Bank Manager Sentiment, Loan Growth and Bank Risk*

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Abstract

We build a measure of the sentiment of bank managers from earnings press release documents. Using this measure, we present evidence on how banks' systematic over-optimism might affect 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 interpret high bank manager sentiment as a positive signal for the risk associated with bank loan growth. Higher values of bank manager sentiment are associated with a weaker relationship between loan growth and the perceived riskiness of a bank.

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 (Benanke 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. causing 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 sentiment of bank managers from bank earnings press release documents using textual analysis methods. According to the accounting literature, managers use corporate disclosures to signal their expectations about future firm outcomes (Li, 2010; Davis et al., 2012). 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 sentiment 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 sentiment score with bank-specific and macroeconomic variables. The results of these analyses strongly suggest that the textual sentiment 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 sentiment 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 sentiment on average. Since we are interested in the incremental informational content of the earnings press release documents, we control for

[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).

the influence of the bank-specific and macroeconomic variables from the textual sentiment score in a linear regression setting and define the residual component as the bank manager sentiment index.[2]

Second, we explore whether the bank manager sentiment index has an extrapolative structure, i.e. whether it is associated with past realizations of economic fundamentals.[3] Expectations with 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).[4] 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 the bank managers' expectations are partially backward looking. First, we document that GDP growth rates have incremental predictive power for future values of the bank manager sentiment index. Second, we find that the bank manager sentiment index is auto-correlated, implying that innovations in variables that were found to be correlated with the bank manager sentiment index are also associated with its subsequent realizations.

Third, we study whether the bank manager sentiment index is associated with the investment decisions of banks and their equity investors. On the part of banks, we explore whether the bank manager sentiment index 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 the bank manager sentiment index 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 the bank manager sentiment index has incremental but weak predictive power for loan growth over the subsequent six months. When we replace the bank manager sentiment by its components, we find that the predictive power of the bank manager sentiment index 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 the sentiment of bank managers 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 the bank manager sentiment index is related to

[2]The name is inspired by the manager sentiment index of Jiang et al. (2019).

[3]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 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).

[4]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.

the perceived risk associated with bank loan growth and that this perceived risk is lower when bank managers are more optimistic.[5] Using *SRISK* (Brownlees and Engle, 2016) as our measure for the risk perception of market participants, we find that the association between loan growth and risk decreases in the bank manager sentiment index. However, the relationship between loan growth and risk is only negative if the bank manager sentiment index is relatively high, i.e. more than two standard deviations above its unconditional mean.

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 sentiment score and other variables used throughout the paper. Section 4 studies the development of textual sentiment scores over time, their relationships with important bank-specific and macroeconomic variables and defines the bank manager sentiment index. Section 5 explores whether bank manager sentiment is extrapolative in past fundamentals. Sections 6.1 examines whether the bank manager sentiment index is predictive for subsequent loan growth rates. Section 6.2 studies whether the perception risk associated with bank loan growth by bank equity investors differs when bank managers are optimistic versus when they are pessimistic. Finally, Section 7 summarizes and discusses the results.

2 Literature Overview

Our paper contributes to three strands of research. First, it is related to the literature that links credit cycles to behavioral factors, which 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

[5] 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.

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.

Second, 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 crisis (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) 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.

Third, 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 approaches, machine learning) and use different ways to calculate an aggregate sentiment score from the classified text contents (Kearney and Liu, 2014). Overall, the empirical evidence suggests that the textual sentiment of corporate disclosures contains incremental informational content about the future performance of the reporting firms and that market participants respond to textual sentiment. 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 sentiment for future earnings. He finds that textual sentiment 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 sentiment 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 sentiment 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 sentiment is more positive if firms have strong incentives to bias investor expectations upward and that higher sentiment 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 index from firm-level textual sentiment. 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. Our paper is the closest related to the strand of the literature that uses a dictionary-based approach to classify words as positive or negative and calculates sentiment by subtracting the share of positive words by the share of negative words (also called net sentiment), i.e. Davis et al. (2012), Huang et al. (2013) and Jiang et al. (2019). Using a new sample of European banks, we extend the literature by showing that textual sentiment of earnings press release documents is associated with the investment decisions of banks and their equity investors.

3 Data

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

3.1 Textual Sentiment

Our measure of bank manager sentiment is based on the textual sentiment of bank earnings press release documents. Our textual sentiment 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).[6] Bank earnings press releases in the SNL database are

[6]The Developed Europe category in the S&P Global Market Intelligence database comprises Austria, Belgium, Cyprus, Denmark, Finland, France, Greece, Iceland, Ireland, Italy,

available starting from the first quarter of the year 2005. Our textual sentiment sample ends in the second quarter of the year 2019.

It takes three steps to transform earnings press release documents into final textual sentiment scores. The first step is to calculate textual sentiment 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.[7] Based on the document-specific word lists, we then classify the words as having a positive connotation, having a negative connotation, or as 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. Finally, we follow Davis et al. (2012), Huang et al. (2013) and Jiang et al. (2019) and calculate the textual sentiment score, $sent_{i,p,d}$, 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.

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

The variables $N^{pos}_{i,t,d}$, $N^{neg}_{i,t,d}$ and $N_{i,t,d}$ 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 sentiment 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 complex sentences formulations, conjunctions, irony, etc). To tackle this issue, we did a robustness check by using a machine learning approach as an alternative method to compute our textual sentiment score. 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 used FinBERT, a financial domain specific BERT (Bidirectional Encoder Representation from Transformers) model [8] created by Yang et al. (2020). In practice, both BERT and FinBERT require a

Luxembourg, Malta, Netherlands, Norway, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom.

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

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

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 did not fine-tune FinBERT to our earnings press release documents. Instead, we used the pre-trained and fine-tuned version provided by Yang et al. (2020) to predict the sentiment of each of the financial statements in our dataset. In order to match the level of analysis of the fine-tuning, we predicted the sentiment of our sample of financial press releases at the sentence level, aggregated the sentences' sentiment at the document level, and adjusted by the number of sentences in each document. As we will see later on, this machine learning approach gives very similar results to our dictionary approach.

