WORKING PAPER

DO ACTIONS FOLLOW WORDS?
HOW BANK SENTIMENT PREDICTS CREDIT GROWTH

Pablo Pastor y Camarasa
Martien Lamers

August 2023
2023/1073

GHENT UNIVERSITY

Department of Economics

Faculty of Economics and Business Administration
Campus Tweekerken, St.-Pietersplein 5, 9000 Ghent - BELGIUM

Do actions follow words?
How bank sentiment predicts credit growth

Pablo Pastor y Camarasa* Martien Lamers†

August 23, 2023

Abstract

This paper constructs a forward-looking bank managerial sentiment index by using earnings call transcripts of US, Canadian, and European banks from 2001 to 2021. First, we validate this index through regressions showing its predictive power for positive stock returns and earnings forecast revisions. Second, we analyze whether managerial sentiment predicts bank credit growth. We find that a one standard deviation increase in the index of future sentiment leads to a 1.85% rise in credit growth over the next year. The results remain robust to various controls and competing explanations, including managers catering to analysts' expectations and macroeconomic expectations.

JEL Codes: G21; G30; G40; D83; M1.

The authors thank Kris Boudt, Francesca Monti, Gert Peersman, Ranoua Bouchouicha, Heiko Hesse, Steve Fazzari, Pawel Galinski (discussant), Alejandro Gonzalez, Mark Setterfield, Tom Michl, Wenzhao Wang (discussant), and participants of the Ghent Banking and Finance Seminar, the 49th Eastern Economic Association Conference, the 16th Annual Conference of the Behavioural Finance Working Group, and the 5th Behavioral Macroeconomics Workshop for helpful comments and feedback.

*Ghent University, Department of Economics, pablo.pastor@ugent.be and pablop@wustl.edu. Corresponding author.

†Ghent University, Department of Economics, martien.lamers@ugent.be.

1 Introduction

Large credit booms are an important predictor of future financial crises and the severity of economic downturns (Mian et al., 2017; Schularick and Taylor, 2012; Bordo and Meissner, 2012; Gourinchas and Obstfeld, 2012; Jordà et al., 2013). When credit crises occur, they lead to significant stock market declines and reduced bank profitability (Baron and Xiong, 2017; Fahlenbrach, Prilmeier and Stulz, 2018). While the consequences of credit booms have widely been studied in the literature, the mechanisms leading up to credit booms are still unexplored empirically.

These mechanisms can be categorized into two main groups. Some explanations focus on the role of fundamental factors. According to the financial accelerator literature, credit booms start with a positive productivity shocks. These shocks strengthen banks' balance sheets enabling them to extend more credit and reinforce credit booms (Kiyotaki and Moore, 1997; Bernanke et al., 1999). Other accounts emphasize the significance of lenders' expectations in credit cycles (Bordalo et al., 2018; Greenwood et al., 2019; Bordalo et al., 2021), whereby agents over-react to positive news leading to a credit boom. However, empirical evidence is still limited to survey data (Ma et al., 2021) and *forward-looking* optimism in the banking sector is never measured directly.

This paper falls into the second stream of research and presents an analysis of the origins of credit booms, recognizing the importance of optimism in macroeconomic fluctuations (Minsky, 1977; Kindleberger, 1978). To measure optimism in the banking sector, our novel approach employs sentiment analysis on earnings call transcripts of American, Canadian, Japanese and European banks between April 2001 and December 2021. We employ two methodological contributions to build an indicator of bank managers' forward-looking sentiment. First, we separate the presentation section of each earnings call from the Q&A section of the transcript and split questions from answers, allowing us to employ textual analysis separately on the presentation and the discussion between analysts and bank managers. Second, using the algorithm developed by Tao et al. (2018), we are able to focus on *forward-looking* sentences. We then build a sentiment index on the forward-looking part of the text with sentiment scores from a sentiment dictionary combining from Shapiro, Sudhof and Wilson (2020), Hu and Liu (2004) and Loughran and Mcdonald (2011). This results in four sentiment indices: (i) bank sentiment, (ii) bank future sentiment (limited to forward-looking sentences), (iii) analyst sentiment (sentiment from all the questions) and (iv) analyst future sentiment. To the best of our knowledge, these indices represent the first time-varying and bank-level indicators of bank managers and analysts' sentiment based on earnings call transcripts.

We conduct three validation tests on our sentiment indices. First, we examine the predictive power of sentiment on stock returns and find that elevated sentiment among managers and analysts reliably predicts future stock returns. Second, our results indicate that analysts' sentiment does not have an impact on their own forecast revisions of long-term earnings. Third, we show that analysts' sentiment predicts their positive forecast errors in a regression analysis similar to Coibion and Gorodnichenko (2015). These validation tests therefore underscore the significance of sentiment in shaping analysts' expectations and provide empirical support for the validity of the indices. Finally, the paper explores stylized facts of the sentiment indices. Similar to others documented in the literature (Baker and Wurgler, 2006; Jiang et al., 2019), manager and analyst sentiment has interesting business cycle dynamics, declining during periods of uncertainty such as the Great Financial Crisis or the COVID-19 crisis.

Having validated the sentiment indices, the main analysis of the paper looks at whether bank managers' optimism plays an important role in the emergence of credit booms. Using a set-up akin to Fahlenbrach et al. (2018), bank future sentiment robustly predicts credit growth at the bank level over a three-year horizon. The baseline regression shows that the lending policy of banks depends on the sentiment of their managers. An increase of one standard deviation in sentiment among bank managers leads credit growth to surge by 1.85% over the next year (0.94% over the next three years). The analysis further reveals that the sentiment of managers revealed in the presentation of earnings is the best predictor of credit dynamics and that the effect is particularly strong for smaller banks. We observe that analyst sentiment, despite predicting stock returns and forecast revisions, is not significantly associated with bank lending policies. Importantly, the results are robust to introducing macroeconomic variables, which capture the general level of optimism as well as economic fundamentals. The study also tests the catering hypothesis, whereby managers cater to analyst sentiment, and finds that when we control for analyst sentiment the predictive power of managers' sentiment actually increases. Finally, we conduct sensitivity analyses by excluding contemporaneous controls and using other sentiment dictionaries such as Loughran and Mcdonald (2011). Both exercises exhibit stronger effects than in our baseline regression.

This paper belongs to the existing literature studying the influence of investor beliefs on credit booms. The diagnostics expectation theory claims that positive news may induce lenders to become overly optimistic and take on excessive risks (Bordalo et al., 2021, 2018, 2020). Empirically, there is evidence that low credit spreads due to exuberant forecasts lead to low economic growth (López-Salido, Stein and Zakrajšek, 2017; Greenwood and Hanson, 2013). Similarly, investors in banks' stocks show some degree of exuberance: excessive risk-taking by banks during credit booms does not necessarily go against the will of the shareholders (Baron and Xiong, 2017). Credit booms are often accompanied by bullish stock prices which plummet once the credit expansion ends (Fahlenbrach, Prilmeier and Stulz, 2018). Indeed, banks ignore excessive credit growth until it materializes in low profitability and greater loan-loss provisions. Overall, these studies stress the significance of exuberant beliefs in driving credit booms. However, the literature on diagnostic expectations has not yet addressed two key points which can provide a comprehensive explanation of the origin of credit booms. First, the hypothesis of extrapolation assumes that credit booms precede waves of optimism, where investors look backward and extrapolate positive news into the future. Second, the explanation focuses on the exuberance of investors and analysts as opposed to the optimism of managers. The paper contributes to this literature by analyzing a different relationship running from managers' optimism to bank lending. We argue that banks engaging in credit booms were already optimistic in the first place, and test empirically if their level of optimism predicts credit growth.

Our argument builds on theoretical papers studying sentiment shocks. Milani (2017) reports that sentiment shocks in a standard DSGE model explain around 40% of the US business cycle. In Ji and De Grauwe (2020), banks' money creating ability is not constrained by savings but animal spirits, which is found to amplify the boom-bust nature of credit booms. Asanuma (2013) builds a model where optimistic lending attitudes result in a surge in banks' credit supply at a lower rate. In line with these studies, we argue that elevated bank sentiment leads to more lending. This hypothesis is supported by recent empirical contributions. Bullish aggregate banks' beliefs precede a fall in loan-loss provisions (Hribar et al., 2017). Negative bank sentiment leads to liquidity hoarding at the bank level (Berger et al., 2020). Sentiment, when instrumented by weather, affects credit approvals without affecting loan pricing (Cortés et al., 2016). All these studies show that sentiment influences banks' behavior but never study the importance of forward-looking sentiment. This contrasts with theoretical literature stressing the role of sentiment about the future in driving lending growth. In Bordalo et al. (2018) lenders are optimistic about the future prospect of borrowers and thus lend at a reduced interest rate. Indeed, evidence shows that banks' expectations matter for credit conditions. Recent findings document that pessimistic expectations about the economic prospects of a metropolitan area reduce credit growth and increase interest rates at the bank level (Ma et al., 2021). Banks' CEOs demonstrating overconfidence in the future by not exercising their stock options tend to lend more and experience larger losses during financial crises (Ho et al., 2016). In line with these studies, we focus on future sentiment throughout the analysis.

Finally, this study contributes to a recent literature using text mining to measure sentiment in the financial system. Correa et al. (2021) construct a financial stability index from central banks' stability reports. The index presents interesting stylized facts such as a rise before the financial crisis and the Euro-area debt crisis. Nyman et al. (2021) build a sentiment index on central banks' market commentary, news and brokers research reports, which provides a predictive signal of the financial crisis. Hanley and Hoberg (2019) identify emerging risks in the banking sector in the risk factor section of their 10-K documents. More exposure to emerging risk in the banking sector predicts negative returns in the Great Financial crisis and a higher probability of bankruptcy. The same relationship holds at the bank level. Price et al. (2012) are the first to separate the presentation and Q&A section of earnings call. Their main finding is that the tone of earnings call predicts abnormal returns after earnings announcements. This motivates our choice to go one step further and separate questions and answers to isolate managers' sentiment. While this research highlights the predictive power of sentiment indices on stock returns, they do not look at the impact of managers' sentiment on their own behavior. Jiang et al. (2019) focuses on the impact of managers' sentiment on their own investment. High sentiment leads to overestimation of future cash-flows and excessive investment. We find that the same holds in the context of banking.

The rest of the paper proceeds as follows. Section 2 explains the construction of the sentiment indices and Section 3 describes our data. In Section 4, we perform validity tests on our sentiment indices. Section 5 outlines the empirical strategy and presents our main findings, while Section 6 comprises several robustness tests. Section 7 concludes.

2 Managers' and analysts' sentiment

2.1 Earnings call transcript

Our sample consists of earnings call transcripts from the Refinitiv Eikon database. Unlike 10-K documents, earnings call transcripts are a conversation between managers and analysts. Banks thus have less control over the content of the discussion. Indeed, the Q&A section of earnings call is a conversation in which analysts can directly ask questions. The spontaneity of the discussion means that managers often reveal their level of optimism contrary to the more controlled communication of 10-K documents (Calomiris et al., 2020).

2.2 Forward-looking Questions and Answers

The paper makes two methodological contributions. First, it measures separately managers' and analyst' sentiment by distinguishing between the questions of analysts and the bank managers' answers in the Q&A section of the transcript. Second, it considers the sentence's tense in the construction of the sentiment index. We separate questions in the Q&A section from answers of CEOs by identifying the name of the speaker. If the speaker is a "Corporate Participants" (CP) representing the bank, the text is an answer. When the "Conference Call Participants" (CCP) speaks, the text is a question.[1] Out of 15378 transcripts, we extract 14819 questions and 14963 answers.

The second step is to extract future sentences. We use three strategies to match forward-looking sentences (Tao et al., 2018). First, key-word matching identifies a forward-looking sentence if a temporal expression refers to the future. For example, 'will' or the bi-gram

[1] Approximately 6.5% of all transcripts mention the participants name in an incomplete manner or not at all. If the earnings call has the name of Corporate Participants but not the Conference Call Participants' name, we assume that unidentified audience members are Conference Call Participants who they speak in the name of the bank. We use the same algorithm the other way around. If there are neither unidentified audience members nor the participants speak in the Q&A, we identify questions if they end with the character "?".

