

Bank Competition, Loan Portfolio Concentration and Stock Price Crash Risk: The Role of Tone Ambiguity

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We examine the association between loan portfolio concentration, competition and stock price crash risk in the US banking industry. We find that during economic downturns, banks with poorly diversified loan portfolios that operate in competitive markets are more likely to crash. Importantly, we show that this link is channelled through aggressive earnings management and ambiguous annual reports. Therefore, managerial ambiguity can serve as an early warning signal of information obfuscation, which can eventually lead to stock price crashes. As a quasi-natural experiment, we use the passage of the Economic Growth, Regulatory Relief, and Consumer Protection Act in 2018. This policy lowered the regulatory requirements and oversight for a specific group of large banks. The results of a difference-in-differences analysis support our baseline findings and add to the ongoing debate on the roots of the 2023 banking crisis. Therefore, our findings can be informative to market participants, regulators and policy makers.

Introduction

In the non-financial sector, stock price crash risk has attracted the interest of both academics and practitioners over the past few decades. The consensus in this literature is that stock price crash risk is explained by managerial bad-news hoarding through earnings management (Andreou, Andreou and Lambertides, 2021; Hutton, Marcus and Tehranian, 2009; Jin and Myers, 2006). Evidence along these lines for the US banking industry, however, is rather thin (Habib, Hasan and Jiang, 2018), with the exception of a few studies (Andreou *et al.*, 2017; Cohen *et al.*, 2014). One potential explanation for this shortcoming might be that the banking regulations that emerged after the financial crisis of 2007–2008, namely the Dodd–Frank Act (DFA) of 2010 and BASEL III, led many to believe that banks were safeguarded from future collapses. Unfortunately, the 2023 banking crisis, triggered by the collapse of Silicon

Valley Bank (SVB), demonstrated that this is not the case.

In this study, we revisit the question of why banks' stock prices crash. Although the literature is scarce, previous studies show that banks with more aggressive earnings management practices are more prone to crashes, particularly during economic downturns (Cohen *et al.*, 2014). We differentiate ourselves from this literature in two ways. First, we provide evidence on the types of banks that are more likely to manage their earnings during bad times. We show that banks with poor loan portfolio diversification that operate in competitive markets are more inclined to camouflage this bad performance through higher-than-expected loan loss provisions. Second, we document that earnings management is accompanied by managerial efforts to misrepresent poor performance through ambiguous annual reports.

Our interest in the interplay between market competition, loan portfolio diversification and crash risk originates from two well-established (but inconclusive) strands of banking literature. First, we are motivated by the banking competition literature, particularly the competition-fragility hypothesis, which suggests

[Correction added on 18 July 2024, after first online publication: The Teaching and Learning Guide link has been updated in this version.]

A free Teaching and Learning Guide to accompany this article is available at: [http://onlinelibrary.wiley.com/journal/10.1111/\(ISSN\)1467-8551/homepage/teaching_learning_guides.htm](http://onlinelibrary.wiley.com/journal/10.1111/(ISSN)1467-8551/homepage/teaching_learning_guides.htm)

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that banks undertake excessive risks when competition increases (Bushman, Hendricks and Williams, 2016; Forssbäck and Shehzad, 2015; Hellmann, Murdock and Stiglitz, 2000; Keeley, 1990). Second, we are inspired by the literature investigating the impact of loan diversification on bank risk (Rossi, Schwaiger and Winkler, 2009; Sinkey and Nash, 1993). By combining these two strands of literature, we find that neither competition nor loan portfolio concentration (our proxy for poor diversification) is sufficient for predicting bank stock price crash risk. Interestingly, what seems to matter is their joint effect, as we find that poorly diversified banks in competitive markets are more prone to crashes.

Our decision to employ textual data is motivated by Andreou, Lambertides and Magidou (2023). The authors propose an alternative agency explanation, based on the economics of expectations, which suggests that poor-performing managers may use ambiguous language to ‘muddy the waters’ and manipulate investors’ expectations. We believe that the banking industry constitutes an ideal setting to test these conjectures because (1) managers have more leeway to exploit soft information in intangible-intensive industries (Barth, Li and McClure, 2023), and (2) the banking industry is an intangible-intensive industry, which is inherently more opaque than non-financial industries (Flannery, Kwan and Nimalendran, 2004; Katsafados *et al.*, 2024).

Conceptually, the managerial ambiguity explanation is not mutually exclusive with the earnings management explanation. In fact, the implicit assumption in both cases is that managers are inclined to conceal information regarding their poor performance. What differs is the means of bad-news hoarding. In practice, however, managers can both record abnormally high loan loss provisions and misrepresent their banks’ fundamentals through hard-to-interpret annual reports. Therefore, it is not surprising that we find banks with high discretionary loan loss provisions (DLLPs) to have more ambiguous annual reports. Furthermore, we find that during economic downturns, managerial ambiguity is positively associated with crash risk for poorly diversified banks that operate in competitive markets. Hence, under these conditions, tone ambiguity could be considered a means of information obfuscation by managers. In fact, during economic downturns, managers may have more leeway to hide their poor performance by attributing their ambiguous tone to the unfavourable macroeconomic environment. To further support our arguments, we show that SVB’s ambiguity had dramatically increased in the years prior to its collapse.

We use a panel of public US bank holding companies (BHCs) that filed annual reports with the Securities Exchange Commission (SEC) between 1997 and 2021. To construct the competition measure of Akins *et al.* (2016), we collect data from the Federal Deposit Insurance Corporation (FDIC) database, Summary of

Deposits (SOD). To proxy for diversification, we rely on the loan portfolio concentration measure of Shim (2019). For the earnings management proxy, we use the DLLP measure of Cohen *et al.* (2014). We measure tone ambiguity using the fractions of uncertain and moderate modal words in the banks’ annual reports (Driouchi *et al.*, 2022; Ertugrul *et al.*, 2017; Kinskey *et al.*, 2018). Furthermore, inspired by Bilinski and Yim (2022) and Malhotra, Zhu and Reus (2023), we combine these two separate textual sentiment proxies into a composite sentiment proxy using the principal component analysis approach. Finally, we condition the state of the economy using the same macroeconomic indicator as in Hegde and Kozlowski (2021).