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 sentiment 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 *sent*, *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 sentiment score time-series. About one third of the banks in the textual sentiment 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 sentiment 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 *sent*, *pos* or *neg* and $p1$ and $p2$ refer to the first and second quarter, respectively, within t. A detailed analysis of the final textual sentiment scores is presented in Section 4.

Our approach to extract textual sentiment 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 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 sentiment 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.

3.2 Accounting Data

We merge the textual sentiment dataset with a dataset containing semi-annual accounting data of European banks from SNL.[9] 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*, that 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 sentiment dataset and the accounting dataset as well as for the banks, for which no textual sentiment 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 1.17 billion) and also very large banks (the ninth decile is 1,275.13 billion), as measured by their total assets (*ta*).[10] 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 (*intinc*)[11]. 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 (*opinc*) was barely sufficient to cover operating expenses (*opexp*) and impairments on loans and securities (*impair*).

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

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

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

[11]We have winsorized the variable *intinc* 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	*ta*	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	*secs*	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	*opinc*	SNL	SNL Codes: 225155 (operating income), 132264 (total assets)
Net interest income to net operating income	*intinc*	SNL	SNL Codes: 132553 (net interest income), 225155 (operating income)
Operating expenses to total assets	*opexp*	SNL	SNL Codes: 225159 (operating expenses), 132264 (total assets)
Total impairments to total assets	*impair*	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	*infl*	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

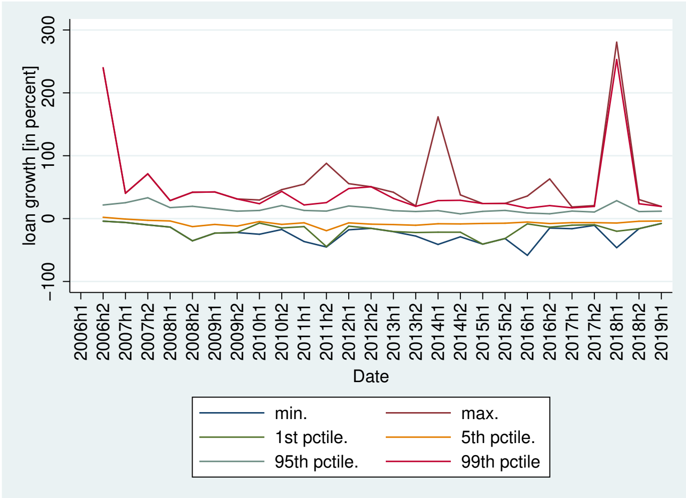
Table 2: Summary statistics

Panel A: Bank-level variables	Textual sentiment sample						No textual sentiment available						
Variable	N	mean	std	p5	p50	p95	N	mean	std	p5	p50	p95	$\Delta mean$
Balance sheet and income variables													
ta (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*
secs (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***
intinc (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													
opinc (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
opexp (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
impair (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 sentiment sample						No textual sentiment 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
infl (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 sentiment is available, are reported in columns 2–7. Columns 8–13 report the summary statistics for European banks, for which no textual sentiment 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



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 sentiment sample account for a large majority of outstanding loans, our results may nevertheless contribute to our understanding of aggregate credit cycles.

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 sentiment scores and accounting data. All macro-level variables are country-specific and relate to the same reporting period as the textual sentiment score and the accounting data.[12] The macro-level variables are GDP growth (nominal, seasonally adjusted; *gdp*), the consumer price inflation rate (*infl*), the three month interbank rate (*interbank*), the OIS swap rate (*ois*) and the term spread (*term*) (see Table 1). The variables *gdp* and *infl* 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.[13] 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

[12]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 sentiment 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. An additional measure to increase the robustness of our results would be to also include these values in our empirical analyses.

[13]Not accounting for publication lags does not seem to pose a problem. Robustness checks (not shown), in which we account for these publication lags, yield very similar results.

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 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 which textual sentiment 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 sentiment 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 formular 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 the Long Run Marginal Expected Shortfall (LRMES), respectively, of bank i in period t. 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.[14] 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

[14]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*.

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 the 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 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 ($W_{i,t} + debt_{i,t}$).[15]

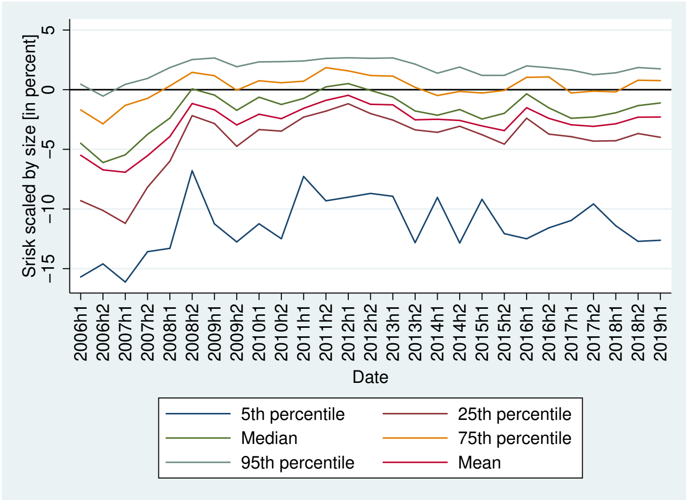
Figure 2 depicts the distribution of scaled *SRISK* over the sample period. *SRISK* has been negative on average in the large majority of periods, meaning that the banks in our sample had capital surpluses on average. Periods with particular high levels of risk have been the second half of 2008 (the 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.

4 The Properties of Textual And Bank Manager Sentiment Scores

The aim of this section is to verify the validity of our textual sentiment scores. We first study the developments of the textual sentiment scores and the shares of positive and negative words, respectively, over time from the dictionary approach. We also compare this score with the one obtained using the machine learning approach. We then explore the relationship between the three textual sentiment variables and important bank-specific and macroeconomic variables. In the last step, we describe how we construct the bank manager sentiment index from textual sentiment scores.