'next quarter' identifies a forward-looking sentence. Second, linguistic matching finds the grammatical structure: subject, verb, object. The algorithm then matches verbs indicating a forward-looking statement such as 'foresee' or 'predict'. Finally, time reference uses future dates to identify forward-looking sentences. Future dates are later in time compared to the date of the document. Appendix A describes the procedure in more detail.

2.3 Sentiment index methodology

We use a bag of words approach to measure the sentiment of each section in the earnings call. We build our sentiment dictionary by combining PMI score from (Shapiro et al., 2020) with Hu and Liu (2004) and Loughran and Mcdonald (2011). We adapt the combined dictionary by removing words used to extract forward-looking statements. We also remove words which relate to polite expressions such as 'thank' and 'okay' in the question section. As a result, we obtain a dictionary in which each word is associated with a sentiment score. Finally, we combine this dictionary with Vader's list of negative words and a negation rule to account for negative sentences (Hutto and Gilbert, 2014). We multiply word's scores by -1 if they are within 3 words of a negative word (using Vader's list of negative words). In our application, we add some negative words present in our corpus to the negation rule.[2]

The algorithm has two main steps. The first step consists in computing the sentiment score of every word in the earnings call transcripts. For every word in each earnings call, we go to the lexicon and find the sentiment score of that word. If a negative word such as 'do not' or 'no' is within three words of the chosen word, we flip the sign of its sentiment score obtained from the lexicon. After every word has been assigned a sentiment score, we determine the sentiment index of the document. The sentiment score of a document is the

[2]Taking the example of the word 'adverserly', the Shapiro score of -0.7595 is summed with 0 in the Hu and Liu (2004) dictionary (indicating the absence of the word in the dictionary) and -1 in Loughran and Mcdonald (2011) (indicating a negative word). The resulting word sentiment score is -1.7595.

average of the sentiment scores of words in that document:

$$\overline{S(w)} = \frac{\sum S(w)}{n} \tag{1}$$

This algorithm is run separately on future sentences and all sentences for each section of the text. As such, for every bank, the first sentiment index is Bank sentiment$_{b,t}$: the average of the sentiment index of the presentation and of the answers of bank managers. Bank future sentiment$_{b,t}$ is the average of the sentiment indices on the forward-looking sentences of the presentation and answers. Finally, we compute the sentiment index on the questions of the analysts in the Q&A, on all the text (Analyst sentiment$_{b,t}$), and only on the future sentences (Analyst future sentiment$_{b,t}$).

2.4 Evolution of sentiment

Figure 1(a) and (b) describes the evolution of the average sentiment of managers and analysts in our sample. Sentiment tends to be high during economic expansions and tumbles during recessions. The difference in the recovery after the GFC and the COVID-19 crisis is striking. While the sentiment of managers took until 2012 to recover from the financial crisis, the recovery after the COVID-19 crisis was swift. The dynamics of analyst sentiment exhibit less pronounced fluctuations, with the sentiment index recovering around 2010. The stylized facts of sentiment across the business cycle highlight that sentiment aligns closely with the ups and downs of the business cycle.

We compare our sentiment indices to other indices in the literature. Baker and Wurgler (2006) and Huang et al. (2015) measure investor sentiment with principal component analysis to predict stock returns. Baker and Wurgler (2006) sentiment index has more impacts on stocks that are hard to value while Huang et al. (2015) measure of investor sentiment forecasts the cross-section of stock returns in the US. In Figure 1, the bottom graph illustrates that the average bank analyst sentiment constructed here aligns more closely with Baker and Wurgler (2006) than Huang et al. (2015), despite both capturing investors' sentiment. This indicates that analysts' sentiment in our sample corresponds to indicators of investor sentiment in the stock market.

Next, we compare the average bank managers' sentiment with Jiang et al. (2019). They build a monthly index of manager sentiment based on 10-Q, 10-K and conference call transcripts of American public firms. Their index follows our manager sentiment ahead of the Great Financial Crisis. Figure1 (a) illustrates that bank manager sentiment is more reactive to the Great Financial Crisis. Indeed, the average sentiment index decreases in 2007 as Jiang et al. (2019) remains elevated. Pessimism thus appears to have started in the banking sector before spreading to the whole economy. This is in line with accounts arguing that the financial crisis started in the banking sector. Finally, our indices exhibit a more stable behavior than the benchmarks. One possible explanation is that our sample consists of earnings call transcripts from the banking sector, while Jiang et al. (2019) incorporate multiple sectors.

3 Sample and data

3.1 Sample Construction

We build the sample by merging the sentiment index from earnings call with banks' balance sheet data from SNL Financial. To get the widest sample possible, we collect earnings call transcripts from all European Banks, Canadian, Japanese and American banks in the Refinitiv Eikon database. The first transcript starts on the 16th of April 2001, and the last transcript dates from the 10th of December 2021. In total, the sample consists of 15639 transcripts for 489 banks. The balance sheet information begins on Q3 2001 until Q4 2021 for 1451 banks in Europe, USA, Canada and Japan. Finally, we merge the fundamentals with the earnings call based on the banks' ISIN, RIC and their name. The resulting sample follows 489 banks for 81 quarters. Appendix B discusses the geographical composition of our sample and its influence on our results.

3.2 Summary statistics

Table 1 reports summary statistics for the variables used in the paper. The unit of observation is the bank-quarter level. We find some evidence that managers tend to be more optimistic than analysts, as their average sentiment indices are higher. For both managers and analysts future sentiment is however generally lower compared to the sentiment calculated on all sentences. Next, we study the degree of sentiment disagreement. The data shows that analyst sentiment has the greatest inter-quartile range of 0.19 compared to only 0.1 for bank sentiment. Analysts thus differ more amongst each other in their level of optimism than managers.

The main dependent variable is $\Delta loans_{b,t+n}$. This variable represents the annualized growth of loans (net of reserves for credit losses) of bank b between time t and $t + n$. The annual loan growth has an average of 11.97% and a standard deviation of 22.83%. This is similar to Fahlenbrach et al. (2018), who report an average of 13.68% in their sample of American firms. Next, we describe some of the bank controls used in the main regressions. The natural logarithm of the total assets of the bank ($log(size)$ is 16.53, which corresponds to \$1.509 million. This is more than twice the average size of banks in Berger et al. (2020), which indicates that banks in our sample are generally big. In our sample, the capital position seems to be robust with a mean capital ratio of 10.12%. The deposit to asset ratio is on average 69.74, showing that banks are mostly financed by deposits. Banks are also very active in the loan market with 96.54% of deposits used for lending activities. The average

Return-on-asset (ROA) is 0.76%, in line with the literature.

Our analysis also uses analyst-level variables to validate the construction of the sentiment indices. LTG_M is the analyst long-term earnings expectation for 3 to 5 years ahead from the I/B/E/S Estimates data. Analysts expect on average an earnings growth of 10.37%. Their forecast errors tend to be negative. They therefore seem to be consistently over-optimistic about the prospect of bank earnings.

Finally, we obtain macroeconomic controls from national sources and the Survey of Professional Forecasters. House price average growth rate is 2.33%, which is above inflation. One explanation is that our sample is not centered on the housing bubble of the Great Financial Crisis with most of the sample after the financial crisis. The Consumer Confidence Index varies a lot with a high standard deviation. Mean inflation is 2% and inflation expectations are anchored around that number. Mean GDP growth is 1.61%. Professional forecasters seem to be optimistic with an average forecast of 3.06%.

4 Sentiment index: Validation

4.1 Analyst sentiment and Stock returns

A common criticism of textual analysis is that sentiment indices are capturing cultural or grammatical differences in the vocabulary of managers without revealing their true level of optimism. If that were true, investors should not react to positive information released in the earnings call transcripts. In Table 2, we regress the stock returns of the bank on the sentiment indices, including bank and time fixed effects. The table shows that all sentiment indices but one are positively and significantly associated with stock returns at the 1% level. A one standard deviation increase in bank future sentiment (0.09) is associated with an increase in stock return over the next quarter of 0.75%. This means that investors are trading on information revealed by the bank. The effect is nonetheless temporary since the sentiment indices lose their predictive power after one year (see Table C1 in the Appendix). This result supports the idea that the information contained in our sentiment index is not 'cheap talk' but has actual implication for bank stock trading in the short run.

4.2 Analyst sentiment and Earnings forecast

This section validates the construction of the analyst sentiment indices with a regression of forecast errors and forecast revisions on analyst sentiment. In Table 3, we study the relationship between sentiment and forecast errors in the long-term. We find that forecast revisions predicts negative forecast errors. This overreaction to news about profitability is in line with the literature. Fahlenbrach et al. (2018) find that analysts' tend to be too optimistic about the prospect of high growth banks whereas Bordalo et al. (2020) report similar coefficients in the Survey of Professional Forecasters. We then further investigate the role of sentiment in long-term forecast errors. The coefficients of the sentiment index in the first two columns of Table 3 are positive and significant at the 1% significance level. This suggests that elevated analyst sentiment predicts periods in which realized earnings per share are higher than anticipated. In contrast, Column (5) and (6) show that analyst sentiment does not play an important role in forecast revisions. All in all, the findings highlight that analysts overreact to news about the long-term profitability of the bank but their sentiment does not influence their long-run forecast revisions.

The dynamics of sentiment and forecast errors in the short-term draws a different picture. Table 4 is the regression of forecast errors at time t on forecast revisions at time $t-1$. We find positive coefficients, indicating that short-term EPS forecasts are sticky and under-react to the introduction of new information which is consistent with Bouchaud et al. (2019). Moreover, average sentiment over the last year predicts positive forecast revisions in year t. An increase of analyst sentiment of one standard deviation (0.082) leads to an upward revision of 0.018 in the earnings per share estimate. Analyst sentiment thus predicts analyst forecast errors. The empirical relationship lends support to the construction of our sentiment index and highlights the importance of soft-information in forming short-term earnings forecasts in banking.

This section validates the construction of our analyst sentiment index in two ways. First, managers' and analysts' sentiment predicts stock returns. The tone of earnings call is thus not only 'cheap talk' since investors trade on it. Second, analysts take their own sentiment into account when forming earnings expectations in the short-term. Therefore, the tone of earnings calls contains relevant information that impacts investors' and analysts' forecasts. In the next section, we will examine whether the tone of earnings call has an impact on the behavior of bank managers on top of driving stock returns and analyst forecast revisions.

5 Results

5.1 Empirical Strategy

To identify the effect of banks' managers' sentiment on bank lending, we estimate the following local projections:

$$y_{b,t+n} = \beta_{0,n} + \beta_{1,n} \times sent_{b,t} + \beta_{2,n} \times X_{b,t} + \sum_{q=1}^{4} \phi_{q,n} \times X_{b,t-q} + \mu_c \times \delta_t + \gamma_b + e_{b,t} \qquad (2)$$

$y_{b,t+n}$ represents the variable of interest: the change in total bank-lending of bank b at quarter t ($\Delta loans_{b,t+n}$) for $n = 4$, 8 and 12. We introduce bank controls $\sum_{q=1}^{4} X_{b,t-q}$ for the last 4 quarters to address concerns about reverse causality running from credit growth to the sentiment indices. This also controls for seasonality effects. On top of this, our main specification introduces bank controls X_b at time t (described in Appendix D). This specification assumes that the sentiment index does not impact bank controls at time t.[3] $\mu_c \times \delta_t$ is a country-time fixed effect. These fixed effects account for time-varying macroeconomic conditions at the country level. γ_i is a bank-invariant fixed effect controlling for the bank's corporate risk culture or communication style. Standard errors are clustered at the bank level to account for serial correlation within a bank.

We have several sentiment indices. $sent_{b,t}$ refers to: Bank sentiment$_{b,t}$ (manager sentiment), Bank future sentiment$_{b,t}$ (manager future sentiment), Analyst sentiment$_{b,t}$ (analyst sentiment) and Analyst future sentiment$_{b,t}$ (analyst future sentiment). These four sentiment indices enter the regression separately to evaluate the impact of the managers' versus analysts' sentiment.