Our findings could be summarized as follows. During economic downturns, banks with high loan concentration that operate in competitive markets are more likely to crash. This relationship is mediated by the stockpiling of negative information through DLLPs and ambiguous annual reports. In general, our results do not apply to expansionary periods. This is expected because bank crash risk is usually observed in bad times (Cohen *et al.*, 2014), and the market reacts negatively to DLLPs only in economic downturns (Hegde and Kozlowski, 2021). Finally, our results survive several additional robustness tests, including alternative dependent variables, instrumental variable regressions, and the exclusion of the global financial crisis of 2007–2008 from our sample.

We conduct several identification strategies to mitigate endogeneity concerns. Initially, we address reverse causality issues in several ways following Andreou, Andreou and Lambertides (2021). Specifically, we rely on a lead–lag relationship between crash risk and tone ambiguity (or loan diversification) and examine whether lagged values of crash risk are associated with future tone ambiguity (or future loan diversification). Importantly, following Chronopoulos, Wilson and Yilmaz (2023), we use the passage of the Economic Growth, Regulatory Relief and Consumer Protection Act (EGRRCPA) on 24 May 2018 as a quasi-natural experiment. In brief, the EGRRCPA was an exogenous legislative shock that removed several regulatory restrictions for a specific subset of banks. Using the difference-in-differences (DD) methodology, we show that treated banks increased their loan portfolio concentration, DLLPs and tone ambiguity after the regulatory relief. Consequently, we show that in the post-EGRRCPA era, treated banks are exposed to higher crash risk relative to control banks. It is noteworthy that SVB was one of the treated banks under the EGRRCPA. Therefore, our DD analysis can contribute to the ongoing policy debate on whether the EGRRCPA was at least partially responsible for the 2023 banking crisis.¹

¹https://www.richmondfed.org/publications/research/econ_focus/2023/q2_policy_update

Our study contributes to several strands of literature. First, we add to the sparse literature that examines the determinants of bank stock price crash risk (Andreou *et al.*, 2017; Cohen *et al.*, 2014). Furthermore, in the non-financial sector, there is strong evidence of a positive relationship between market competition and stock price crash risk (Li and Zhan, 2019). In our study, we show that market competition alone is not sufficient to predict stock price crashes, a fact that highlights the unique nature of the banking industry. Second, we provide supportive evidence for the alternative expectations channel proposed by Andreou, Lambertides and Magidou (2023), by showing that managers can utilize ambiguous language to hide their poor performance in difficult-to-interpret annual reports. Third, our study is related to the growing literature in the non-financial sector that employs textual data to explain stock price crash risk (Ertugrul *et al.*, 2017; Kim, Wang and Zhang, 2019; Lonare, Nart and Tuncez, 2022). Fourth, we provide insights into why the relationship between DLLPs (and tone ambiguity), and crash risk is conditional upon the state of the economy. To this end, we contribute to the strand of literature that examines the impact of macroeconomic conditions on bank valuation and risk-taking (Hegde and Kozlowski, 2021; Ongena, Savaşer and Ciamarra, 2022). Finally, we complement the study of Shim (2019), which examines the joint impact of market structure and portfolio diversification on banks' Z-scores.

As a final remark, our study could add to the growing literature that examines the reasons behind the 2023 banking crisis. Recent studies have identified several contributing factors, such as the increase in interest rates (Drechsler *et al.*, 2023), the massive unbooked losses (Flannery and Sorescu, 2023) and the held-to-maturity securities (Granja, 2023). However, anecdotal evidence could also support a competition-diversification story. As a matter of fact, SVB's loan portfolio was poorly diversified, as the largest portion of its loan book consisted of loans to private equity and venture capital firms.² At the same time, SVB was operating mainly in California, a very competitive banking market. Furthermore, the case of Signature Bank (SB) can provide additional support for our conjectures. SB was headquartered in New York (also a very competitive banking market) and collapsed 2 days after SVB. The loan portfolio of SB was also quite concentrated, because more than 40% of its loans were granted to multifamily homeowners in New York.³

The rest of the paper is organized as follows. In the following section, we discuss the related literature and our testable hypotheses. Next, we outline the data-

gathering process and methodology, and then present our main empirical analysis. This is followed by the DD analysis, and, finally, our conclusions.

Related literature and hypothesis development

In the banking literature, there are two opposing theories regarding the relationship between competition and financial stability. On the one hand, the competition-fragility view suggests that competition creates incentives for excessive risk-taking and thus increases the likelihood of bank failures (Keeley, 1990). On the other hand, the competition-stability view posits that competition can promote financial stability by decreasing bank risk-taking (Boyd and De Nicoló, 2005). While no consensus has emerged in the empirical literature, studies focusing on the US market typically support the competition-fragility view (Bushman, Hendricks and Williams, 2016).

Another strand of literature examines how loan portfolio diversification impacts financial stability. Again, this literature is not conclusive, but the prevailing view is that loan diversification enhances bank stability. In his early study, Diamond (1984) theorizes that diversification allows banks to include more uncorrelated risks in their portfolios, thereby decreasing their default probabilities. Interestingly, later empirical studies confirm these predictions. For instance, Sinkey and Nash (1993) find that banks with concentrated loan portfolios have a higher insolvency risk. Similarly, Rossi, Schwaiger and Winkler (2009) show that loan portfolio diversification is negatively correlated with banks' realized risk. By contrast, other studies suggest that bank diversification is associated with intensified agency problems (Laeven and Levine, 2007) and higher earnings volatility (DeYoung and Roland, 2001; Stiroh and Rumble, 2006), both of which could increase solvency risk. However, these studies primarily attribute the negative consequences of diversification to activity diversification (substituting traditional lending activities with fee-generating activities).