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

Figure 2: The distribution of SRISK over the sample period

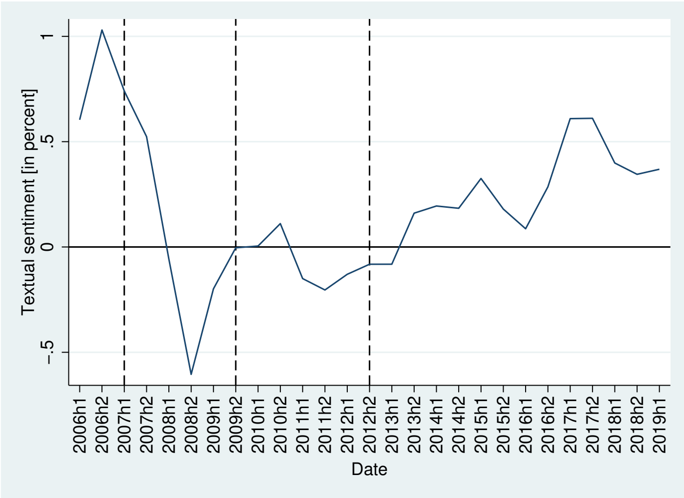


4.1 Textual Sentiment Scores Over Time

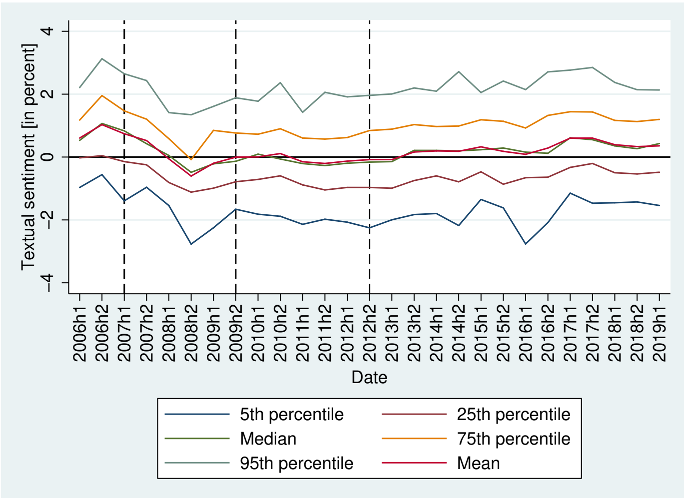
Figures 3a and 3b depict the textual sentiment score using the dictionary approach over the sample period.

As shown by Figure 3a, the average textual sentiment score is pro-cyclical. Consistent with global events, the average of *sent* 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 *sent* 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 *sent* 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 *sent*, which has its start in the year 2013, is driven by opposing trends in *pos* and *neg*.

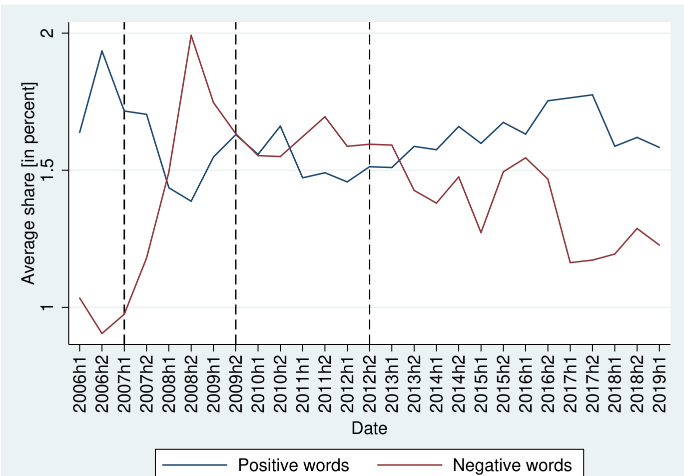
Figure 3: Textual sentiment (dictionary approach)



(a) Average textual sentiment score over time



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



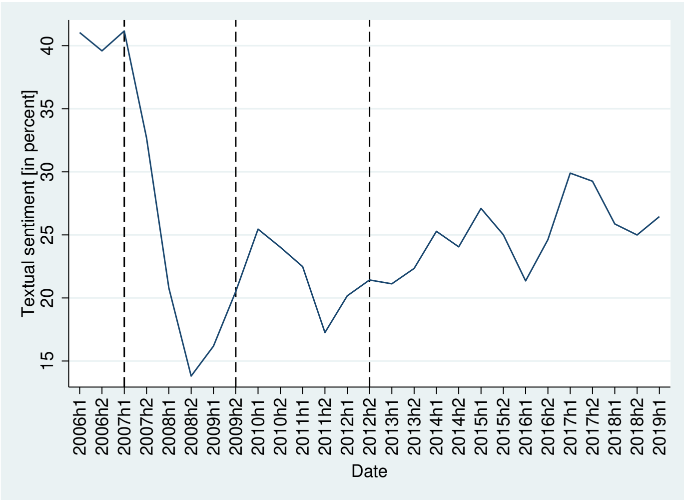
(c) The averages of *pos* and *neg*

Note: These figures plot properties of the average sentiment score (Figure 3a), the distributions of *sent* (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.

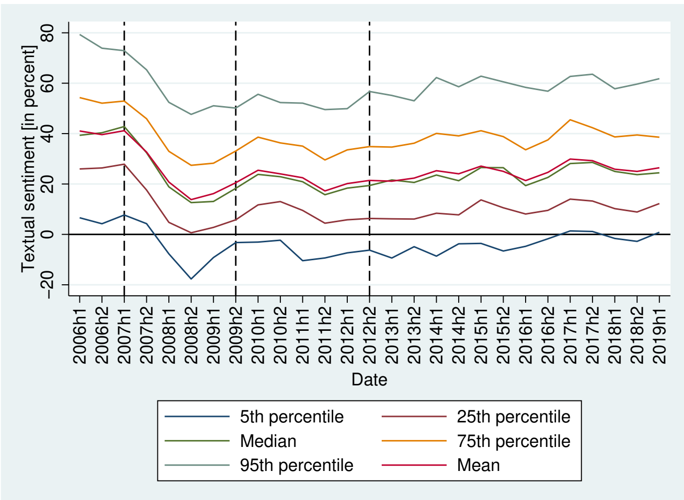
As a robustness check, we then compute the sentiment score for each press release obtained by using a machine learning approach (FinBERT). As FinBERT is fine-tuned at the sentence level, we compute a sentiment score for each sentence of our press releases. We then aggregate those scores at the press release level by summing the sentences' scores and by dividing this sum by the number of sentences in the press release. The average sentiment score over time and its distribution across banks are shown in the Figures 4a and 4b. The evolution of both the average sentiment 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 sentiment score obtained from the machine learning approach over the sentiment score obtained from the dictionary approach at the bank-time level. Including bank fixed effects has the advantage of taking into account the specificity of each bank when computing our sentiment score. However, if the rank of the sentiment 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 sentiment 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 sentiment 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 sentiments 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 sentiment scores obtained from both approaches, we choose to focus only on the sentiment score obtained from the dictionary approach in the rest of the paper.