5.2 Sentiment shocks and credit growth

Results in Panel A of Table 5 show that a high level of managers' optimism predicts more credit growth over the next years. Bank future sentiment in Panel B of Table 5 presents similar results but the effect is only consistently significant after two years. Taken together, these results support the expectation bias hypothesis argued in Arif and Lee (2014). Optimistic managers tend to overvalue the present value of future cash-flows and increase lending. The findings corroborate results in the empirical literature. In Fahlenbrach et al. (2018) and Baron and Xiong (2017), high-credit growth banks are excessively optimistic about the future. They do not provision when expanding credit and then suffer from subdued Return-on-assets. The nexus between optimism and high credit growth found in the literature is thus supported by this study.

[3]We relax this assumption in a robustness test in section 5.5.

The results are also economically significant. A one standard deviation increase in bank sentiment (0.071) is associated with an increase of 1.64 % in loan growth over the next year from a sample average of 11.97 %. The same increase only leads to a surge of 0.92 % at a 3 year horizon. Elevated manager sentiment thus precedes periods where banks expand their credit but the effect tends to diminish over time. Another way to quantify the effect is to measure the growth in lending associated with a jump from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile in bank future sentiment. Over the next three years, this increase in future sentiment is associated with an *annual* increase of 1.45% in credit growth which represents $375 million in loan growth compared to the sample average of $6,920 million. The economic impact of sentiment is thus not negligible.

We find that managerial sentiment is a better predictor of credit growth than analyst sentiment. Analyst sentiment and its future counterpart are not significant in panels C and D of Table 5. Analyst sentiment is therefore not related to the lending policy of the bank. This is coherent with evidence in Baron and Xiong (2017) and Fahlenbrach et al. (2018) who document that investors' optimism is a good predictor of stock returns but remains essentially backward-looking.

The results in Figure 2 are qualitatively the same as in Table 5: bank overall and future sentiment predicts credit growth while analyst sentiment is not. We run local projections with the same specification as in Table 5 up to 16 quarters ahead to identify the upper bound of the impact of sentiment shocks. Both bank sentiment and future sentiment drive credit growth up to 13 quarters ahead. In Fahlenbrach et al. (2018) and Baron and Xiong (2017), credit booms are defined as excessive credit growth over a period of 3 years either at the bank or the country level. Hence, the effect reported here is long enough to drive credit booms documented in these studies. Moreover, Figure 2 reveals that the dynamics of bank sentiment and future sentiment are different. The effect of bank sentiment peaks for two and three quarters ahead. Sentiment-driven credit growth then falls while remaining significant. Bank future sentiment has first no impact on bank credit growth. It then reaches a peak at around 8 and 12 quarters. The present findings highlight that bank future sentiment impacts credit dynamics with a lag whereas overall sentiment has more of an immediate effect.

5.3 Presentation and Answers

Table 6 presents the individual components of the sentiment indices: presentation and answers sentiment indices. Thus far, bank sentiment was defined as the average of the sentiment indices on the presentations and answers in the earnings calls. However, this average masks important differences between the two components. The presentation section represents a more controlled form of communication, where CEOs and CFOs are trained and drilled. On the contrary, the Q&A section is spontaneous, with questions forcing the managers to reveal their genuine level of optimism.

Both panels A and B show that the sign of the coefficient is the same as for the average of both presentation and answers. The magnitude is however smaller than in Table 5. For instance, a one standard deviation increase in the presentation future sentiment (0.105) is associated with a credit growth rise of 0.756% over the next two years. The same increase leads to a surge of credit of 1.004% for the average of both indices. Furthermore, the results indicate that statements in the presentation of earnings are better predictors of credit growth. While answers about both the present and the future forecast credit growth over the next year, forward-looking answers impact credit growth over the next three years. This finding sheds new light on the communication of banks. Short-term optimism is often conveyed through more controlled speeches during presentations, while optimism driving long-term decisions tends to be revealed in managers' answers.

5.4 Size and Sentiment Sensibility

In this section, we examine whether there is cross-sectional heterogeneity in the effect of bank sentiment on credit growth. In particular, we investigate whether the impact of bank sentiment on credit expansions differs across banks of different **size**. The expected coefficient of the interaction term is not clear. On the one hand, larger banks may benefit from a financial safety net from being "Too Big To Fail" (TBTF) (Anginer et al., 2018). On the other hand, public scrutiny following the financial crisis makes them more risk-averse (Bhagat et al., 2015). Results in Table 7 support the latter hypothesis. Column (2), (4) and (6) confirm that, as banks' total asset increase, the impact of managers' sentiment shock on credit growth decreases. The effect between two banks is also confirmed by the data. A one standard deviation surge in bank future sentiment is associated with a credit growth of 0.599 % over the next year for an average bank, but with a decrease of 0.411% in credit growth for a bank that is one standard deviation bigger. Hence, we observe strong heterogeneity in the effect of bank future sentiment on credit expansions. This is likely attributable to the presence of extended communication training, larger risk departments or stricter macro-prudential policy on bigger banks.

6 Robustness test

We conduct a set of sensitivity analyses to corroborate the stability of our results. First, we check that bank sentiment is not capturing the level of optimism in the economy by controlling for macroeconomic expectations. Second, we introduce bank and analyst sentiment to eliminate the possibility that managers are catering to analysts' optimism. We also check the orthogonality assumption between bank sentiment and bank controls by removing contemporary controls. Finally, we test the external validity of the results by using sentiment measures from Loughran and Mcdonald (2011), which is more commonly used.

6.1 Bank future sentiment and macroeconomic expectations

Forward-looking optimism is often measured from survey data. Bordalo et al. (2018) use the Blue Chip Financial Forecasts survey to capture optimism in the consensus forecast of analysts. Research on managers' beliefs employs the same type of data. Hribar et al. (2017) capture bank managers' sentiment index from the Duke University Outlook Survey, whereas Barrero (2021) use several Surveys of Business Uncertainty. The authors find that managers tend to extrapolate positive shocks in the future. We therefore replace country-time fixed effects in Table 5 with macroeconomic expectations to compare our results with the findings of the literature. In the absence of country-time fixed effects, we also introduce macroeconomic variables controlling for time-varying economic conditions.

Table 8 presents the results with macroeconomic variables. The overall significance of bank sentiment remains unchanged, and the effect is similar to that in the main regression. We begin by introducing five variables controlling for the macroeconomic conditions at the country level. GDP growth and the monetary policy shadow rate (SR) exhibit interesting dynamics. High GDP growth is associated with greater credit growth over the next year. This finding supports the diagnostic expectations theory of Bordalo et al. (2018) where positive macroeconomic news is extrapolated in the future, influencing lending growth. Nevertheless, the effect is not significant after the second year. This suggests that these extrapolations have a short-lived impact compared to the long-lasting effect of sentiment shocks. The coefficient of the monetary policy shadow rate indicates that credit growth responds with a lag of two years to monetary policy shocks. This is in line with the literature highlighting the persistence of the credit channel of monetary policy (Jiménez et al., 2014, 2012; Heider et al., 2019).

The next rows introduce macroeconomic expectations from surveys of professional forecasters in the US and the Euro Area. Higher expected inflation is associated with lower credit growth over the next two years, while higher expected GDP growth has long-term negative effects on credit dynamics. These findings suggest that periods characterized by optimistic expectations on inflation and GDP growth are often indicators of an overheated economy heading towards a credit bust. The magnitude of the effect is large. A one standard deviation increase in expected CPI (GDP growth) leads to a fall in credit growth of 3.92% (3.79%) over the next two (three) years. These results indicate that high expected GDP or inflation tends to precede a credit crunch whereas high sentiment is rather a driver of credit booms.

We also address an alternative interpretation of our results by considering proxies for credit demand. One possible interpretation is that high future bank sentiment is a result of banks predicting elevated credit demand. To explore this possibility, we introduce proxies of future credit demand such as expected unemployment and GDP growth. Column (4) illustrates that high expected GDP growth leads to a fall in the equilibrium credit quantity. To the extent that expected credit demand and expected GDP are correlated, this is the furthest we can go in tackling this interpretation.

6.2 Catering Hypothesis

A possible concern in our identification strategy is the Catering Hypothesis (Simpson, 2013). The empirical accounting literature argues that investors sentiment influences managerial decisions. In particular, previous studies have found that periods of high investors sentiment result in managers providing more optimistic forecasts (Hribar and McInnis, 2012; Simpson, 2013; Polk and Sapienza, 2009). In our setting, the concern is that high management sentiment may not drive loan growth but rather cater to the optimistic expectations of analysts. Indeed, Table 9 reveals that a significant correlation between the sentiment of managers and analysts at the 1% degree of significance. The correlation between bank and analyst sentiment is 0.47 and 0.14 for their future counterparts. To address the possibility of catering, we introduce analyst sentiment in our baseline regression. The results are largely unchanged; higher bank sentiment predicts greater credit growth.

Results in Table 10 indicate that bank sentiment has a larger effect on credit growth once we control for analyst sentiment. On top of this, the significance of bank future sentiment is enhanced. All the coefficient are now significant at the 10% level and the between-effect is now particularly robust. These findings suggest some evidence of catering in the baseline regression up to two years ahead. Managers may be optimistic because they are catering to analyst expectations. They therefore do not disclose the true sentiment driving their decision. Nonetheless, once we isolate their true level of optimism without the influence of analyst sentiment, idiosyncratic variations in bank sentiment have a stronger effect.

6.3 Removing contemporaneous controls

The main regression assumes that controls at time t and bank sentiment are orthogonal. This means that the sentiment of managers and analysts does not impact controls over the quarter. Assuming this absence of relationship is justified for analyst who discover bank earnings a few minutes before the earnings call. Their questions then react to the new information revealed in the earnings presentation. This might not be the case for managers. We measure managers' sentiment at the time of the earnings call but it may be impacting decisions during the quarter. In other words, one of the possible criticism of our empirical approach is that managers optimism at time t might have already affected controls at time t. If the quarter runs from January to March and managers receive a positive news impacting their profits in February, the resulting optimism might be impacting loan-loss provisions during that period. Introducing controls at time t assumes that this channel is impossible: sentiment cannot impact future credit growth through better fundamentals at time t. To test the robustness of this assumption, Table 11 does not introduce contemporaneous controls in the regression. The results are qualitatively the same as in Table 5 with a somewhat stronger economic magnitude. Therefore, the initial assumption of orthogonality at time t does not affect the nature of our results.

6.4 Different dictionary

In this section, we evaluate to what extend our results are robust to changing the dictionary used to construct the sentiment indices. A large literature has established that dictionaries with domain-specific languages better predict economic variables. Recently, Price et al. (2012) uses different dictionaries to predict abnormal returns around earnings announcement. Building on evidence from Loughran and Mcdonald (2011), they report that dictionaries with economic words are stronger predictors of stock returns. In this robustness test, we therefore employ the Loughran and Mcdonald (2011) dictionary to build the sentiment indices. The pre-processing of text is exactly the same as in the baseline index and is described in appendix A. Instead of combining PMI scores with sentiment dicitonaries as in the main analysis, the score of positive or negative words is either 1 or -1. The scores are then simply summed and divided by the number of words as in equation (1).

Table 12 describes the predictive ability of bank sentiment on bank lending growth. The statistical significance of the results are improved for most time horizons. Furthermore, the results have a larger order of magnitude. While a standard deviation shock in bank sentiment leads to a surge in lending of 6.05 % over the next two years with the Loughran and Mcdonald (2011) dictionary , the same shock in column (4) leads to a surge of 1.24 % in the baseline regression. Using a more common dictionary strengthens the significance and magnitude of our results.