Overall, most of the conflicting previous literature had focused either on the effect of competition on stability or on the effect of loan diversification on stability. Thus, little is known about the joint effect of competition and loan portfolio diversification on banks' stock price fragility. We propose that loan portfolio diversification can help explain under which circumstances competition increases banks' fragility to stock price crashes. We do so for two reasons. First, the effect of competition on banks' fragility varies with the level of loan portfolio diversification (Shim, 2019). Second, bank managers manipulate earnings typically by recording abnormally high loan loss provisions (Cohen *et al.*, 2014).

²Source: <https://www.ft.com/content/0db9092d-9f19-43a1-be52-03e375e59eb6>.

³<https://www.wsj.com/articles/community-bank-stocks-hit-by-new-york-rent-reform-11560855601>.

To understand the importance of the joint effect, we illustrate four scenarios: one favourable, two intermediate, and one unfavourable. In scenario 1, the bank has a well-diversified portfolio and operates in an uncompetitive market. This is the favourable scenario, as both dimensions are related to lower bank risk. In scenario 2 (3), the bank has a well- (poorly) diversified portfolio but operates in a competitive (uncompetitive) market. In these intermediate scenarios, the positive effect of one of the dimensions on crash risk could be offset by the negative effect of the other dimension. For instance, in scenario 2, competitive pressures may increase the bank's fragility, but a well-diversified loan portfolio could moderate the positive relationship between competition and crash risk. In scenario 3, a poorly diversified portfolio could increase crash risk, but market power benefits could moderate the positive relationship between loan portfolio concentration and crash risk. Finally, in scenario 4, the bank faces competitive pressure and has a poorly diversified loan portfolio. Therefore, under this scenario, both dimensions increase the bank's fragility to stock price crashes. Hence, our first hypothesis is as follows:

H1a: Banks that operate in highly competitive market environments and possess low diversified loan portfolios are more likely to experience a stock price crash.

How does the macroeconomic environment impact the above relationship? Previous literature supports a countercyclical relationship between managerial risk-taking incentives and bank risk (Ongena, Savaşer and Ciamarra, 2022). As moral hazard increases during economic downturns, bank managers may alter the composition of their loan portfolio towards riskier loan categories, thereby reducing the diversification of their portfolio (Duchin and Sosyura, 2014). Therefore, we expect more banks to move to scenario 4 during economic downturns, as managers will provide credit to riskier borrowers. Therefore, we refine *H1a* by conditioning for the state of the economy, as follows:

H1b: During non-expansionary periods, banks that operate in highly competitive market environments and possess low diversified loan portfolios are more likely to experience a stock price crash.

What is the likelihood of managerial bad-news hoarding under the four scenarios? We expect this likelihood to be greater under scenario 4, as managers may have more bad news to hide compared with the other three scenarios. How do we expect managers to conceal this information? Consistent with the literature, we expect managers to manipulate earnings through DLLPs. However, another avenue of camouflaging poor performance could be through ambiguous annual reports, as

managers may engage in 'cheap talk' to manipulate investors' expectations (Andreou, Lambertides and Magidou, 2023; Balvers, Gaski and McDonald, 2016; Ni, Wang and Yin, 2021). In the case of banks, managers have more leeway to manipulate expectations through ambiguous text, because the banking industry is an intangible-intensive and inherently opaque industry (Barth, Li and McClure, 2023; Katsafados *et al.*, 2024). Therefore, we hypothesize that poor-performing managers would conceal bad news through DLLPs and/or ambiguous text. Note that the tone ambiguity channel is not interchangeable with the earnings management channel. Rather, we expect the former to complement the latter, as managers who manipulate earnings would be more likely to also use ambiguous text in their reports. Therefore, our next hypothesis is as follows:

H2a: Banks that operate in highly competitive market environments and possess low diversified loan portfolios have higher DLPPs and more ambiguous annual reports.

The conditional association between bad-news hoarding and stock market crashes is not new in banking. Cohen *et al.* (2014) find that DLLPs can explain bank crash risk only in recessions because bank tail risk is not typically observed in normal periods. Hedge and Kozlowski (2021) show that during recessions, DLLPs trigger a negative market response because they convey managers' inside knowledge of existing loan impairment. We believe that during economic downturns, managers may also have greater flexibility in 'muddying the waters' through ambiguous reports, as they can attribute their previous poor performance to the worsening macroeconomic conditions. Consequently, we also refine *H2a* by conditioning for the state of the economy, as follows:

H2b: During non-expansionary periods, banks that operate in highly competitive market environments and possess low diversified loan portfolios have higher DLPPs and more ambiguous annual reports.

Research design

Sample selection

To obtain our sample, we follow a four-step methodology. First, we collect from the SEC website the annual reports of all publicly traded US banks reported in the Federal Reserve Bank of New York (FRBNY) CRSP-FRB Link dataset. We include banks with filing dates over the period 1997–2021. In line with Loughran and McDonald (2011), each annual report must contain at least 2,000 words. Furthermore, we delete two observations owing to the existence of multiple filings per year.

Second, to construct the employed competition measure, we utilize the regulatory identification numbers (RSSD IDs), reported in the CRSP-FRB Link dataset, and collect the required data from the FDIC's SOD database.

