how equity investors perceive the riskiness of a bank, but does not support the hypothesis that it has a statistically significant negative influence on the association between the sentiment of bank managers and loan growth.[20] In both cases, the coefficients on $tone_{t-1}$ are negative (and statistically significant at the 10% level in the case of the Arellano–Bover/Blundell–Bond system estimation), respectively. The coefficients on the interaction between $loangrowth_{t-1}$ and $tone_{t-1}$ are negative but statistically insignificant for both the OLS and Arellano–Bover/Blundell–Bond estimations, respectively. Given that dynamic panel bias might be an issue when estimating Equation (9), the estimates from the Arellano–Bover/Blundell–Bond system estimator are likely to have the lowest bias. We therefore consider the estimates reported in column 6 of Table 9 as the best estimate of the effect of bank manager sentiment and of the interaction between loan growth and bank manager sentiment.

Table 9: Does bank manager sentiment spill over to equity investors?

	(1)	(2)	(3)	(4)	(5)	(6)
	$SRISK_t$	$SRISK_t$	$SRISK_t$	$SRISK_t$	$SRISK_t$	$SRISK_t$
$loangrowth_{t-1}$	-0.0204*	-0.0197	-0.0195	0.0013	0.0019	0.0040
	(0.0122)	(0.0120)	(0.0119)	(0.0101)	(0.0101)	(0.0099)
$tone^*_{t-1}$		-0.0208	-0.0208		-0.0272**	-0.0204*
		(0.0160)	(0.0159)		(0.0132)	(0.0119)
$loangrowth_{t-1} \times sent^*_{t-1}$			-0.0053			-0.0254
			(0.0174)			(0.0185)
$SRISK_{t-1}$	0.6686***	0.6678***	0.6677***	0.4229***	0.4207***	0.4214***
	(0.0547)	(0.0546)	(0.0549)	(0.0596)	(0.0587)	(0.0560)
Constant	5.0103*	4.8347*	4.6930	21.0017	20.7769	21.2870
	(2.7924)	(2.8090)	(2.8718)	(29.3188)	(30.0985)	(29.2500)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1169	1169	1169	1169	1169	1169
R^2	0.8685	0.8689	0.8690	NA	NA	NA
Adj. R^2	0.8100	0.8110	0.8110	NA	NA	NA

Note: This table reports the results from regressions of scaled $SRISK$ on *loangrowth*, *tone* and bank-specific and macroeconomic control variables. The control variables include *impairments*, *operatingincome*, *operatingexpenses*, *logta*, *loans*, *deposits*, *equity*, *interestincome*, *gdp*, *inflation*, *interbank*, *term*, *ois* and a dummy for whether missing values for an observation have been estimated via interpolation. All variables are standardized. Specifications 1–3 are estimated with the fixed-effects estimator (OLS). The standard errors are clustered on the bank level and are reported in parentheses. Specifications 4–6 are estimated with the Arellano–Bover/Blundell–Bond system estimator with robust standard errors. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

[20] In this context, a negative influence means lower risk.

7 Summary and Discussion

This paper provides evidence on how systematic over-optimism on the part of bank managers directly or indirectly affects the amount of credit that they supply to the real sector. Based on a textual tone score extracted from earnings press release documents and identifying bank manager sentiment as the variation of the score orthogonal to current realizations of bank-specific and macroeconomic fundamentals, we have documented three main findings. First, bank manager sentiment is partially backward-looking, i.e. it depends positively on past realizations of economic fundamentals, implying that it is on average too high relative to current fundamentals. Second, bank manager sentiment is on average positively associated with loan growth rates over the subsequent six months. Third, bank manager sentiment influences equity investors' assessments of the bank's systemic risk in that, the banks with the most over-optimistic managers are perceived as less risky than the banks with the most over-pessimistic managers.

Taken together, these three findings suggest that systematic over-optimism on the part of banks and their investors affect credit market outcomes. More specifically, findings one and two suggest that decisions on the volume of new loans partially depend on past realizations of economic fundamentals. If this is the case, a financial stability implication will be that banks extend too much credit in a scenario where recent economic fundamentals were good, but where these fundamentals have already started to deteriorate. As a result, banks will be overly exposed to loan default risk, which threatens their solvency and adversely affects their ability to extend new loans. Findings one and three suggest that over-optimism on the part of bank managers also spills over to their equity investors, who then underestimate their perceived risk of the banks.

An interesting question for future research is whether bank managers are aware of investors' increasing use of textual analysis tools and have started to strategically alter their language in their corporate disclosures so that they appear more optimistic than they actually are (see e.g. Huang et al. (2013) and Cao et al. (2020)). One possible implication of such a behavior in the context of this paper is that textual tone scores are biased upwards, whereas the biases are likely to be specific to each bank, depending on whether and when European bank managers have started to strategically manage the textual tone score of their corporate disclosures. Moreover, our decision to define bank manager sentiment as the part of textual tone scores orthogonal to a set of bank-specific and macroeconomic variables might introduce additional biases as the decision to begin managing the content of corporate disclosures might alter the relationships between the resulting textual tone score and economic fundamentals.

In relation to whether and to what extend bank managers strategically manage the content of their corporate disclosures, another question for future research is whether investors eventually recognize such a behavior. In general, it would be very interesting to explore whether there is a feedback loop between how optimistic bank managers choose to appear and how investors assess current and future bank performance and risk.

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