Figure 4: Textual sentiment (machine learning approach)



(a) Average textual sentiment score over time



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

Note: These figures plot properties of the average sentiment score (Figure 4a) and the distributions of *sent* (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 sentiment score from the machine learning approach ($sent_t(ML)$) over the sentiment score from the dictionary approach ($sent_t(DICT)$)

	$sent_t(ML)$	$sent_t(ML)$	$sent_t(ML)$
$sent_t(DICT)$	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 parenthesis. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

Table 4: Spearman's rank correlation (ρ) between the sentiment score from the dictionary and from the machine learning approaches

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 Sentiment Scores At The Bank Level

To shed some light on the informational content of the textual sentiment scores, we run separate regressions of *sent*, *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 *opinc*, *opexp* and *impair*. Given that textual sentiment scores are extracted from earnings press release documents, we expect that the profitability variables are directly related to *sent*. The business model indicators include *loans*, *deposits*, *equity*, *intinc* and the logarithm of *ta*. 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 *sent*. Finally, the set of country-specific macroeconomic state variables encompasses *gdp*, *infl*, *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 *sent* and *ois* to be negatively associated with *sent*.

4.2.1 Country-specific And Bank-specific Differences In Textual Sentiment Scores

Differences in culture and communication styles across countries and banks may have a significant impact on textual sentiment 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 *sent*, *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 sentiment 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 the three textual sentiment variables. 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 *sent*, *pos* and *neg*. They also highlight the necessity to control for bank fixed effects in the following investigations.

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

Adjusted R^2 (in %)	(1) I (baseline)	(2) II	(3) III
sent	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 *sent*, *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 variabes. The second model (II) is augmented by country fixed effects. In the third model (III), country fixed effects are replaced by bank fixed effects.

4.2.2 The Textual Sentiment Score, Bank Characteristics And The Macroeconomic Environment

Next, we study the relationships between the three textual sentiment variables and the profitability, business model and macroeconomic state variables in detail. The empirical model is

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

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 $sent_{i,t}$, $pos_{i,t}$ 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.[16]

The regression results are reported in Table 6. Somewhat surprisingly, *impair* is the only profitability variable in the regression on *sent* that is statistically different from zero (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 *sent*. While the variable *opinc* has only a positive and statistically significant relationship with *pos*, the variable *opexp* is statistically insignificant in all three regressions.

Of the business model variables, *deposits*, *equity* and *intinc* 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 *sent*. 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 bank manager sentiment on average, whereby larger values of *intinc* coincide with lower values of *pos* and higher values of *neg* on average.

Of the macroeconomic variables, all variables with exception of *infl* are statistically significant at the 5 % level. While *gdp* and *interbank* are on average

[16]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.

positively associated with *sent*, the variables *term* and *ois* are on average negatively associated with *sent*. 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 textual sentiment.

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

	(1) $sent_t$	(2) pos_t	(3) neg_t
$impair_t$	-0.12***	-0.07***	0.11***
	(0.02)	(0.02)	(0.03)
$opinc_t$	0.10*	0.09**	-0.06
	(0.06)	(0.04)	(0.05)
$opexp_t$	-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)
$intinc_t$	-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)
$infl_t$	-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 *sent*, *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 parenthesis. Bank fixed effects are included as dummy variables. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

4.2.3 The Bank Manager Sentiment Index

In the previous section, we have shown that the textual sentiment score and its components are related to variables that capture important bank characteristics and the macroeconomic environment in which the banks operate. We have also shown that bank fixed effects, which are likely to capture time-invariant aspects of the banks' culture and communication styles, are the most important determinant of textual sentiment. Together, these variables explain about 60 % of the variation in textual sentiment. The high overlap between the textual sentiment score and these variables indicates that the textual sentiment score is a valid indicator of the sentiment of bank managers.

We assume that the non-overlapping part of the textual sentiment score, i.e. the remaining 40 % of the variance that remains unaccounted for, reflects information about the sentiment of bank managers. We therefore define a new sentiment variable, the bank manager sentiment index, which are the residuals from the regression of the textual sentiment score on the profitability variables, business model variables, macroeconomic variables, seasonal (half-year) fixed effects and bank fixed effects:[17]

$$sent^{*}_{i,t} = sent_{i,t} - (\hat{\alpha} + \mathbf{X}^{profit}_{i,t}\hat{\boldsymbol{\beta}}^{profit} + \mathbf{X}^{bm}_{i,t}\hat{\boldsymbol{\beta}}^{bm} + \mathbf{X}^{macro}_{c,t}\hat{\boldsymbol{\beta}}^{macro} + \hat{u}_i + \hat{v}_h). \quad (7)$$

The components of the textual sentiment score *pos* and *neg* are orthogonalized accordingly, resulting in the variables pos^* and neg^*.

4.3 Summary

The results of the analyses carried out in this chapter strongly suggest that the bank manager sentiment index captures relevant information about the fundamentals of the bank. The development of the bank manager sentiment over the sample period is consistent with global events. Moreover, the bank manager sentiment index and its components co-vary with important profitability, business 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?