Third, we employ the permanent company numbers (PERMCOs) of the FRBNY dataset and collect the required market-based variables from the Center for Research in Security Prices (CRSP) dataset. Then, we eliminate observations with (i) a stock price of <2.5\$ at the fiscal-year end (Andreou *et al.*, 2017) and (ii) <26 weeks of available equity returns in a fiscal year (Andreou *et al.*, 2017; Kim and Zhang, 2016).

Fourth, we collect the required accounting data from the Compustat database. We filter out observations with (i) negative book value of equity or total assets (Kosmidou *et al.*, 2017) and (ii) missing financial data needed to construct the control variables of our analysis. Furthermore, we utilize the RSSD ID of the FRBNY dataset and collect the required loan data from the FR Y-9C and Call reports.⁴ After applying these filters, the sample consists of 7,070 bank-year observations. Finally, we drop 89 singleton observations because their inclusion may overstate the explanatory power of our fixed-effects models (Golubov, Yawson and Zhang, 2015). Hence, our final sample consists of 6,981 bank-year observations (711 unique banks).

Crash risk measures

To construct our stock price crash risk measures for the year t , we follow a two-step procedure. First, following the related literature (Andreou *et al.*, 2017; Battaglia *et al.*, 2021; Dewally and Shao, 2013; Jin and Wu, 2023), we calculate the bank-specific weekly returns (W) by estimating for each bank in year t the following expanded market model:

$$r_{it} = \alpha_i + \beta_{1,i}r_{mt-2} + \beta_{2,i}r_{mt-1} + \beta_{3,i}r_{mt} + \beta_{4,i}r_{mt+1} + \beta_{5,i}r_{mt+2} + \varepsilon_{it}, \quad (1)$$

where r_{it} is the weekly return of stock i in week τ , r_{mt} is the CRSP value-weighted market index in week τ , and the year t is defined as the 12-month period starting from the 4th month after the end of the fiscal year $t - 1$ (Kim, Wang and Zhang, 2019; Zhu, 2016). We control for non-synchronous trading (Dimson, 1979) by including the lead and lag terms of the market return. Then, from the estimation of model 1, we obtain the bank-specific weekly return for bank i in week τ , let W_{it} , defined as the natural logarithm of 1 plus the residual return (ε_{it}).

In the second step, we employ the two measures of crash risk that are frequently used in the literature

(Abedifar *et al.*, 2019; Chen, Hong and Stein, 2001; Li, Xing and Zhao, 2022). The first one is the negative coefficient of skewness (NSkew), and the second one is the down-to-up volatility measure (Duvol).

Particularly, for bank i in year t , NSkew is calculated as follows:

$$NSkew_{it} = -\frac{n(n-1)^{3/2} \sum_{\tau} W_{it}^3}{(n-1)(n-2) \left(\sum_{\tau} W_{it}^2 \right)^{3/2}}, \quad (2)$$

where n denotes the number of bank-specific weekly returns during the 12-month period in which stock price crash risk is measured. This measure captures the negative asymmetry of the specific weekly return distribution in year t . Similarly, Duvol is calculated as follows:

$$Duvol_{it} = \log \left(\frac{\sum_{Down} W_{it}^2 / (n_{Down} - 1)}{\sum_{Up} W_{it}^2 / (n_{Up} - 1)} \right) \quad (3)$$

that is, as the natural logarithm of the ratio of the standard deviations of the Down and Up weeks for bank i in year t . The Down (Up) weeks are the weeks in a year when the bank-specific weekly returns are below (above) the mean of the 12-month estimation period. Finally, n_{Down} and n_{Up} represent the number of up and down weeks during the 12-month period. For both measures, higher values indicate greater crash risk.

Bank competition

Following Akins *et al.* (2016), we measure competition at the bank level as follows. For each bank-year observation of our sample, we identify the states in which the bank operates. For each state, we calculate the Herfindahl–Hirschman index (HHI), using midyear branch-level deposit data from the SOD database. For the calculation of HHI, we use the geographic region (state, county, city and zip).⁵ Therefore, if bank i operates in state s , state-level HHI is calculated as follows:

$$HHI_s = \sum_{i=1}^N \left(\frac{DEPOSITS_{si}}{DEPOSITS_s} \right)^2, \quad (4)$$

where $DEPOSITS_{si}$ represents the deposits of bank i in state s , $DEPOSITS_s$ represents the total deposits of all banks in that state, and N denotes the total number of banks operating in that state.

Then, the bank-level competition measure for bank i is calculated as follows:

$$Competition_i = - \left(\sum_{s=1}^S \frac{DEPOSITS_{si}}{DEPOSITS_i} \times HHI_s \right), \quad (5)$$

⁴We do not use Compustat owing to data unavailability.

⁵In our calculations, we aggregate deposit data up to the BHC level.

where $DEPOSITS_i$ represents the total deposits of bank i , and S is the total number of states in which the bank operates. Higher values for this measure indicate greater competition.

Loan portfolio concentration

To construct the loan portfolio concentration measure (LPC), we follow Shim (2019) and employ a HHI based on the following loan categories: residential real estate (RRE), commercial real estate (CRE), construction and industrial (C&I), consumer (CON), agricultural (AGR) and other loans (OTH). Then, the LPC measure is defined as follows:

$$LPC = \left(\left(\frac{RRE}{TOL} \right)^2 + \left(\frac{CRE}{TOL} \right)^2 + \left(\frac{C\&I}{TOL} \right)^2 + \left(\frac{CON}{TOL} \right)^2 + \left(\frac{AGR}{TOL} \right)^2 + \left(\frac{OTH}{TOL} \right)^2 - 1 \right), \quad (6)$$

where TOL is equal to the sum of the RRE, CRE, C&I, CON, AGR and OTH. Echoing Shim (2019), higher values of the LPC imply that the bank has a highly concentrated loan portfolio.⁶