7 Conclusion

We construct a sentiment index of managers' and analysts' sentiment from earnings calls of banks from Q1 2001 until Q1 2021, using the Shapiro et al. (2020) dictionary. We validate our sentiment indices through two empirical tests. Firstly, we regress bank stock returns on the sentiment indices and find that sentiment predicts bank stock returns. Secondly, we run Coibion and Gorodnichenko (2015) regressions. Analysts' sentiment drives forecast revisions and leads to negative forecast errors in the short-term. These results provide empirical support to the construction of our indices.

We find that bank managers' forward-looking optimism predicts bank credit growth. The predictability of managers' optimism is mostly due to directed communication in their earnings presentation rather than more spontaneous answers in the Q&A section of earnings calls. Furthermore, our findings challenge the conventional view that investors' biased expectations are the primary drivers of credit booms. Instead, we argue that managers' optimism precedes the emergence of credit booms. The effect persists for up to 13 quarters and thus explains long periods of credit growth that often precede financial crises and prolonged recoveries.

Taken together with the existing the literature in Fahlenbrach et al. (2018) and Baron and Xiong (2017), we can draw the anatomy of sentiment-driven credit booms. Managers' future optimism precedes credit booms at the bank level. These optimistic banks then become high-credit growth banks, who fuel the credit boom and then suffer from the ensuing crisis. Our measure of forward-looking bank optimism therefore supports the existence of sentiment-driven credit booms, 40 years after Minsky (1977) and Kindleberger (1978).

The existence of sentiment-driven credit booms has implications for understanding the emergence of financial instability in the banking sector. Our findings encourage macro-prudential authorities to go beyond examining banks' fundamentals and address the emergence of over-optimism before it leads to prolonged credit expansions. The sentiment index not only allows for monitoring the average level of optimism among banks in a given quarter but also enables the identification of specific banks exhibiting optimism. As such, regulators can take preemptive measures to prevent the emergence of credit booms before they become significant predictors of financial crises.

References

Anginer, D., Demirguc-Kunt, A., Huizinga, H., Ma, K. 2018. Corporate governance of banks and financial stability. Journal of Financial Economics. 130 (2), 327–346.

Arif, S., Lee, C. M. C. 2014. Aggregate Investment and Investor Sentiment. The Review of Financial Studies. 27 (11), 3241–3279.

Asanuma, D. 2013. Lending attitude as a financial accelerator in a credit network economy. Journal of Economic Interaction and Coordination. 8 (2), 231–247.

Baker, M., Wurgler, J. 2006. Investor Sentiment and the Cross-Section of Stock Returns. The Journal of Finance. 61 (4), 1645–1680.

Baron, M., Xiong, W. 2017. Credit Expansion and Neglected Crash Risk. 132 (2), 713–764.

Barrero, J. M. 2021. The micro and macro of managerial beliefs. Journal of Financial Economics. 143 (2), 640–667.

Berger, A. N., Kim, H. H., Ma, X. F. 2020. Bank Management Sentiment and Liquidity Hoarding. SSRN Scholarly Paper ID 3586500, Social Science Research Network, Rochester, NY.

Bernanke, B. S., Gertler, M., Gilchrist, S. 1999. Chapter 21 The financial accelerator in a quantitative business cycle framework. In Handbook of Macroeconomics. 1, 1341–1393, Elsevier.

Bhagat, S., Bolton, B., Lu, J. 2015. Size, leverage, and risk-taking of financial institutions. Journal of Banking & Finance. 59, 520–537.

Bordalo, P., Gennaioli, N., Ma, Y., Shleifer, A. 2020. Overreaction in macroeconomic expectations. American Economic Review. 110 (9), 2748–82.

Bordalo, P., Gennaioli, N., Shleifer, A. 2018. Diagnostic Expectations and Credit Cycles. The Journal of Finance. 73 (1), 199–227.

Bordalo, P., Gennaioli, N., Shleifer, A., Terry, S. J. 2021. Real Credit Cycles. Working Paper 28416, National Bureau of Economic Research, Series: Working Paper Series.

Bordo, M. D., Meissner, C. M. 2012. Does inequality lead to a financial crisis? Journal of International Money and Finance. 31 (8), 2147–2161.

Bouchaud, J.-P., Krüger, P., Landier, A., Thesmar, D. 2019. Sticky Expectations and the Profitability Anomaly. The Journal of Finance. 74 (2), 639–674.

Calomiris, C. W., Mamaysky, H., Yang, R. 2020. Measuring the Cost of Regulation: A Text-Based Approach.Technical report, National Bureau of Economic Research.

Coibion, O., Gorodnichenko, Y. 2015. Information rigidity and the expectations formation process: A simple framework and new facts. American Economic Review. 105 (8), 2644–78.

Correa, R., Garud, K., Londono, J. M., Mislang, N. 2021. Sentiment in Central Banks' Financial Stability Reports*. Review of Finance. 25 (1), 85–120.

Cortés, K., Duchin, R., Sosyura, D. 2016. Clouded judgment: The role of sentiment in credit origination. Journal of Financial Economics. 121 (2), 392–413, Publisher: Elsevier.

Fahlenbrach, R., Prilmeier, R., Stulz, R. M. 2018. Why Does Fast Loan Growth Predict Poor Performance for Banks? The Review of Financial Studies. 31 (3), 1014–1063.

Gourinchas, P.-O., Obstfeld, M. 2012. Stories of the Twentieth Century for the Twenty-First. American Economic Journal: Macroeconomics. 4 (1), 226–265.

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

Greenwood, R., Hanson, S. G., Jin, L. J. 2019. Reflexivity in credit markets.Technical report, National Bureau of Economic Research.

Hanley, K. W., Hoberg, G. 2019. Dynamic Interpretation of Emerging Risks in the Financial Sector. The Review of Financial Studies. 32 (12), 4543–4603.

Heider, F., Saidi, F., Schepens, G. 2019. Life below Zero: Bank Lending under Negative Policy Rates. The Review of Financial Studies. 32 (10), 3728–3761.

Ho, P.-H., Huang, C.-W., Lin, C.-Y., Yen, J.-F. 2016. CEO overconfidence and financial crisis: Evidence from bank lending and leverage. Journal of Financial Economics. 120 (1), 194–209.

Hribar, P., McInnis, J. 2012. Investor Sentiment and Analysts' Earnings Forecast Errors. Management Science. 58 (2), 293–307.

Hribar, P., Melessa, S. J., Small, R. C., Wilde, J. H. 2017. Does managerial sentiment affect accrual estimates? Evidence from the banking industry. Journal of Accounting and Economics. 63 (1), 26–50.

Hu, M., Liu, B. 2004. Mining and summarizing customer reviews. In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, KDD '04, 168–177, New York, NY, USA, Association for Computing Machinery.

Huang, D., Jiang, F., Tu, J., Zhou, G. 2015. Investor Sentiment Aligned: A Powerful Predictor of Stock Returns. The Review of Financial Studies. 28 (3), 791–837.

Hutto, C., Gilbert, E. 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In Proceedings of the International AAAI Conference on Web and Social Media. 8, Issue: 1.

Ji, Y., De Grauwe, P. 2020. Banks and Macroeconomic Stability: A Behavioural Macroeconomic Approach. Rebuilding Macroeconomics Working Paper Series. (14).

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

Jiménez, G., Ongena, S., Peydró, J.-L., Saurina, J. 2012. Credit Supply and Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications. American Economic Review. 102 (5), 2301–2326.

Jiménez, G., Ongena, S., Peydró, J.-L., Saurina, J. 2014. Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk-Taking? Econometrica. 82 (2), 463–505, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA10104.

Jordà, O. 2005. Estimation and Inference of Impulse Responses by Local Projections. American Economic Review. 95 (1), 161–182.

Jordà, O., Schularick, M., Taylor, A. M. 2013. When Credit Bites Back. Journal of Money, Credit and Banking. 45 (s2), 3–28.

Kindleberger, C. P. 1978. Manias, Panics and Crashes: A History of Financial Crises, Sixth Edition. Palgrave Macmillan.

Kiyotaki, N., Moore, J. 1997. Credit Cycles. Journal of Political Economy. 105 (2), 211–248, Publisher: The University of Chicago Press.

Loughran, T., Mcdonald, B. 2011. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. The Journal of Finance. 66 (1), 35–65.

López-Salido, D., Stein, J. C., Zakrajšek, E. 2017. Credit-Market Sentiment and the Business Cycle*. The Quarterly Journal of Economics. 132 (3), 1373–1426.

Ma, Y., Paligorova, T., Peydro, J.-L. 2021. Expectations and bank lending. Work. Pap., Chicago Booth Sch. Bus., Chicago.

Mian, A., Sufi, A., Verner, E. 2017. Household Debt and Business Cycles Worldwide*. The Quarterly Journal of Economics. 132 (4), 1755–1817.

Milani, F. 2017. Sentiment and the U.S. business cycle. Journal of Economic Dynamics and Control. 82, 289–311.

Minsky, H. P. 1977. The Financial Instability Hypothesis: An Interpretation of Keynes and an Alternative to 'Standard' Theory. Challenge (05775132). 20 (1), 20.

Nyman, R., Kapadia, S., Tuckett, D. 2021. News and narratives in financial systems: Exploiting big data for systemic risk assessment. Journal of Economic Dynamics and Control. 127, 104119.

Polk, C., Sapienza, P. 2009. The Stock Market and Corporate Investment: A Test of Catering Theory. The Review of Financial Studies. 22 (1), 187–217.

Price, S. M., Doran, J. S., Peterson, D. R., Bliss, B. A. 2012. Earnings conference calls and stock returns: The incremental informativeness of textual tone. Journal of Banking & Finance. 36 (4), 992–1011.

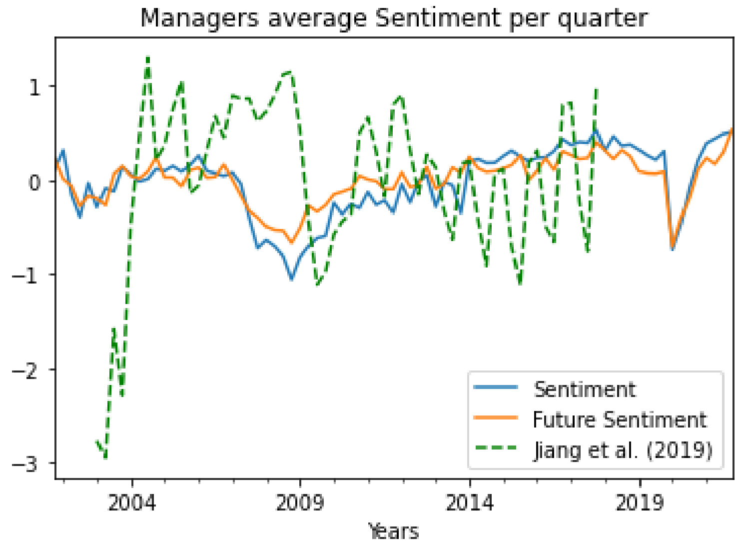
Schularick, M., Taylor, A. M. 2012. Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. American Economic Review. 102 (2), 1029–61.

Shapiro, A. H., Sudhof, M., Wilson, D. 2020. Measuring news sentiment. Federal Reserve Bank of San Francisco.

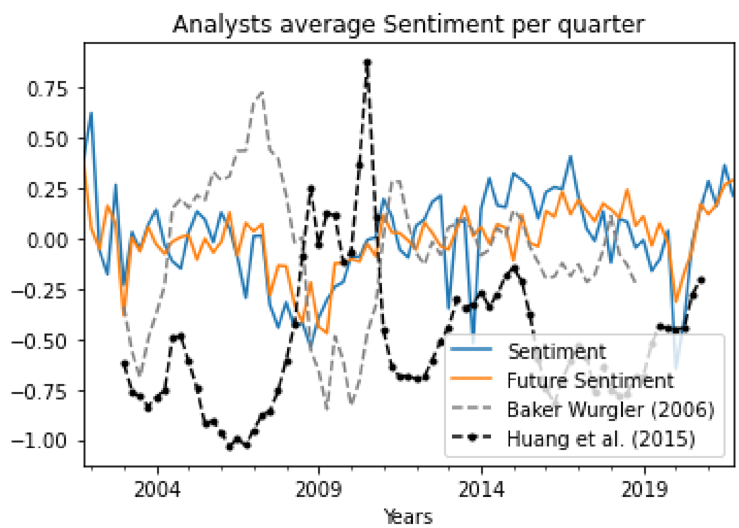
Simpson, A. 2013. Does Investor Sentiment Affect Earnings Management? Journal of Business Finance & Accounting. 40 (7-8), 869–900.