In this section, we explore whether the bank manager sentiment index has an extrapolative structure, i.e. whether it is associated with past realizations of the bank-specific and macroeconomic variables. We therefore estimate the model

$$S^{*}_{i,t} = \alpha + \beta_1 S^{*}_{i,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\beta}_2 + X^{bm}_{i,t-1}\boldsymbol{\beta}_3 + v_h + u_i + \epsilon_{i,t}, \quad (8)$$

[17] With this definition of the bank manager sentiment index, we treat the relationships between textual sentiment scores and bank-specific and macroeconomic fundamentals as linear and time-invariant. This assumption might be inappropriate, for example because the relationships between textual sentiment scores and bank-specific and macroeconomic fundamentals might be dependent on whether the macro-economy is booming or in a recession period or whether a bank has financial problems or not. If this is the case, the bank manager sentiment index will still contain information about fundamentals. However, the relatively low number of sample periods constitute a problem for the estimation of more complex, non-linear models of textual sentiment. We therefore do not consider more complex models.

where the variable $S^*_{i,t}$ represents either $sent^*_{i,t}$, $pos^*_{i,t}$ or $neg^*_{i,t}$, respectively. The vector $\boldsymbol{\beta}_2$ holds the coefficients on the variables of interest, which are the bank-specific and macroeconomic state variables, $\mathbf{X} = \left(X^{profit}_{i,t}, X^{macro}_{i,t}\right)$, lagged by one month. To isolate the effect of past fundamentals on sentiment, we control for lagged business model variables, $X^{bm}_{i,t}$ and lagged bank sentiment variables, $S^*_{i,t-1}$, whereas the lagged sentiment variables are not included in all specifications. Finally, we include bank fixed effects u_i and seasonal dummies v_h to control for unobserved time-invariant bank heterogeneity and seasonal effects, respectively.[18]

Table 7 documents the regression results. We begin by estimating Equation (8) without controlling for the auto-correlation inherent in the sentiment variables, i.e. we drop $S^*_{i,t-1}$. The results of these regressions are shown in columns 1 to 3. These columns reveal that there is a statistically significant relationship between lagged *gdp* and $sent^*$ (column 1), as well as both components of the latter (columns 2 and 3). One standard deviation increase in lagged *gdp* is associated with average increase in $sent^*$ of approximately 0.10 standard deviations. While lagged *gdp* is positively associated with *pos*, it is negatively associated with neg^*.

Next, we estimate Equation (8), i.e. we do not drop the lagged textual sentiment variables. Columns 4 to 6 of Table 7 document the regression results. The coefficients on the lagged textual sentiment variables all are positive and statistically significant at the 5% level. With respect to *gdp*, controlling for lagged sentiment has virtually no impact on its coefficients and standard errors in the regressions of $sent^*$, pos^* and neg^*. In contrast to the specifications in which the first lags of the dependent variables are not included (columns 1–3), the coefficient on lagged *ois* is statistically significant at the 5% level in column 4. As the result in column 4 suggests, a one standard deviation increase in lagged *ois* is on average associated with an increase in $sent^*$ of 0.07 standard deviations. 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 (8) (columns 7–9 of Table 7).[19] The results documented in columns 7–9 also suggest that lagged *ois* is not associated with either $sent^*$, pos^* or neg^*, which contradicts the results obtained by the OLS estimator.

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 the bank manager sentiment index. Furthermore, the results suggest that the bank manager sentiment index is auto-correlated, implying that innovations in variables that were found to be correlated with $sent^*$ are also associated with subsequent realizations of $sent^*$.

[18]To take into account the uncertainty of our estimation, in an additional exercise, we estimated both Equations (7) and (8) by using the block-bootstrap method resampling over the banks' dimension . We found similar results to the ones presented in this section.

[19]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 quiet large when the panel length is as large as 30.

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

	(1) $sent^*_t$	(2) pos^*_t	(3) neg^*_t	(4) $sent^*_t$	(5) pos^*_t	(6) neg^*_t	(7) $sent^*_t$	(8) pos^*_t	(9) neg^*_t
$impair_{t-1}$	-0.04	-0.03	0.02	-0.04	-0.03	0.02	-0.02	-0.04	-0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.04)
$opinc_{t-1}$	-0.00	-0.01	-0.01	0.00	-0.01	-0.01	-0.11	-0.05	-0.01
	(0.05)	(0.06)	(0.04)	(0.04)	(0.05)	(0.04)	(0.10)	(0.04)	(0.05)
$opexp_{t-1}$	-0.01	0.03	0.04	-0.00	0.03	0.03	0.06	0.08	0.15
	(0.12)	(0.11)	(0.08)	(0.10)	(0.10)	(0.07)	(0.16)	(0.15)	(0.13)
gdp_{t-1}	0.10***	0.07**	-0.08***	0.11***	0.08**	-0.09***	0.12***	0.10***	-0.09***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$interbank_{t-1}$	0.01	0.01	-0.01	0.00	0.01	0.00	0.11	0.06	-0.09
	(0.08)	(0.06)	(0.08)	(0.07)	(0.06)	(0.06)	(0.09)	(0.07)	(0.11)
$term_{t-1}$	0.07	0.05	-0.06	0.07*	0.05	-0.05	0.12*	0.11*	-0.01
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)	(0.07)	(0.06)
ois_{t-1}	0.07*	0.06*	-0.04	0.07**	0.07*	-0.04	0.04	0.06	-0.01
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)
$sent^*_{t-1}$				0.23***			0.09**		
				(0.04)			(0.05)		
pos^*_{t-1}					0.14***			-0.03	
					(0.04)			(0.05)	
neg^*_{t-1}						0.26***			0.17***
						(0.04)			(0.03)
Constant	-0.00	-0.03	-0.03	-0.01	-0.03	-0.02	-0.00	-0.03	-0.00
	(0.05)	(0.06)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)	(0.05)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,138	2,138	2,138	2,138	2,138	2,138	2,138	2,138	2,138
R^2	0.01	0.00	0.01	0.06	0.02	0.08	NA	NA	NA
Adjusted R^2	0.00	-0.02	0.00	0.06	0.02	0.07	NA	NA	NA

Note: This table documents the results of separate regressions of $sent^*$, pos^* and neg^* on lagged bank-specific and macroeconomic variables. All specifications include the lagged version of the business model variables specified 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 parenthesis. 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.