Earnings management

We develop our earnings management proxy following Cohen *et al.* (2014) and Grougiou *et al.* (2014). More precisely, we follow a two-step approach. In the first step, we estimate the following regression:

$$\begin{aligned} Loss_{it-1} = & \beta_0 + \beta_1 \ln(TA)_{it-1} + \beta_2 ALL_{it-1} + \beta_3 NPL_{it-1} \\ & + \beta_4 RRE^*_{it-1} + \beta_5 CRE^*_{it-1} + \beta_6 C\&I^*_{it-1} \\ & + \beta_7 CON^*_{it-1} + Year\ FE + \varepsilon_{it-1}, \end{aligned} \quad (7)$$

where Loss is loan loss provisions to total loans, $\ln(TA)$ is the natural logarithm of total assets, ALL is an allowance for loan losses to total loans, NPL is non-performing loans to total loans, RRE^* is residential real estate loans to total loans, CRE^* is commercial real estate loans to total loans, $C\&I^*$ is commercial and industrial loans to total loans, and CON^* is consumer loans to total loans.⁷ The fitted values of Equation (7) represent the ‘normal’ loan loss provisions based on the loan portfolio composition.

As a second step, we obtain the residuals of Equation (7) and standardize them by total assets as follows:

$$DLLPs_{it-1} = \varepsilon_{it-1} \cdot \frac{TL_{it-1}}{TA_{it-1}}, \quad (8)$$

where TL is total loans and TA is total assets. DLLPs stands for discretionary loan loss provisions and is our earnings management measure.

Tone ambiguity

In this study, we examine whether poorly performing managers use ambiguous language in their annual reports to ‘muddy the waters’ and manipulate investors’ expectations. To quantify such textual information, Loughran and McDonald (2011, 2013) apply textual analysis in public firms’ disclosures (e.g. 10-K, S-1 filings) and compile categories of word lists that reflect managerial tone in the financial text. In the non-financial sector, several recent studies employ the uncertain word list to quantify managerial ambiguity in annual reports (Driouchi *et al.*, 2022; Ertugrul *et al.*, 2017). In detail, the authors calculate the percentage of words in the annual reports that belong in the uncertain word list of Loughran and McDonald (2011). Examples of uncertain words are ‘assume’, ‘indefinite’ and ‘approximate’, and they emphasize imprecision.

Besides uncertain words, we also employ one more sentiment word list, introduced in a recent version of Loughran and McDonald’s Master Dictionary, namely moderate modal words (Kinskey *et al.*, 2018). Examples of moderate modal words are ‘likely’, ‘generally’ and ‘usually’, which can further increase the tone ambiguity of the annual report. We believe that moderate modal words may be of particular relevance in the banking industry, because heavy regulatory scrutiny may incentivize managers to avoid strong language.⁸

To compute our textual proxies, we follow a three-step process. First, we collect the annual reports from the SEC website, and we clean each file of extraneous material by adopting the parsing procedure of Bodnaruk, Loughran and McDonald (2015). Second, we exclude tables if their ratio of numeric characters to the total number of table characters exceeds 15%. In addition, we eliminate abbreviations, numbers, and punctuation marks. Third, from the ‘cleaned’ textual data, we calculate the percentages of the words belonging to the uncertain (Uncertain) and moderate modal (Moderate modal) sentiment word lists of Loughran and McDonald.

⁶By construction, both Competition and LPC are bounded between -1 and 0 .

⁷We do not include other loan categories (e.g. agricultural loans) to ensure the maximum number of observations. Consistent with Cohen *et al.* (2014), we include year-fixed effects to capture time trends.

⁸In untabulated analysis, we also use the weak modal words as in Ertugrul *et al.* (2017). Consistent with our expectations, we find that results for banks are stronger with moderate modal words.

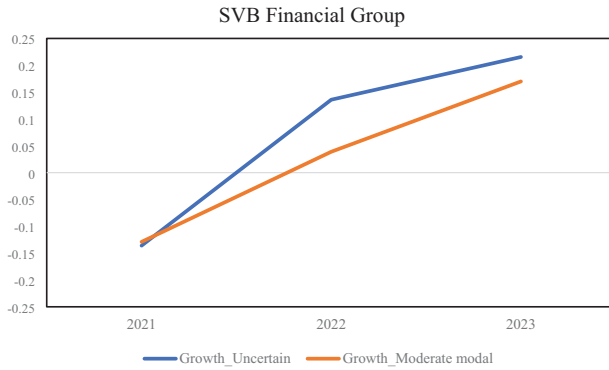


Figure 1. SVB's report ambiguity prior to its collapse. The figure depicts the year-on-year (YoY) growth rate of Uncertain and Moderate modal for SVB, over the 3-year period prior to its collapse

To illustrate the relevance of textual information in our setting, Figure 1 depicts the year-on-year (YoY) growth of Uncertain and Moderate modal for SVB over the 3-year period prior to its collapse. Consistent with our predictions, both ambiguity proxies follow a clear upward trend throughout the 3-year period.

Ideally, we would like to use both textual variables in the same model to examine the impact of tone ambiguity on stock price crash risk. However, because these variables are typically strongly correlated, the most standard approach is to include them in separate regressions (Lougran and McDonald, 2013). To address this issue, we follow Bilinski and Yim (2022) and Malhotra, Zhu and Reus (2023), and we combine the two textual variables using factor analysis. More precisely, we extract the first principal component of the factor analysis, and we use this variable as an additional proxy for managerial ambiguity (Managerial ambiguity).⁹ Our principal component explains up to 80% of the variance of the two individual textual proxies.