Tao, J., Deokar, A. V., Deshmukh, A. 2018. Analysing forward-looking statements in initial public offering prospectuses: a text analytics approach. Journal of Business Analytics. 1 (1), 54–70.

Figures and Tables



(a) Bank sentiment

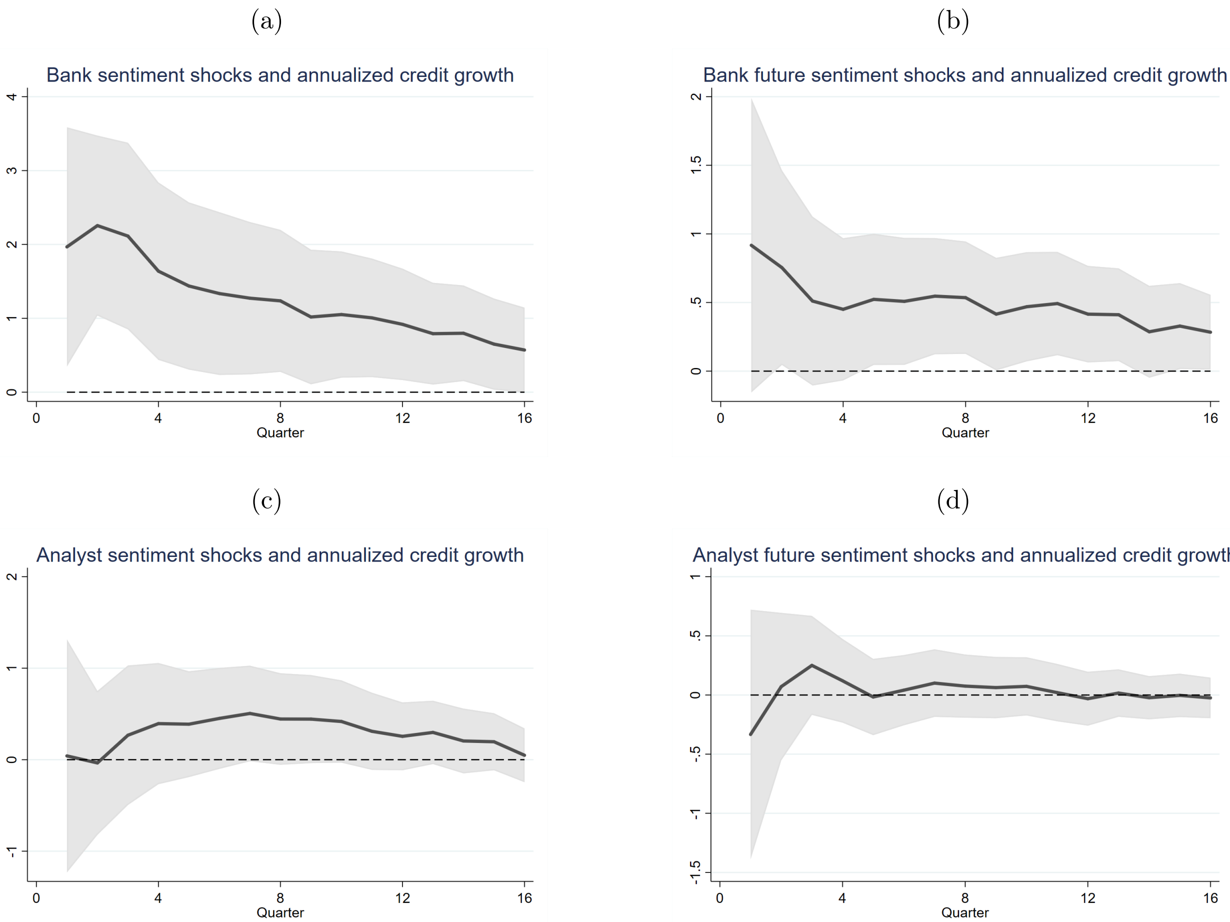


(b) Analyst sentiment

Figure 1: Manager and analyst present and future sentiment

The solid blue line in (a) depicts the cross-sectional average of *Bank sentiment* while the solid orange line is the cross-sectional average of *Bank future sentiment*. See section 2.2 and 2.4 for more details on the construction. The dotted green line in (a) is the Jiang et al. (2019) aggregate manager sentiment index computed on 10-Ks, 10-Qs and conference calls. Panel (b) depicts Analyst sentiment and *Analyst future sentiment* in blue and orange respectively. These indices are only computed on the analysts' questions in the earnings call. The black dotted line is Huang et al. (2015) aligned investor index which is obtained after applying partial least square method on 6 investor sentiment indices of Baker and Wurgler (2006). The grey dotted line is Baker and Wurgler (2006) from the first principal component of these same indices. All the indices are standardized with mean 0 and unit variance.

Figure 2: Sentiment shocks and credit growth: Impulse Response Function



This figure presents local projections a la Jordà (2005). Across the specification, we regress the annualized loan growth up to 16 quarters ahead on the same controls of equation (2) with country-time and bank fixed effects. The impulse response functions show the reaction of n quarter ahead loan growth to a one standard deviation sentiment shock with 90% confidence bands.

Table 1: Descriptive statistics

	N	Mean	SD	p25	p50	p75
Sentiment indices						
Bank sentiment	13289	0.19	0.07	0.14	0.19	0.24
Bank future sentiment	13187	0.15	0.09	0.09	0.15	0.20
Analyst sentiment	12834	0.13	0.09	0.07	0.13	0.19
Analyst future sentiment	11871	0.10	0.17	-0.00	0.09	0.19
Bank-level variables						
$\Delta loans_{b,t+4}$	9552	11.97	22.83	-1.25	6.88	18.36
$\Delta loans_{b,t+8}$	8208	11.32	16.15	0.97	7.52	18.02
$\Delta loans_{b,t+12}$	6958	10.97	13.42	2.13	7.92	17.37
log(Size)	11193	16.53	2.06	15.00	16.01	17.81
Equity-to-assets ratio	11191	10.12	3.71	7.83	10.07	12.11
Deposit-to-assets	11026	69.74	16.13	64.11	74.60	80.45
Problem loans	9867	2.56	5.28	0.52	1.05	2.50
ROA	11087	0.76	1.82	0.50	0.92	1.25
ROE	11072	7.42	23.19	5.59	9.07	12.52
Loans-to-deposit	10852	96.54	32.33	81.68	92.77	103.72
Loan loss provisions	10567	0.17	0.36	0.02	0.07	0.18
Analyst variables						
LTG_M	3053	10.08	9.62	6.00	9.00	12.00
$(\text{EPS}_{t+3}/EPS_t)^{\frac{1}{3}} - LTG_t$	2417	-9.29	9.07	-10.96	-8.16	-5.38
$(\text{EPS}_{t+4}/EPS_t)^{\frac{1}{4}} - LTG_t$	2219	-9.34	9.15	-10.93	-8.15	-5.33
$(\text{EPS}_{t+5}/EPS_t)^{\frac{1}{5}} - LTG_t$	2033	-9.36	9.30	-10.92	-8.07	-5.33
Macro-economic variables						
House price index growth	12033	2.33	5.42	-0.51	3.81	5.53
Consumer Confidence Index	12574	71.66	47.38	51.00	91.05	104.40
Inflation	12807	1.90	1.32	1.20	1.89	2.66
GDP growth	12708	1.61	2.93	1.26	2.11	2.93
Expected inflation	11546	1.91	0.61	1.76	1.93	2.15
Expected GDP growth	11116	3.06	4.44	1.18	1.90	2.78
Expected Unemployment rate	11116	6.66	2.32	4.70	5.90	8.70

This table shows descriptive statistics for our sample of 13 291 earnings calls. The earning calls are extracted from Refinitiv for 484 Banks from Q1 2001 until Q1 2021. The calls are then merged with SNL Financials at the quarterly frequency as shown in panel A. The analyst expectations (LTG_m) and earnings forecast errors ($(EPS_{t+n}/EPS_t)^{\frac{1}{n}} - LTG_t$) are extracted from Refinitiv and the I/B/E/S database.

Table 2: Relationship between stock returns and managers' and analysts' sentiment

	(1)	(2)	(3)	(4)
	$ret_{b,t+1}$	$ret_{b,t+1}$	$ret_{b,t+1}$	$ret_{b,t+1}$
Bank sentiment	0.336^{***}			
	(0.040)			
Bank future sentiment		0.084^{***}		
		(0.024)		
Analyst sentiment			0.155^{***}	
			(0.025)	
Analyst future sentiment				0.007
				(0.010)
Time FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes
N	10740	10705	10434	9632
R2	0.456	0.449	0.460	0.456

This table shows regression of quarterly stock returns of banks on the sentiment index computed on their earning calls. Bank sentiment is the average of the sentiment index computed on the Presentation and Answers in the Earning calls. The Analyst sentiment is the sentiment index of analysts' questions. The future index runs the sentiment algorithm on the future sentences of the respective texts using a sentiment dictionary which combines PMI score from (Shapiro et al., 2020) with Hu and Liu (2004) and Loughran and Mcdonald (2011). Standard errors are in parentheses and ***, ** and * refer to significance at the 1%, 5% and 10%.

Table 3: Coibon-Gorodnichenko Regressions with EPS and Analysts' Sentiment

	(1)	(2)	(3)	(4)	(5)	(6)
	LT Er_3	LT Er_5	LT Er_3	LT Er_5	ΔLTG_{t+1}	ΔLTG_{t+1}
$\mathrm{LTG}_t - LTG_{t-1}$	-0.159***	-0.188***	-0.157***	-0.182***		
	(0.028)	(0.031)	(0.028)	(0.031)		
$\mathrm{LTG}_t - LTG_{t-2}$	-0.244***	-0.192***	-0.246***	-0.193***		
	(0.027)	(0.029)	(0.027)	(0.029)		
$\mathrm{LTG}_t - LTG_{t-3}$	-0.352***	-0.341***	-0.353***	-0.348***		
	(0.024)	(0.027)	(0.025)	(0.028)		
Analyst sentiment	16.63***	15.46***				
	(3.585)	(3.902)				
Analyst future sentiment			3.790	2.426		
			(2.330)	(2.374)		
Analyst sentiment$_{t-1}$					-5.569	
					(5.605)	
Analyst future sentiment$_{t-1}$						-2.753
						(3.444)
N	803	668	799	664	1165	1158
R2	0.640	0.572	0.631	0.562	0.060	0.060

This table regresses forecasts errors of analysts banks' publishing earning calls on their forecast revisions and their sentiment expressed in the earning call. The data is from the Refinitiv's I/B/E/S Estimates and Refinitiv. EPS_t is the earnings reported by the bank. LTG_t is the mean of analyst estimates of the compound average growth of EPS over the next three to 5 years. Both variables are winsorized at the 1st and 99th percentile. $LTEr_n$ is $(EPS_{t+n}/EPS_t)^{\frac{1}{n}} - LTG_t$, that is, the forecast error for year n = 1, 2 and 3. ΔLTG_{t+1} is $LTG_{t+1} - LTG_t$, the forecast revision. Following Bordalo et al. (2018), growth rates are only computed for positive EPS_t. The regressions have time fixed effects to control for time-varying macro-economic conditions. ***, ** and * refer to significance at the 1%, 5% and 10%.