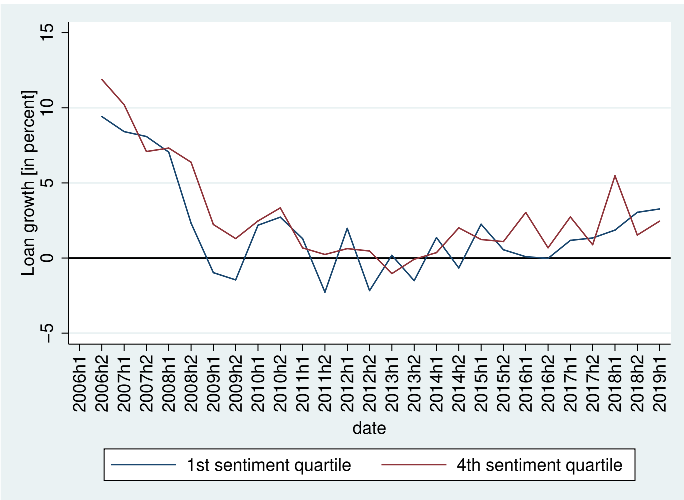
6 Bank Manager Sentiment And The Investment Decisions Of Banks and Their Investors

In this section, we study whether the bank manager sentiment index is associated with the investment decisions of banks and their equity investors. In Section 6.1, we explore whether the bank manager sentiment index 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 most optimistic and the most pessimistic banks depicted in Figure 5 suggests that the bank manager sentiment index is positively associated with loan growth rates.[20]

Figure 5: Average loan growth rates for high sentiment and low sentiment banks



Note: This figure compares the development of loan growth rates for high sentiment banks and low sentiment banks. It has been constructed as follows: every six months, banks have been sorted into quartiles based on the bank manager sentiment index. 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 $sent^*$ and control

[20] The figure has been constructed as follows: every six months, banks have been sorted into quartiles based on bank manager sentiment. The loan growth rates depicted in Figure 5 are then calculated as the average of the seasonal-adjusted growth rates over the next six months within the quartiles.

variables. Therefore, we estimate variants of the following models

$$loan\ growth_{i,t+1} = \alpha + \beta_1 sent^*_{i,t} + \mathbf{X}_{i,t}\boldsymbol{\gamma} + u_i + v_t + w_{c,t} + \epsilon_{i,t}, \tag{9}$$

$$loan\ growth_{i,t+1} = \alpha + \beta_1 pos^*_{i,t} + \beta_2 neg^*_{i,t} + \mathbf{X}_{i,t-1}\boldsymbol{\gamma} + u_i + v_t + w_{c,t} + \epsilon_{i,t}, \tag{10}$$

where $loan\ growth_{i,t+1}$ is the one-period ahead loan growth rate and $\mathbf{X}_{i,t}$ is a vector holding the control variables *cash*, *secs* and *reserves*. The variables u_i, v_t and $w_{c,t}$ capture bank, time and country-time fixed effects, respectively. All variables are standardized, which enables a better assessment of economic significance.[21]

The regression results documented in the first column of Table 8 suggest that the bank manager sentiment index on its own is predictive of subsequent loan growth, but has only very weak predictive power. While the coefficient on $sent^*$ is statistically significant at the 1% level, the variation in $sent^*$ accounts only for about 0.6 % of the variation in loan growth rates, adjusted for the number of variables in the model. A one standard deviation increase in $sent^*$ is associated with an average increase in the loan growth rate of 0.07 standard deviations. As column 2 Table 8 reveals, the association between *loangrowth* and lagged $sent^*$ is mainly driven by neg^*. Whereas the coefficient on neg^* has a similar magnitude as that on $sent^*$ in column 1, while pos^* appears to be not associated with loan growth. Interestingly, the combination of pos^* and neg^* accounts for a larger fraction of the variance of *loangrowth* than $sent^*$. As robustness tests, we include additional control variables and estimate models (9) and (10) with time and country-time fixed effects. When we include the control variables *cash*, *secs* and *reserves* into the model, we find that the coefficients on $sent^*$ and neg^* (columns 3 and 4 of Table 8) are somewhat smaller in magnitude than those from the model without those variables (columns 1 and 2), but remain highly statistically significant. The introduction of time and country-time fixed effects further reduces the coefficients on $sent^*$ and neg^*, the former being only statistically significant at the 10% level as a result (column 5). Another difference is that the coefficient on pos^* in column 6 of Table has a negative sign.

In summary, our empirical results suggest that $sent^*$ has weak predictive power for subsequent loan growth. Its predictive power derives from neg^*. The use of pos^* and neg^* for the purpose of predicting loan growth promises a superior prediction accuracy than $sent^*$.

[21] To take into account the uncertainty of our estimation, in an additional exercise, we estimated both Equations (7) and (9) as well as Equations (7) and (10) by using the block-bootstrap method resampling over the banks' dimension . We found similar results to the ones presented in this section.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$	$loangrowth_t$
$sent^*_{t-1}$	0.0746***		0.0658***		0.0519*	
	(0.0218)		(0.0218)		(0.0269)	
pos^*_{t-1}		0.0159		0.0096		-0.0053
		(0.0119)		(0.0127)		(0.0203)
neg^*_{t-1}		-0.0848***		-0.0797***		-0.0789**
		(0.0269)		(0.0289)		(0.0324)
$imputed$	0.1063	0.1020	0.0733	0.0698	-0.0136	-0.0109
	(0.1107)	(0.1106)	(0.1069)	(0.1069)	(0.1344)	(0.1340)
Constant	-0.0146	-0.0139	-0.0256*	-0.0256*	0.9157***	0.8984***
	(0.0106)	(0.0105)	(0.0133)	(0.0132)	(0.2241)	(0.2208)
Controls	No	No	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	No	No	No	Yes	Yes
Country-time fixed effects	No	No	No	No	Yes	Yes
N	2,251	2,251	2,211	2,211	2,211	2,211
R^2	0.0069	0.0092	0.0332	0.0355	0.2903	0.2927
Adj. R^2	0.0060	0.0080	0.0310	0.0330	0.1080	0.1100

Note: This table reports the results of separate regressions of loan growth on $sent^*$, pos^*, neg^* and bank-level and macroeconomic control variables. All variables are standardized. The control variables include $cash$, $secs$, 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 parenthesis. ***, ** 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 informational content of the bank manager sentiment index for the purpose of explaining bank behavior, i.e. lending decisions. Now, we turn to the question of whether the sentiment of bank managers as measured by the bank manager sentiment index 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 hypothesis:

Hypothesis 1: Investors interpret high bank manager sentiment as a positive signal for the risk associated with bank loan growth. Higher values of the bank manager sentiment index are negatively associated with the relationship between $SRISK$ and loan growth.