Control variables

We include several control variables frequently used in the literature (Andreou *et al.*, 2017; Chen, Hong and Stein, 2001; Cohen *et al.*, 2014; Ertugrul *et al.*, 2017; Kim, Wang and Zhang, 2019). These variables are the 1-year-lagged value of NSkew (NSkew_{t-1}), the natural logarithm of the banks' market value of equity (Ln(Size)), the return on assets (ROA), the market-to-book ratio (MTB), the leverage ratio (Leverage), the detrended turnover (DTurnover), the mean of the

firm-specific weekly returns (Returns) and the standard deviation of firm-specific weekly returns (Sigma). Furthermore, in line with Andreou *et al.* (2017), we use the tier 1 risk-adjusted capital ratio (Tier 1) and the ratio of deposits over total assets (Deposits). Finally, following Park (2015), we control for the degree of fear among market participants by employing the Volatility Index (VIX).¹⁰

Model specification

To address our main research question, we examine the link between market competition, loan portfolio concentration and stock price crash risk. Specifically, we test *H1a* by estimating the following regression model:

$$\begin{aligned} Crashrisk_{it} = & \beta_0 + \beta_1 Competition_{it-1} + \beta_2 LPC_{it-1} \\ & + \beta_3 Competition_{it-1} \times LPC_{it-1} + \gamma X_{it-1} \\ & + BankFE + YearFE + \varepsilon_{it}, \end{aligned} \quad (9)$$

where Crash risk (NSkew or Duvol) in year *t* is measured over a 12-month period starting from the 4th month after the previous fiscal year end.¹¹ Competition and LPC are defined in the sections 'Bank competition' and 'Loan portfolio concentration', respectively, and they are measured at year *t* - 1 to avoid reverse causality issues. Similarly, *X*_{*it*-1} represents the vector of our baseline control variables, measured at year *t* - 1. Finally, Bank FE and Year FE denote bank and year fixed effects, respectively, which are included to control for bank-level time-invariant characteristics and time trends. We winsorize all continuous variables at the 1% and 99% levels to account for the presence of outliers. Finally, the standard errors are clustered at the bank and year level.

To further explore our research question, we examine whether the link, if any, between Competition, LPC and Crash risk is more pronounced in economic downturns. Specifically, to test *H1b*, we re-estimate Equation (9) by controlling for the state of the economy as follows:

$$\begin{aligned} Crashrisk_{it} = & \beta_0 + \beta_1 Competition_{it-1} + \beta_2 LPC_{it-1} \\ & + \beta_3 Competition_{it-1} \times LPC_{it-1} + \beta_4 EC_{it-1} \\ & + \beta_5 Competition_{it-1} \times EC_{it-1} \\ & + \beta_6 LPC_{it-1} \times EC_{it-1} + \beta_7 Competition_{it-1} \\ & \times LPC_{it-1} \times EC_{it-1} + \gamma X_{it-1} \\ & + BankFE + YearFE + \varepsilon_{it}, \end{aligned} \quad (10)$$

where EC stands for the general economic conditions and is an indicator variable that equals 1 if the real

⁹We repeat the factor analysis by including other relevant textual-based proxies (weak modal and/or negative). Results remain similar, but they are stronger when we focus only on uncertain and moderate modal words. This might be because negative words may also reflect business and economic uncertainty, and weak modal words are a subset of uncertain words.

¹⁰Table B1 in the Internet Appendices includes a detailed definition of all variables.

¹¹We use this 3-month interval because banks are required to file annual reports within 3 months from their fiscal year end.

Table 1. Summary statistics

Variables	Mean	Std dev.	Q1	Median	Q3
<i>Crash risk measures</i>					
NSkew	−0.162	0.756	−0.495	−0.107	0.260
DuVol	−0.089	0.482	−0.383	−0.071	0.226
Crash	0.146	0.353	0.000	0.000	0.000
<i>Main variables of interest</i>					
Moderate modal %	0.323	0.077	0.268	0.323	0.377
Uncertain %	1.309	0.266	1.116	1.314	1.503
Managerial ambiguity	0.000	1.258	−0.916	0.095	0.936
Competition	−0.092	0.048	−0.104	−0.082	−0.064
LPC	−0.622	0.123	−0.709	−0.642	−0.573
<i>Baseline controls</i>					
Ln(Size)	12.799	1.766	11.454	12.551	13.902
ROA	0.009	0.006	0.007	0.009	0.012
MTB	1.606	0.743	1.090	1.457	1.995
Leverage	0.903	0.024	0.888	0.905	0.920
DTurnover	0.002	0.029	−0.006	0.001	0.010
Returns	−0.074	0.086	−0.083	−0.046	−0.028
Sigma	0.035	0.017	0.024	0.030	0.041
Tier 1	0.122	0.031	0.102	0.118	0.137
Deposits	0.765	0.086	0.717	0.782	0.827
DLLPs	−0.003	0.279	−0.122	−0.008	0.103
VIX	20.251	9.194	14.090	17.400	23.370

This table reports the summary statistics of the variables employed in our analysis. The sample consists of 6,981 bank-year observations with filing dates from 1997 to 2021. Refer to Table B1 in the Internet Appendices for detailed variable definitions.

GDP growth rate was above its sample series median at the start of the 12-month window in which stock price crash risk is measured, and 0 otherwise.

In Equation (9), the main coefficient of interest is β_3 , as it captures how the effect of poor loan portfolio diversification on banks' crash risk varies with the level of banking competition. In Equation (10), the main coefficient of interest is again β_3 , as it captures the joint effect of competition and LPC on crash risk during economic downturns. To examine what happens during expansions, we test the statistical significance of the marginal association ($\beta_3 + \beta_7$). Finally, we discuss how we test the validity of *H2a* and *H2b* in the sections 'Poor managerial performance and earnings management', 'Earnings management and tone ambiguity' and 'Tone ambiguity and stock price crash risk'.