Table 4: Coibon-Gorodnichenko Regressions with EPS and Analysts' Sentiment: Short-term forecast errors

	(1)	(2)	(3)	(4)	(5)	(6)
	Er_t	Er_t	Er_t	Er_t	$Revision_t$	$Revision_t$
$Analyst\ revision_t$	0.093***	0.045**	0.041*	0.042**		
	(0.015)	(0.021)	(0.021)	(0.021)		
$Analyst\ future\ sentiment_{t-1}$		-0.002		-0.010		0.023***
		(0.008)		(0.008)		(0.007)
$Analyst\ sentiment_{t-1}$			0.019	0.032**	0.049***	
			(0.012)	(0.014)	(0.012)	
N	4587	2383	2401	2383	2401	2383
R2	0.155	0.184	0.184	0.185	0.156	0.154

This table regresses forecasts errors of analysts banks' publishing earning calls on their forecast revisions and their sentiment expressed in the earning call. The data is from the Refinitiv's I/B/E/S Estimates and at the annual frequency from 2001 to 2021. Analyst future sentiment and Analyst sentiment is the annual average of the sentiment in year t. $Analystrevision_t$ and $Revision_t$ is the forecast revision: $(F_{b,t-1}EPS_{b,t} - F_{b,t-2})/P_{b,t-2}$. The forecast error Er_t is: $(EPS_{b,t} - F_{b,t-1}EPS_{b,t})$. Both variables are winzorized at the 5th and 95th percentile. All regressions are with time fixed effects. ***, ** and * refer to significance at the 1%, 5% and 10%.

Table 5: Relationship between loan growth and sentiment shocks

	(1) $\Delta loans_{b,t+4}$	(2) $\Delta loans_{b,t+4}$	(3) $\Delta loans_{b,t+8}$	(4) $\Delta loans_{b,t+8}$	(5) $\Delta loans_{b,t+12}$	(6) $\Delta loans_{b,t+12}$
Panel A: Bank sentiment shocks						
Bank sentiment$_{b,t}$	27.90***	23.23**	22.41***	17.53**	17.92**	13.02**
	(8.603)	(10.35)	(7.682)	(8.282)	(7.085)	(6.500)
N	6331	6331	5282	5282	4369	4369
R2	0.377	0.529	0.422	0.660	0.448	0.742
Panel B: Bank future sentiment shocks						
Bank future sentiment$_{b,t}$	8.854**	5.239	9.303***	6.227**	7.379**	4.828*
	(3.599)	(3.663)	(3.245)	(2.895)	(3.112)	(2.486)
N	6324	6324	5280	5280	4369	4369
R2	0.373	0.526	0.418	0.658	0.445	0.741
Panel C: Analysts sentiment shocks						
Analyst sentiment$_{b,t}$	3.225	4.407	3.702	4.967	2.974	2.852
	(4.395)	(4.497)	(3.660)	(3.398)	(3.169)	(2.520)
N	6225	6225	5191	5191	4291	4291
R2	0.378	0.532	0.421	0.663	0.448	0.746
Panel D: Analysts future sentiment shocks						
Analyst future sentiment$_{b,t}$	0.324	0.692	0.184	0.433	0.0274	-0.180
	(1.337)	(1.239)	(1.169)	(0.935)	(1.080)	(0.798)
N	5737	5737	4781	4781	3940	3940
R2	0.384	0.539	0.428	0.668	0.456	0.751
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effect	No	Yes	No	Yes	No	Yes

The table shows the OLS estimates from regressions of $\Delta loans_{b,t+n}$ on bank and analysts sentiment shocks, bank and macro controls. $\Delta loans_{b,t+n}$ is annualized percentage growth of net loans for n quarters ahead. Panel A uses the initial bank sentiment index. Panel B uses bank future sentiment index. The index is the average of the Presentation and Answers sentiment index run on forward-looking sentences of the Presentation and Answers using a sentiment dictionary which combines PMI score from (Shapiro et al., 2020) with Hu and Liu (2004) and Loughran and Mcdonald (2011). Panel C uses the analyst sentiment index. The index is run on the Questions section of the earning calls using the same dictionary. Panel D uses the analyst future sentiment index. The index is run on forward-looking sentences of the Questions. The bank controls are log(Size), Equity-to-assets ratio, Deposit-to-assets, Problem loans over total loans, Return-on-assets (ROA), Return-on-equity (ROE), Loans-to-deposit, Loan loss provisions. The sample runs from Q1 2001 until Q1 2021. The sample includes European, American, Canadian and Japanese banks publishing earning calls since Q1 2001 and for which we can retrieve fundamentals in SNL financials. All bank controls are winsorized at the 1st and 99th percentile. Banks quarterly controls are introduced for time t-1 up to t-4 to control for seasonality effects and contemporaneously at time t. All columns include country-time fixed effects and, when specified, bank fixed effects. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%.

Table 6: Relationship between loan growth and managers' sentiment shocks

	(1) Δloans$_{b,t+4}$	(2) Δloans$_{b,t+4}$	(3) Δloans$_{b,t+8}$	(4) Δloans$_{b,t+8}$	(5) Δloans$_{b,t+12}$	(6) Δloans$_{b,t+12}$
Panel A: Bank sentiment shocks						
Bank sentiment$_{b,t}$	113.0	205.6***	57.77	160.7***	32.81	98.28*
	(70.18)	(70.22)	(63.62)	(60.49)	(56.17)	(52.16)
log(Size)$_{b,t}$	4.575	-30.65***	6.761*	-23.35***	8.152**	-17.34***
	(3.904)	(4.669)	(3.560)	(3.389)	(3.591)	(3.126)
Bank sentiment*log(Size)$_{b,t}$	-5.339	-11.48***	-2.226	-9.039**	-0.940	-5.388*
	(4.316)	(4.286)	(3.895)	(3.661)	(3.398)	(3.150)
N	6331	6331	5282	5282	4369	4369
R2	0.377	0.530	0.422	0.662	0.449	0.743
Panel B: Bank future sentiment shocks						
Bank future sentiment$_{b,t}$	81.07**	117.6***	45.93	77.70***	37.06	60.64**
	(36.31)	(36.24)	(29.26)	(27.80)	(27.32)	(24.93)
log(Size)$_{b,t}$	4.695	-31.66***	6.896*	-24.22***	8.360**	-17.78***
	(3.817)	(4.605)	(3.521)	(3.387)	(3.566)	(3.150)
Bank future sentiment*log(Size)$_{b,t}$	-4.567**	-7.121***	-2.318	-4.532***	-1.881	-3.543**
	(2.275)	(2.268)	(1.827)	(1.695)	(1.674)	(1.512)
N	6324	6324	5280	5280	4369	4369
R2	0.373	0.528	0.419	0.659	0.445	0.742
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes

The table shows the OLS estimates from regressions of $\Delta loans_{b,t+n}$ on bank sentiment shocks and bank controls. $\Delta loans_{b,t+n}$ is annualized percentage growth of net loans for n quarters ahead. Panel A uses the initial bank sentiment index. Panel A uses the initial bank future sentiment index. The index is the average of the Presentation and Answers sentiment index run on forward-looking sentences of the Presentation and Answers using a sentiment dictionary which combines PMI score from (Shapiro et al., 2020) with Hu and Liu (2004) and Loughran and Mcdonald (2011). The bank controls are log(Size), Equity-to-assets ratio, Deposit-to-assets, Problem loans over total loans, Return-on-assets (ROA), Return-on-equity (ROE), Loans-to-deposit, Loan loss provisions. The sample runs from Q1 2001 until Q1 2021. The sample includes European, American, Canadian and Japanese banks publishing earning calls since Q1 2001 and for which we can retrieve fundamentals in SNL financials. All bank controls are winsorized at the 1st and 99th percentile. Banks quarterly controls are introduced for time t-1 up to t-4 to control for seasonality effects and contemporaneously at time t. All columns include country-time fixed effects and, when specified, bank fixed effects. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%.

Table 7: Relationship between loan growth and managers' sentiment shocks

	(1) $\Delta\text{loans}_{b,t+4}$	(2) $\Delta\text{loans}_{b,t+4}$	(3) $\Delta\text{loans}_{b,t+8}$	(4) $\Delta\text{loans}_{b,t+8}$	(5) $\Delta\text{loans}_{b,t+12}$	(6) $\Delta\text{loans}_{b,t+12}$
Panel A: Bank sentiment shocks						
$\text{Presentation}_{b,t}$	24.32***	15.22*	22.70***	13.12*	20.36***	12.71**
	(7.208)	(8.030)	(6.580)	(6.715)	(6.256)	(5.403)
$\text{Answers}_{b,t}$	5.962	10.42*	2.131	6.289	0.161	2.984
	(4.868)	(5.436)	(4.127)	(3.843)	(3.944)	(2.889)
N	6257	6257	5219	5219	4315	4315
R2	0.384	0.534	0.429	0.664	0.457	0.746
Panel B: Bank future sentiment shocks						
$\text{Presentation}_{b,t}$	5.639*	2.831	7.009**	4.845**	5.294*	3.050
	(3.045)	(2.980)	(2.887)	(2.359)	(2.796)	(1.964)
$\text{Answers}_{b,t}$	2.728	1.963	1.968	1.278	2.157	1.957*
	(2.281)	(2.012)	(1.658)	(1.402)	(1.677)	(1.182)
N	6215	6215	5183	5183	4284	4284
R2	0.378	0.531	0.423	0.663	0.450	0.745
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country- Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes

The table shows the OLS estimates from regressions of $\Delta loans_{b,t+n}$ on bank sentiment shocks and bank controls. $\Delta loans_{b,t+n}$ is annualized percentage growth of net loans for n quarters ahead. The Presentation and Answers sentiment index are computed on forward-looking sentences of the Presentation and Answers using a sentiment dictionary which combines PMI score from (Shapiro et al., 2020) with Hu and Liu (2004) and Loughran and Mcdonald (2011). The bank controls are log(Size), Equity-to-assets ratio, Deposit-to-assets, Problem loans over total loans, Return-on-assets (ROA), Return-on-equity (ROE), Loans-to-deposit, Loan loss provisions. The sample runs from Q1 2001 until Q1 2021. The sample includes European, American, Canadian and Japanese banks publishing earning calls since Q1 2001 and for which we can retrieve fundamentals in SNL financials. All bank controls are winsorized at the 1st and 99th percentile. Banks quarterly controls are introduced for time t-1 up to t-4 to control for seasonality effects and contemporaneously at time t. All columns include country-time fixed effects and, when specified, bank fixed effects. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%.

Table 8: Relationship between loan growth and managers' sentiment shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\text{loans}_{b,t+4}$	$\Delta\text{loans}_{b,t+4}$	$\Delta\text{loans}_{b,t+8}$	$\Delta\text{loans}_{b,t+8}$	$\Delta\text{loans}_{b,t+12}$	$\Delta\text{loans}_{b,t+12}$
Bank sentiment$_{b,t}$	26.28**		17.96**		13.33**	
	(10.63)		(8.177)		(6.454)	
Bank future sentiment$_{b,t}$		5.700		6.303**		4.960**
		(3.761)		(2.866)		(2.488)
HPg$_{c,t}$	0.0633	-0.0371	-0.805*	-0.784	-0.660	-0.640
	(0.566)	(0.607)	(0.482)	(0.494)	(0.642)	(0.638)
Consumer Confidence$_{c,t}$	-0.246	-0.268	0.0717	0.0742	-0.0620	-0.0632
	(0.171)	(0.168)	(0.126)	(0.124)	(0.195)	(0.200)
CPIg$_{c,t}$	-2.654	-2.746	1.858	1.870	0.708	0.601
	(2.156)	(2.332)	(1.432)	(1.443)	(0.540)	(0.501)
GDPg$_{c,t}$	2.018**	2.222**	-0.537	-0.570	-0.0856	-0.0720
	(0.982)	(1.034)	(0.783)	(0.815)	(0.627)	(0.634)
SR$_{c,t}$	3.012*	2.931*	-2.213***	-2.224***	0.531	0.564
	(1.572)	(1.545)	(0.818)	(0.793)	(0.775)	(0.788)
Expected CPI$_{c,t}$	-5.936***	-6.455***	-6.464***	-6.602***	-2.951	-3.063
	(2.130)	(2.272)	(1.886)	(1.894)	(2.260)	(2.224)
Expected GDP$_{c,t}$	-0.251	-0.362	0.263	0.262	-0.861***	-0.886***
	(0.260)	(0.280)	(0.213)	(0.215)	(0.228)	(0.230)
Expected Unemployment$_{c,t}$	-3.628	-3.008	3.384*	3.525**	-0.701	-0.747
	(2.784)	(2.991)	(1.770)	(1.739)	(3.463)	(3.581)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	5500	5493	4879	4877	4076	4076
R2	0.503	0.501	0.644	0.643	0.730	0.729

The table shows the OLS estimates from regressions of $\Delta loans_{b,t+n}$ on bank sentiment shocks, bank and macro controls. $\Delta loans_{b,t+n}$ is annualized percentage growth of net loans for n quarters ahead. The macro controls are merge with the bank data based on the country of the bank's headquarters. All macro controls are at the country level except for expected GDP growth ($Exp.\Delta GDP$), expected unemployment growth ($Exp.\Delta Unemployment$) and main monetary policy reference rate which are given at the level of the US, the Euro Area and Japan. The sample runs from Q1 2001 until Q1 2021. The sample includes European, American, Canadian and Japanese banks publishing earning calls since Q1 2001 and for which we can retrieve fundamentals in SNL financials. All bank and macro controls are winsorized at the 1st and 99th percentile. Banks quarterly controls are introduced for time t up to t-4 to control for seasonality effects and contemporaneously at time t-4 (lagged one year). Macro controls are introduced at time t. All columns include time fixed effects and bank fixed effects. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%.