To test this hypothesis, we estimate the following model:

$$\begin{aligned} SRISK_{i,t} = {} & SRISK_{i,t-1} + \alpha + \beta_1 \times loangrowth_{i,t-1} \\ & + \beta_2 \times sent^*_{i,t} + \beta_3 \times sent^*_{i,t-1} \times loangrowth_{i,t-1} \\ & + \mathbf{X}_{i,t-1}\gamma + u_i + v_t + w_{c,t} + \epsilon_{i,t}, \end{aligned} \tag{11}$$

where the vector $\mathbf{X}_{i,t} = \left(X^{profit}_{i,t}, X^{bm}_{i,t}\right)$ holds the bank-specific control variables used in the previous regressions and the variables u_i, v_t and $w_{c,t}$ are bank, time and country-time fixed effects, respectively. The coefficient of interest is β_3, which captures how the relationship between $SRISK$ and loan growth depends on the bank manager sentiment index.

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.[22]

[22] To take into account the uncertainty of our estimation, in an additional exercise, we

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 (11). These nested versions only include $loangrowth_{t-1}$ (column 1) and $loangrowth_{t-1}$ and $sent^{*}_{t-1}$ (column 2), respectively. The results reported in both columns suggest that none of the two variables are associated with $SRISK$, implying that bank equity investors neither consider loan growth nor the sentiment of bank managers when assessing the systemic risk of banks. When we distinguish by bank manager sentiment, however, we are able to detect a statistically significant relationship between bank loan growth and bank risk for banks with the most optimistic bank managers. The coefficient on the interaction between $loangrowth_{t-1}$ and $sent^{*}_{t-1}$ documented in column 3 of Table 9 suggests that a one standard deviation increase in $sent^{*}_{t-1}$ is on average associated with an 0.0130 standard deviations decrease in the coefficient on $loangrowth_{t-1}$. The model implies that the coefficient on $loangrowth_{t-1}$ is statistically significant at the 5% level when $sent^{*}_{t-1}$ is more than one standard deviation higher than its mean (see Figure **??**).

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 coefficients on $sent^{*}_{t-1}$ in column 5 and the interaction term in column 6 are statistically significant at the 5% level. The results in column 6 suggest that an one standard deviation increase in $sent^{*}_{t-1}$ is on average associated with an 0.0243 standard deviations decrease in the coefficient on $loangrowth_{t-1}$. The coefficient on the interaction between $loangrowth_{t-1}$ and $sent^{*}_{t-1}$ from the Arellano–Bover/Blundell–Bond system estimation thus has nearly double the size of that from the OLS estimation.[23]

In summary, the results documented in columns 3 and 6 of Table 9 are in support of our hypothesis that the sentiment of bank managers has a negative influence on how equity investors assess the risk associated with bank loan growth.[24] In both cases, the coefficients on the interaction between $loangrowth_{t-1}$ and $sent^{*}_{t-1}$ are negative and statistically significant at the 10% (OLS) and 5% (Arellano–Bover/Blundell–Bond) level, respectively, where the Arellano–Bover/Blundell–Bond system estimator yields the strongest negative interaction effect between the two variables. Given that dynamic panel bias might be an issue when estimating Equation (11), 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 interaction effect between loan growth and the bank manager sentiment index.

estimated both Equations (7) and (11) by using the block-bootstrap method resampling over the banks' dimension . We found similar results to the ones presented in this section.

[23]Because the STATA command *xtdpdsys* we use for the Arellano–Bover/Blundell–Bond estimation of Equation (11) does not support STATA operators, we are currently not able to calculate confidence intervals for the estimates of the coefficients on $loangrowth_{t-1}$ conditional on $sent^{*}_{t-1}$. As a consequence, we are currently not able to report this information.

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

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

	(1) SRISK$_t$	(2) SRISK$_t$	(3) SRISK$_t$	(4) SRISK$_t$	(5) SRISK$_t$	(6) SRISK$_t$
$loangrowth_{t-1}$	-0.0204*	-0.0197	-0.0163	0.0013	0.0021	0.0074
	(0.0122)	(0.0120)	(0.0101)	(0.0101)	(0.0100)	(0.0093)
$sent^*_{t-1}$		-0.0135	-0.0124		-0.0196**	-0.0116
		(0.0104)	(0.0096)		(0.0090)	(0.0078)
$loangrowth_{t-1} \times sent^*_{t-1}$			-0.0130*			-0.0243**
			(0.0078)			(0.0102)
$SRISK_{t-1}$	0.6686***	0.6678***	0.6685***	0.4229***	0.4209***	0.4258***
	(0.0547)	(0.0546)	(0.0556)	(0.0596)	(0.0585)	(0.0554)
Constant	5.0103*	4.8342*	4.9164*	21.0017	21.0051	21.0112
	(2.7924)	(2.8091)	(2.7844)	(29.3188)	(29.9607)	(29.0984)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time 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	0.8695	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 $loangrowth$, $sent^*$ and bank-specific and macroeconomic control variables. The control variables include $impair$, $opinc$, $opexp$, $logta$, $loans$, $deposits$, $equity$, $intinc$, gdp, $infl$, $interbank$, $term$, ois and a dummy for whether values of an observations were interpolated. 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 parenthesis. 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.

7 Summary and Discussion

This paper provides evidence on how systematic over-optimism on the part of banks directly or indirectly affects the amount of credit that they supply to the real sector. Based on a measure of the sentiment of bank managers extracted from earnings press release documents, we have documented that bank manager sentiment i) 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, ii) is on average positively associated with loan growth rates over the subsequent six months and iii) interacts with equity investors' assessments of the risk associated with bank loan growth in that, for a given loan growth rate, the banks with the most optimistic managers are perceived as less risky than the banks with the most 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 the risk associated with the loan growth decisions of banks. If this is the case, these lower risk assessments then will translate into lower costs of capital for banks, which in turn is positive for the banks' lending businesses.