Summary statistics

Table 1 presents the summary statistics. Overall, the reported statistics are in line with previous relevant studies (Akins *et al.*, 2016; Andreou *et al.*, 2017; Ertugrul *et al.*, 2017; Shim, 2019). Furthermore, Table 2 presents the correlations among the employed variables. As expected, the strongest correlation is reported between our tone ambiguity proxies and their first

Table 2. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Moderate modal (1)	1.000														
Uncertain (2)	0.581 ^a	1.000													
Managerial ambiguity (3)	0.889 ^a	0.889 ^a	1.000												
Competition (4)	−0.060 ^a	−0.133 ^a	−0.109 ^a	1.000											
LPC (5)	0.185 ^a	0.035 ^b	0.124 ^a	−0.132 ^a	1.000										
Ln(Size) (6)	−0.158 ^a	0.175 ^a	0.010	−0.086 ^a	−0.189 ^a	1.000									
ROA (7)	−0.145 ^a	−0.092 ^a	−0.133 ^a	0.036 ^b	−0.073 ^a	0.286 ^a	1.000								
MTB (8)	−0.274 ^a	−0.263 ^a	−0.302 ^a	0.076 ^a	−0.079 ^a	0.325 ^a	0.495 ^a	1.000							
Leverage (9)	−0.227 ^a	−0.289 ^a	−0.290 ^a	0.094 ^a	−0.047 ^a	−0.242 ^a	−0.147 ^a	0.257 ^a	1.000						
DTurnover (10)	−0.080 ^a	−0.029 ^c	−0.061 ^a	0.013	0.013	0.061 ^a	−0.063 ^a	0.035 ^b	0.049 ^a	1.000					
Returns (11)	−0.002	0.007	0.003	0.023	−0.111 ^a	0.211 ^a	0.504 ^a	0.275 ^a	−0.111 ^a	−0.216 ^a	1.000				
Sigma (12)	−0.022	−0.023 ^c	−0.026 ^c	−0.020	0.110 ^a	−0.244 ^a	−0.475 ^a	−0.264 ^a	0.135 ^a	0.223 ^a	−0.964 ^a	1.000			
Tier 1 (13)	0.166 ^a	0.140 ^a	0.172 ^a	−0.049 ^a	0.007	−0.094 ^a	0.088 ^a	−0.134 ^a	−0.480 ^a	−0.094 ^a	0.040 ^a	−0.039 ^b	1.000		
Deposits (14)	0.097 ^a	0.107 ^a	0.115 ^a	−0.009	−0.066 ^a	−0.305 ^a	−0.034 ^b	−0.048 ^a	−0.024 ^c	−0.040 ^a	−0.025 ^c	0.046 ^a	0.077 ^a	1.000	
DLLPs (15)	−0.000	0.008	0.004	−0.011	0.040 ^a	−0.025 ^c	−0.318 ^a	−0.028 ^c	0.055 ^a	0.073 ^a	−0.104 ^a	0.084 ^a	−0.112 ^a	−0.023	1.000
VIX (16)	−0.190 ^a	−0.119 ^a	−0.174 ^a	0.044 ^a	0.005	−0.011	−0.030 ^c	−0.056 ^a	0.021	0.098 ^a	−0.212 ^a	0.230 ^a	−0.098 ^a	−0.065 ^a	−0.019

This table presents pairwise correlations between the variables of our sample. The sample consists of 6,981 bank-year observations with filing dates from 1997 to 2021. Refer to Table B1 in the Internet Appendices for detailed variable definitions. The symbols *c*, *b* and *a* denote statistical significance at the 10%, 5% and 1% levels, respectively, using a two-tail test.

Table 3. Baseline regressions

Variables	NSkew (1)	Duval (2)	NSkew (3)	Duval (4)	NSkew (5)	Duval (6)	NSkew (7)	Duval (8)	NSkew (9)	Duval (10)
Competition	0.652 (1.33)	0.565 (1.68)			0.653 (1.34)	0.566 (1.69)	5.573** (2.74)	3.595** (2.68)	7.229*** (3.38)	4.560*** (3.19)
LPC			−0.026 (−0.12)	−0.034 (−0.28)	−0.028 (−0.14)	−0.022 (−0.18)	0.744* (2.03)	0.434 (1.68)	0.928** (2.29)	0.507* (1.85)
Competition × LPC							7.960** (2.46)	4.778** (2.25)	10.357*** (3.01)	6.223** (2.75)
EC									−0.637** (−2.37)	−0.379* (−1.88)
Competition × EC									−5.414** (−2.32)	−3.302* (−1.86)
LPC × EC									−0.638 (−1.53)	−0.299 (−0.95)
Competition × LPC × EC									−7.781* (−2.06)	−4.958* (−1.84)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,981	6,981	6,981	6,981	6,981	6,981	6,981	6,981	6,981	6,981
Adjusted R ²	0.105	0.087	0.105	0.093	0.105	0.087	0.105	0.094	0.106	0.096
p-value ($\beta_1 + \beta_5 = 0$)									0.44	0.50
p-value ($\beta_2 + \beta_6 = 0$)									0.47	0.53
p-value ($\beta_3 + \beta_7 = 0$)									0.50	0.65

This table presents our baseline regression results. The sample consists of 6,981 bank-year observations with filing dates from 1997 to 2021. The dependent variable is NSkew in models 1, 3, 5, 7 and 9 and Duval in models 2, 4, 6, 8 and 10, respectively. Refer to Table B1 in the Internet Appendices for detailed variable definitions. All continuous variables are winsorized at the 1% and 99% level. T-statistics (in parentheses) are based on standard errors with firm and year clustering. The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively, using a two-tail test.

principal component. All our remaining control variables exhibit a modest degree of correlation, suggesting that multicollinearity should not bias our results.