Table 9: Correlation of Sentiment indexes

	(1)	(2)	(3)	(4)
(1) Bank sentiment	1.00			
(2) Bank future sentiment	0.61***	1.00		
(3) Analyst sentiment	0.47***	0.26***	1.00	
(4) Analyst future sentiment	0.19***	0.14***	0.36***	1.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Relationship between loan growth and managers' sentiment shocks

	(1) $\Delta\text{loans}_{b,t+4}$	(2) $\Delta\text{loans}_{b,t+4}$	(3) $\Delta\text{loans}_{b,t+8}$	(4) $\Delta\text{loans}_{b,t+8}$	(5) $\Delta\text{loans}_{b,t+12}$	(6) $\Delta\text{loans}_{b,t+12}$
Panel A: Bank sentiment shocks						
Bank sentiment$_{b,t}$	30.78***	26.07**	23.56***	17.16**	18.88**	12.82**
	(8.605)	(10.46)	(7.713)	(8.290)	(7.418)	(6.485)
Analyst sentiment$_{b,t}$	-3.048	-0.0546	-1.183	2.075	-0.989	0.549
	(4.076)	(4.192)	(3.386)	(3.033)	(3.294)	(2.263)
N	6225	6225	5191	5191	4291	4291
R2	0.383	0.535	0.427	0.665	0.454	0.747
Panel B: Bank future sentiment shocks						
Bank future sentiment$_{b,t}$	10.87***	6.311*	9.913***	5.619*	8.240**	5.222**
	(3.658)	(3.764)	(3.449)	(3.113)	(3.306)	(2.589)
Analyst future sentiment$_{b,t}$	0.0181	0.565	-0.0665	0.335	-0.196	-0.282
	(1.336)	(1.253)	(1.166)	(0.938)	(1.081)	(0.796)
N	5737	5737	4781	4781	3940	3940
R2	0.385	0.540	0.430	0.668	0.459	0.752
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes

The table shows the OLS estimates from regressions of $\Delta loans_{b,t+n}$ on bank and analysts sentiment shocks and bank. $\Delta loans_{b,t+n}$ is annualised percentage growth of net loans for n quarters ahead. The bank future sentiment index is the average of the Presentation and Answers sentiment index run on forward-looking sentences of the Presentation and Answers using a sentiment dictionary which combines PMI score from (Shapiro et al., 2020) with Hu and Liu (2004) and Loughran and Mcdonald (2011). The bank controls are log(Size), Equity-to-assets ratio, Deposit-to-assets, Problem loans over total loans, Return-on-assets (ROA), Return-on-equity (ROE), Loans-to-deposit, Loan loss provisions. The sample runs from Q1 2001 until Q1 2021. The sample includes European, American, Canadian and Japanese banks publishing earning calls since Q1 2001 and for which we can retrieve fundamentals in SNL financials. All bank controls are winsorized at the 1st and 99th percentile. Banks quarterly controls are introduced for time t-1 up to t-4 to control for seasonality effects and contemporaneously at time t. All columns include country-time fixed effects and, when specified, bank fixed effects. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%.

Table 11: Relationship between loan growth and managers' sentiment shocks

	(1) Δloans$_{b,t+4}$	(2) Δloans$_{b,t+4}$	(3) Δloans$_{b,t+8}$	(4) Δloans$_{b,t+8}$	(5) Δloans$_{b,t+12}$	(6) Δloans$_{b,t+12}$
	Panel A: Bank sentiment shocks					
Bank sentiment$_{b,t}$	32.45***	27.65***	26.04***	20.09**	21.76***	15.58**
	(8.524)	(9.984)	(7.590)	(7.927)	(7.058)	(6.255)
N	6400	6400	5341	5341	4423	4423
R2	0.370	0.515	0.414	0.644	0.437	0.733
	Panel B: Bank future sentiment shocks					
Bank future sentiment$_{b,t}$	10.45***	6.508*	10.59***	6.844**	8.850***	5.432**
	(3.671)	(3.697)	(3.284)	(2.914)	(3.174)	(2.464)
N	6393	6393	5339	5339	4423	4423
R2	0.364	0.512	0.408	0.642	0.432	0.731
Lagged Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes

The table shows the OLS estimates from regressions of $\Delta loans_{b,t+n}$ on bank sentiment shocks, bank and macro controls. $\Delta loans_{b,t+n}$ is annualized percentage growth of net loans for n quarters ahead. The index is the average of the Presentation and Answers sentiment index run on forward-looking sentences of the Presentation and Answers using a sentiment dictionary which combines PMI score from (Shapiro et al., 2020) with Hu and Liu (2004) and Loughran and Mcdonald (2011). The bank controls are log(Size), Equity-to-assets ratio, Deposit-to-assets, Problem loans over total loans, Return-on-assets (ROA), Return-on-equity (ROE), Loans-to-deposit, Loan loss provisions. The macro controls are merge with the bank data based on the country of the bank's headquarters. All macro controls are at the country level except for expected GDP growth ($Exp.\Delta GDP$), expected unemployment growth ($Exp.\Delta Unemployment$) and main monetary policy reference rate which are given at the level of the US, the Euro Area and Japan. The sample runs from Q1 2001 until Q1 2021. The sample includes European, American, Canadian and Japanese banks publishing earning calls since Q1 2001 and for which we can retrieve fundamentals in SNL financials. All bank and macro controls are winsorized at the 1st and 99th percentile. Banks quarterly controls are introduced for time t-1 up to t-4 to control for seasonality effects and contemporaneously at time t-4 (lagged one year). Macro controls are introduced at time t. All columns include country-time fixed effects and, when specified, bank fixed effects. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%.

Table 12: Relationship between loan growth and managers' sentiment shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Δloans$_{b,t+4}$	Δloans$_{b,t+4}$	Δloans$_{b,t+8}$	Δloans$_{b,t+8}$	Δloans$_{b,t+12}$	Δloans$_{b,t+12}$
Panel A: Bank sentiment shocks						
Bank sentiment$_{b,t}$	186.1***	102.8**	154.9***	85.76**	128.9***	65.66**
	(37.41)	(45.75)	(32.19)	(36.35)	(28.13)	(29.50)
N	6329	6329	5280	5280	4368	4368
R2	0.383	0.529	0.429	0.659	0.455	0.743
Panel B: Bank future sentiment shocks						
Bank future sentiment$_{b,t}$	29.84*	0.810	40.58***	17.55	36.70***	18.43*
	(16.22)	(16.62)	(14.28)	(12.47)	(13.57)	(10.76)
N	6216	6216	5190	5190	4289	4289
R2	0.372	0.529	0.419	0.657	0.447	0.741
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes

The table shows the OLS estimates from regressions of $\Delta loans_{b,t+n}$ on bank and analysts sentiment shocks, bank and macro controls. $\Delta loans_{b,t+n}$ is annualized percentage growth of net loans for n quarters ahead. The bank future sentiment index is the average of the Presentation and Answers sentiment index run on forward-looking sentences using Loughran and Mcdonald (2011) dictionary. The bank controls are log(Size), Equity-to-assets ratio, Deposit-to-assets, Problem loans over total loans, Return-on-assets (ROA), Return-on-equity (ROE), Loans-to-deposit, Loan loss provisions. The sample runs from Q1 2001 until Q1 2021. The sample includes European, American, Canadian and Japanese banks publishing earning calls since Q1 2001 and for which we can retrieve fundamentals in SNL financials. All bank and macro controls are winsorized at the 1st and 99th percentile. Banks quarterly controls are introduced for time t-1 up to t-4 to control for seasonality effects and contemporaneously at time t. Macro controls are introduced at time t. All columns include country-time fixed effects and, when specified, bank fixed effects. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%.

Appendix

Appendix A. Sentiment extraction

Initial Pre-processing

The earnings calls are extracted from Refinitiv in .txt format that is difficult to read for our sentence extraction algorithm. We thus conduct an initial pre-processing. In this initial cleaning, we delete proper nouns, non-alphanumeric punctuation such as '?!€£¥$%', white-spaces and '', a character that is ubiquitous in the transcripts. The texts are then lemmatized. Lemmatization is a process which consists in reducing words to their lemma. For example, the words 'going' and 'gone' are reduced to the lemma 'go'. At this stage of pre-processing, the text is not stemmed and there is no removal of the stop words. This is because we try to keep as many words as possible before extracting forward-looking statements. Some words, such as 'will' for example, are later used in key-word matching but would be eliminated if we removed stop-words. The choice of not tokenizing our text at this stage allows an identification of forward-looking sentences based on the grammatical structure of the sentence.

Future sentences extraction

Key-word Matching: This technique uses the presence of a word or temporal expression with regard to the future. The first three key words are: "will", "future" and "'ll". Next, we match bi-grams out of two lists. The first list is an adjective indicating the future such as ('next', 'future', 'following', 'upcoming'). The second element is an indicator of periods ('quarter', 'quarters', 'month', 'months', 'year', 'years'). With respect to the reference paper Tao et al. (2018), we add 'years', 'quarters' to match more sentences. Temporal bi-grams are any combination of these two lists:

Time prefix = ['next', 'future','following','upcoming','incoming','coming','succeeding','carryforward’]

Period synonyms = [’quarter’,’quarters’,’month’,’months’,’year’,’years’,’fiscal’,’taxable’ ,’period’,’periods’]

Linguistic Patterns: This is a type of matching that is based not only on the presence of a word in a sentence but also on the place and role of the word in the sentence. A good example is the verb anticipate. If we did not do linguistic matching and simply matched the verb anticipate, we would run into sentences like ‘we are opening new branches to anticipate the growth of depositors base’. The sentence nonetheless does not refer to expectations but rather to a current action of the bank. Therefore, we must add another level of analysis which is the role or position of the verb in the sentence. We would indeed like to match sentences in which the verb ’anticipate’ is conjugated, that is, where ’anticipate’ is the main verb in the sentence. The first objective is to match sentences with a verb that indicates a forward-looking statement such as ’foresee’, ’predict’, ’plan’. These verbs are taken from Tao et al. (2018). Then, we check that there is a subject attached to this verb. This is often "we" or "the bank". We check that the verb has an object complement. This guarantees that we are facing a subject-verb-complement structure. The full list of forward-looking verbs is: [’aim’,’anticipate’,’assume’,’commit’,’estimate’,’expect’,’forecast’,’foresee’,’hope’,’intend’, ’plan’,’project’,’seek’,’predict’,’target’]

Time reference: This is a somewhat different strategy that the two previous strategies. The main idea is that if a sentence contains a future date with respect to the document, this sentence must be referring to the future. The strategy has five steps:

- Extract the date of the document from the filename (name of the transcripts). You get the reference date: $dateref$.
- Only take the year of the document out of $dateref$.