As discussed in Section 3.1, our approach to extract textual sentiment scores from earnings press release documents has one weakness that needs to be addressed to increase the robustness of our results. We are currently not able to determine to which reporting period a specific part of an earnings press release document relates to. Since we do not have this information, we cannot rule out that the correlations between the bank manager sentiment index and past realizations of economic fundamentals documented in this paper are just the result of bank managers also writing about earlier reporting periods and not the result of backward-looking expectation formation rules of bank managers. One option to address this weakness is that we modify the algorithm that processes the earnings press release documents so that it looks for keywords that provide information about the reporting period a specific text passage relates to (e.g. "full year" or "last year"). When all words are classified by reporting period, the next steps are to drop all words that do not refer to the current reporting period and to check whether all results still hold when we consider only words that relate to the main reporting period.

Another very interesting question that we currently do not account for is that bank managers might be aware of investors' increasing use of sentiment 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 sentiment 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 sentiment of their corporate disclosures. Moreover, our decision to define the bank manager sentiment index as the residuals from a regression of textual sentiment scores on a set of bank-specific and macroeconomic variables might introduce additional biases as the decision to begin managing the textual sentiment of corporate disclosures might alter the relationships between the resulting textual sentiment and economic fundamentals.

Interesting questions for future research thus are whether and to what extend bank managers strategically manage the textual sentiment of their corporate disclosures and 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.

References

Aikman, D., A. G. Haldane, and B. D. Nelson (2014). Curbing the credit cycle. *The Economic Journal 125*(585), 1072–1109.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies 58*(2), 277–297.

Baltagi, B. (2008). *Econometric analysis of panel data*. John Wiley & Sons.

Baron, M. and W. Xiong (2017). Credit expansion and neglected crash risk. *The Quarterly Journal of Economics 132*(2), 713–764.

Benanke, B. and M. Gertler (1989). Agency costs, net worth, and business fluctuations. *American Economic Review 79*(1), 14–31.

Blundell, R. and S. Bond (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics 87*(1), 115–143.

Bordalo, P., N. Gennaioli, and A. Shleifer (2018). Diagnostic expectations and credit cycles. *The Journal of Finance 73*(1), 199–227.

Brownlees, C. and R. F. Engle (2016). Srisk: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies 30*(1), 48–79.

Brunnermeier, M. K., T. M. Eisenbach, and Y. Sannikov (2012). Macroeconomics with financial frictions: A survey. Technical report, National Bureau of Economic Research.

Cao, S., W. Jiang, B. Yang, A. L. Zhang, et al. (2020). How to talk when a machine is listening: Corporate disclosure in the age of ai. Technical report, National Bureau of Economic Research.

Das, S. R. and M. Y. Chen (2007). Yahoo! for amazon: Sentiment extraction from small talk on the web. *Management Science 53*(9), 1375–1388.

Davis, A. K., J. M. Piger, and L. M. Sedor (2012). Beyond the numbers: Measuring the information content of earnings press release language. *Contemporary Accounting Research 29*(3), 845–868.

Devlin, J., M.-W. Chang, K. Lee, and K. Toutanova (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Fahlenbrach, R., R. Prilmeier, and R. M. Stulz (2017). Why does fast loan growth predict poor performance for banks? *The Review of Financial Studies 31*(3), 1014–1063.

Foos, D., L. Norden, and M. Weber (2010). Loan growth and riskiness of banks. *Journal of Banking & Finance 34*(12), 2929–2940.

Gandhi, P., T. Loughran, and B. McDonald (2019). Using annual report sentiment as a proxy for financial distress in us banks. *Journal of Behavioral Finance*, 1–13.

Gennaioli, N., Y. Ma, and A. Shleifer (2016). Expectations and investment. *NBER Macroeconomics Annual 30*(1), 379–431.

Gentzkow, M., B. Kelly, and M. Taddy (2019). Text as data. *Journal of Economic Literature 57*(3), 535–74.

Gertler, M. and N. Kiyotaki (2010). Financial intermediation and credit policy in business cycle analysis. In *Handbook of Monetary Economics*, Volume 3, pp. 547–599. Elsevier.

Gorton, G. and A. Metrick (2012). Securitized banking and the run on repo. *Journal of Financial Economics 104*(3), 425–451.

Greenwood, R. and S. G. Hanson (2013). Issuer quality and corporate bond returns. *The Review of Financial Studies 26*(6), 1483–1525.

Greenwood, R. and A. Shleifer (2014). Expectations of returns and expected returns. *The Review of Financial Studies 27*(3), 714–746.

Greenwood, R. M., S. G. Hanson, and L. J. Jin (2016). A model of credit market sentiment. *Harvard Business School working paper series# 17-015*.

Huang, X., S. H. Teoh, and Y. Zhang (2013). Tone management. *The Accounting Review 89*(3), 1083–1113.

Jiang, F., J. Lee, X. Martin, and G. Zhou (2019). Manager sentiment and stock returns. *Journal of Financial Economics 132*(1), 126–149.

Jordà, Ò., M. Schularick, and A. M. Taylor (2013). When credit bites back. *Journal of Money, Credit and Banking 45*(s2), 3–28.

Judson, R. A. and A. L. Owen (1999). Estimating dynamic panel data models: a guide for macroeconomists. *Economics Letters 65*(1), 9–15.

Kearney, C. and S. Liu (2014). Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis 33*, 171–185.

Kindleberger, C. P. (1978). Manias, panics, and crashes: A history of financial crises.

Kiyotaki, N. and J. Moore (1997). Credit cycles. *Journal of Political Economy 105*(2), 211–248.

Li, F. (2010). The information content of forward-looking statements in corporate filings—a naïve bayesian machine learning approach. *Journal of Accounting Research 48*(5), 1049–1102.

López-Salido, D., J. C. Stein, and E. Zakrajšek (2017). Credit-market sentiment and the business cycle. *The Quarterly Journal of Economics 132*(3), 1373–1426.

Loughran, T. and B. McDonald (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of Finance 66*(1), 35–65.

Minsky, H. P. (1977). A theory of systemic fragility.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society*, 1417–1426.

Renganathan, H. and B. W. Low (2010). Sentiment analysis using maximum entropy and support vector machine. In *Knowledge Engineering Conference (STAKE 2010)*, pp. 1.

Schularick, M. and A. M. Taylor (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review 102*(2), 1029–61.

Yang, Y., M. C. S. Uy, and A. Huang (2020). Finbert: A pretrained language model for financial communications. *arXiv preprint arXiv:2006.08097*.