- Run the entity names recognition of Spacy.
- Out of the recognized entities, find all date.
- If the date is missing some elements such as the year or the month, assume that they are talking about the year of the document. For example, if the document mentions the 30th of June and the document dates from February 2004, assume that the sentence is referring to June 2004. With this strategy, all the dates recognized by the Named Entity Recognizer are complete and can be compared to $dateref$

All the routine described above is run in Python using the library Spacy and regular expressions to clean the text. The algorithm ran for 90 hours and according to previous research averages a inter-rater reliability of 91.7% (Tao et al., 2018). The main weakness of this algorithm is that it tends to find the same forward-looking sentence with keyword matching and time reference. To address this short-coming, we remove the sentences that are duplicated before joining all the sentences about the future into a text. The table below describes the number of remaining texts after separating the transcripts into presentations and Q&A sections and the extraction of forward-looking statements.

Number of obs	Presentation	Questions	Answers
Full text	15282	14813	14926
Only future sentences	15239	13977	14791
Loss of observations (%)	0.28%	5.6%	0.9%

Pre-processing

Pre-processing consists of tokenization, removal of stop-words and lowering all cases. Tokenization refers to extracting of words from sentences and storing them in a list of separate words. In the tokenization stage, we remove pronouns, conjunctions, punctuation, determinants and white spaces. Only tokens that are uni-grams or bi-grams are accepted as tokens. The removal of stop words is a standard procedure in text-mining which makes sure that words with a high frequency that do not give valuable information are removed. In our approach, we do not stem the words. While this is a standard procedure in pre-processing, the stems returned by the stemmer are not in our sentiment dictionary which would falsify our results.

Appendix B. US and Canada vs Europe

Sample Composition

Table B1:Sample Composition - Number of Observations

Number of obs	bank sentiment	bank future sentiment	analyst sentiment	analyst future sentiment
United States	9112	9112	8842	8010
Europe	3431	3431	3369	3259
Canada	595	595	591	575
Japan	151	49	32	27

Table B2: Sample Composition - Number of Banks

	Number of banks
United States	325
Europe	132
Canada	10
Japan	17

In this appendix, we examine the geographical composition of our sample and explore how the effects vary between Europe and the United States and Canada. Table B1 provides an overview of the observations in our data, indicating a majority of banks headquartered in the United States. This skew towards American banks can be attributed to the fact that the transcription of earnings calls is a recommendation by the Securities and Exchange Commission (SEC) for all companies filing reports with the SEC. Given that a significant number of banks filing to the SEC are American, it is natural that our sample predominantly consists of US banks.

Tabl B2 further demonstrates the distribution of banks across different regions. Although there are more Japanese banks compared to Canadian banks, our panel of Canadian banks is more comprehensive, comprising 595 observations, while we have 151 observations for

Japanese banks. The proportions of American and European banks shown in Table B2 mirror the proportions presented in Table B1 in terms of observations.

US vs Europe: Differentiated effect

In this section, we conduct a comparative analysis of the impact of bank sentiment shocks between Europe and the United States and Canada. These two economic areas exhibit notable distinctions in terms of their financial institutions, which may yield divergent results. Table B3 runs the main regression of this study on both European and American data. The findings support the idea that American banks are more behavioural compared to their European counterparts. This is consistent with the fact that the Great Financial crisis first unfolded in the American banking sector. However, caution should be taken when interpreting these results. The difference in results stem from discrepancies in sample size, as the European data lacks comprehensive country controls. Moreover, we observe that when statistically significant, the intermediate effect of bank sentiment in Europe has a larger economic significance. All in all, we can conclude that while the majority of the effects emphasized in this paper are prevalent in the United States and Canada, they are not entirely absent in Europe.

Table B3: Relationship between loan growth and sentiment shocks in Europe and the US

	(1) $\Delta \text{loans}_{b,t+4}$	(2) $\Delta \text{loans}_{b,t+4}$	(3) $\Delta \text{loans}_{b,t+8}$	(4) $\Delta \text{loans}_{b,t+8}$	(5) $\Delta \text{loans}_{b,t+12}$	(6) $\Delta \text{loans}_{b,t+12}$
	Panel A: Overall sentiment US sample					
Bank sentiment$_{b,t}$	29.37***	26.55**	22.71***	17.98**	18.22**	13.43**
	(9.122)	(10.88)	(7.830)	(8.319)	(7.158)	(6.499)
N	5322	5322	4740	4740	4000	4000
R2	0.337	0.500	0.393	0.641	0.417	0.726
	Panel B: Future sentiment US sample					
Bank future sentiment$_{b,t}$	9.034**	5.875	9.495***	6.343**	7.586**	4.983**
	(3.802)	(3.839)	(3.299)	(2.915)	(3.151)	(2.502)
N	5322	5322	4740	4740	4000	4000
R2	0.333	0.498	0.389	0.640	0.413	0.725
	Panel C: Overall sentiment European sample					
Bank sentiment$_{b,t}$	56.72**	10.16	31.11**	22.52	3.515	4.614
	(21.26)	(6.415)	(12.57)	(19.17)	(5.581)	(.)
N	161	161	132	132	75	75
R2	0.908	0.979	0.891	0.928	1.000	1
	Panel D: Future sentiment European sample					
Bank future sentiment$_{b,t}$	14.08	0.604	15.81	3.125	0.159	1.864
	(9.460)	(3.894)	(9.580)	(6.792)	(3.664)	(.)
N	161	161	132	132	75	75
R2	0.884	0.978	0.888	0.926	1.000	1
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effect	No	Yes	No	Yes	No	Yes

The table shows the OLS estimates from regressions of $\Delta loans_{b,t+n}$ on bank and analysts sentiment shocks, bank and macro controls. $\Delta loans_{b,t+n}$ is annualised percentage growth of net loans for n quarters ahead. Panel A uses the initial bank sentiment index. Panel B uses bank future sentiment index. The index is the average of the Presentation and Answers sentiment index run on forward-looking sentences of the Presentation and Answers using a sentiment dictionary which combines PMI score from (Shapiro et al., 2020) with Hu and Liu (2004) and Loughran and Mcdonald (2011). Panel C uses the analyst sentiment index. The index is run on the Questions section of the earning calls using the same dictionary. Panel D uses the analyst future sentiment index. The index is run on forward-looking sentences of the Questions. The bank controls are log(Size), Equity-to-assets ratio, Deposit-to-assets, Problem loans over total loans, Return-on-assets (ROA), Return-on-equity (ROE), Loans-to-deposit, Loan loss provisions. The sample runs from Q1 2001 until Q1 2021. The sample includes European, American, Canadian and Japanese banks publishing earning calls since Q1 2001 and for which we can retrieve fundamentals in SNL financials. Macro controls include house price growth, the consumer confidence index, inflation, GDP growth. All macro controls are at the country level except for expected GDP growth ($Exp.\Delta GDP$), expected unemployment growth ($Exp.\Delta Unemployment$) and main monetary policy reference rate which are given at the level of the US and the Euro Area level. All controls are winsorized at the 1st and 99th percentile. Banks quarterly controls are introduced for time t-1 up to t-4 to control for seasonality effects and contemporaneously at time t. Columns include bank fixed effects. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%

Appendix C. Validation test 1

Table C1: Relationship between stock returns and managers' and analysts' sentiment

	(1)	(2)	(3)	(4)
	$\text{ret}_{b,t+4}$	$\text{ret}_{b,t+4}$	$\text{ret}_{b,t+8}$	$\text{ret}_{b,t+8}$
Panel A: Bank sentiment shocks				
bank sentiment$_{b,t}$	0.579***		0.128	
	(0.200)		(0.370)	
bank future sentiment$_{b,t}$		0.303**		0.378
		(0.132)		(0.248)
N	2238	2229	1076	1070
R2	0.217	0.207	0.307	0.311
Panel B: Analyst sentiment shocks				
analyst sentiment$_{b,t}$	0.544***		0.233	
	(0.173)		(0.265)	
analyst future sentiment$_{b,t}$		0.0965		0.0795
		(0.0765)		(0.115)
N	2174	2035	1035	967
R2	0.225	0.203	0.314	0.287
Time FEs	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes

This table shows regression of quarterly stock returns of banks on the sentiment index computed on their earning calls. Bank sentiment is the average of the sentiment index computed on the Presentation and Answers in the Earning calls. The Analyst sentiment is the sentiment index of analysts' questions. The future index runs the sentiment algorithm on the future sentences of the respective texts. Following Fahlenbrach et al. (2018), $ret_{b,t+4}$ and $ret_{b,t+8}$ are the subsequent one and two year non-overlapping returns. Overlapping returns are dropped to avoid an upward bias on the t-statistics. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%

Appendix D. Bank controls

Table D1: Relationship between loan growth and managers' sentiment shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Δloans$_{b,t+4}$	Δloans$_{b,t+4}$	Δloans$_{b,t+8}$	Δloans$_{b,t+8}$	Δloans$_{b,t+12}$	Δloans$_{b,t+12}$
Bank sentiment$_{b,t}$	27.90***	23.23**	22.41***	17.53**	17.92**	13.02**
	(8.603)	(10.35)	(7.682)	(8.282)	(7.085)	(6.500)
log(Size)$_{b,t}$	3.614	-32.60***	6.381*	-24.76***	7.997**	-18.16***
	(3.860)	(4.638)	(3.515)	(3.358)	(3.564)	(3.142)
Equity-to-assets$_{b,t}$	0.576	0.628	0.504	0.420*	0.430	0.254
	(0.437)	(0.455)	(0.306)	(0.237)	(0.284)	(0.226)
Deposit-to-assets$_{b,t}$	-0.148	-0.658***	0.0499	-0.381***	-0.00347	-0.385***
	(0.196)	(0.214)	(0.152)	(0.141)	(0.135)	(0.115)
Problem loans$_{b,t}$	-1.478***	-0.802	-1.452***	-0.762*	-1.108***	-0.608**
	(0.496)	(0.529)	(0.410)	(0.431)	(0.299)	(0.277)
ROA$_{b,t}$	2.785*	3.298**	2.405**	2.993**	2.877***	2.718***
	(1.467)	(1.569)	(1.134)	(1.209)	(0.956)	(0.997)
ROE$_{b,t}$	-0.176	-0.210	-0.149	-0.187*	-0.200**	-0.189**
	(0.126)	(0.128)	(0.100)	(0.103)	(0.0843)	(0.0857)
Loans-to-deposit$_{b,t}$	0.0719	-0.250**	0.0521	-0.223***	0.0628	-0.190***
	(0.118)	(0.114)	(0.0971)	(0.0798)	(0.0886)	(0.0695)
Loan loss provisions$_{b,t}$	-4.255**	-1.828	-2.612	-0.471	-3.291**	-0.804
	(2.072)	(2.091)	(1.674)	(1.600)	(1.306)	(1.224)
Lagged Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Country-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	6331	6331	5282	5282	4369	4369
R2	0.334	0.495	0.357	0.642	0.333	0.730

The table shows the OLS estimates from regressions of $\Delta loans_{b,t+n}$ on bank and analysts sentiment shocks and bank controls. $\Delta loans_{b,t+n}$ is annualized percentage growth of net loans for n quarters ahead. The Table uses the initial bank sentiment index. The index is the average of the Presentation and Answers sentiment index using Shapiro et al. (2020) dictionary. The bank controls are log(Size), Equity-to-assets ratio, Deposit-to-assets, Problem loans over total loans, Return-on-assets (ROA), Return-on-equity (ROE), Loans-to-deposit and Loan loss provisions. The sample runs from Q1 2001 until Q1 2021. The sample includes European, American, Canadian and Japanese banks publishing earning calls since Q1 2001 and for which we can retrieve fundamentals in SNL financials. All bank controls are winsorized at the 1st and 99th percentile. Banks quarterly controls are introduced for time t-1 up to t-4 to control for seasonality effects and contemporaneously at time t. All columns include country-time fixed effects and, when specified, bank fixed effects. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%.