Empirical findings

Baseline results

Table 3 presents our baseline results. In columns 1–6, we build up our baseline model by gradually adding the variables of interest. We observe that neither Competition nor LPC enters the regressions (alone or together) with statistically significant coefficients. Columns 7 and 8 report results from the estimation of Equation (9), where we add the interaction term. In both models, Competition × LPC is positive and statistically significant at the 5% level. This finding supports *H1a*, as it provides preliminary evidence on the importance of the joint effect in explaining stock price crashes.

Columns 9 and 10 report results from the estimation of Equation (10). The interaction term Competition × LPC is positive and statistically significant at the 1% level in column 9 and at the 5% level in column 10, and the magnitude of its coefficient is substantially larger than what is reported in columns 7 and 8. Furthermore, we examine what happens in expansions by looking at the marginal associations at the end of the table. In

both models, the marginal associations are statistically insignificant. These results suggest that our interaction term has little explanatory power during expansions, but it has a big impact on crash risk during recessions. This is not surprising, because unlike the case for non-financial firms, bank crash risk is not usually evident during good periods (Cohen *et al.*, 2014). Collectively, our findings support *H1b*.

A handful of control variables enter our baseline regressions with statistically significant coefficients. In all models, the 1-year lagged value of NSkew is negative and statistically significant at the 1% level, while both Ln(Size) and VIX are positive and statistically significant at the 1% level. Furthermore, Leverage is positive and marginally statistically significant (see Table A1 in the Internet Appendices).

To further alleviate omitted variable bias concerns, we augment our baseline regressions with additional controls. At the bank level, we use the following controls: (1) the bank's allowance for loan loss provisions (ALL), (2) the natural logarithm of the non-missing Compustat items to proxy for business complexity (Complexity) as in Kleyenova and Tomy (2022), and (3) the bank's age (Ln(Age)). We also employ the CBOE SKEW index (SKEW index), the sentiment index (Investor sentiment) of Baker and Wurgler (2006), and the Michigan consumer sentiment index (Consumer

sentiment). Our results remain qualitatively similar (see Table A2 in the Internet Appendices).

To provide a better insight into our findings, we estimate the average marginal effect of Competition on crash risk for different values of LPC. Consistent with our interpretation of the joint effect, market competition is positively related to stock price crash risk only for banks with above-median values of LPC. In other words, a well-diversified loan portfolio can effectively moderate the impact of competition on crash risk (see Table A3 in the Internet Appendices).

Finally, to ensure the robustness of our results, we re-run our baseline models using alternative measures of crash risk as the dependent variable, an alternative proxy for EC, our textual proxies as controls, the heteroskedasticity and autocorrelation consistent (HAC) instrumental variable generalized method of moments (IV-GMM) estimation technique to account for the endogenous nature of LPC, and a different examination period that excludes the global financial crisis of 2007–2008. Our results hold (see Table A4 in the Internet Appendices).

Poor managerial performance and earnings management

So far, our results support *H1a* and *H1b*, because we find that the joint effect is significant in explaining stock price crash risk, particularly during economic downturns. In what follows (the sections titled ‘Poor managerial performance and earnings management’, ‘Earnings management and tone ambiguity’ and ‘Tone ambiguity and stock price crash risk’), we examine the validity of *H2a* and *H2b*. Specifically, in this section, we examine whether there is any significant relationship between market competition, loan portfolio concentration and the propensity of bank managers to record higher-than-expected loan loss provisions. To this end, we re-run Equations (9) and (10) by replacing Crash risk with DLLPs.

We present the results of this analysis in Table 4. Column 1 shows the relationship between Competition, LPC and DLLPs when we do not differentiate for the state of the economy. At first glance, it appears that there is no significant relationship between those variables. However, when we account for the state of the economy, we obtain more insightful results. More precisely, in column 2, the interaction term Competition $\times$ LPC is positive and statistically significant at the 5% level, indicating that banks with high loan portfolio concentration that operate in competitive states record higher-than-expected loan loss provisions during bad times. The marginal association ($\beta_3 + \beta_7$) at the end of the table shows that this relationship loses any significance in good times (p-value = 0.91).

Table 4. Loan portfolio concentration, market competition and earnings management

Variables	DLLPs	
	(1)	(2)
Competition	0.724 (0.95)	1.177 (1.64)
LPC	0.098 (0.80)	0.176 (1.46)
Competition $\times$ LPC	1.538 (1.28)	2.357** (2.11)
EC		−0.121 (−1.47)
Competition $\times$ EC		−1.410 (−1.67)
LPC $\times$ EC		−0.249* (−2.03)
Competition $\times$ LPC $\times$ EC		−2.547* (−1.96)
Baseline controls	Yes	Yes
Bank FE	Yes	Yes
Year FE	Yes	Yes
N	6,981	6,981
Adjusted R ²	0.393	0.393
p-value ($\beta_1 + \beta_5 = 0$)		0.83
p-value ($\beta_2 + \beta_6 = 0$)		0.65
p-value ($\beta_3 + \beta_7 = 0$)		0.91

This table presents panel regression results for a sample of 6,981 bank-year observations with filing dates from 1997 to 2021. The dependent variable is the discretionary loan loss provisions (DLLPs) in both models. Refer to Table B1 in the Internet Appendices for detailed variable definitions. All continuous variables are winsorized at the 1% and 99% level. T-statistics (in parentheses) are based on standard errors with firm and year clustering. The symbols * and ** denote statistical significance at the 10% and 5% levels, respectively, using a two-tail test.

Earnings management and tone ambiguity

We now test whether there is a positive association between earnings management, our proxy for bad-news hoarding and tone ambiguity. According to our conjectures, this relationship, if any, should be more profound for banks with poorly diversified loan portfolios. Hence, to examine this question empirically, we break down the sample into high-versus-low-LPC banks (according to the sample median), and we estimate the following regression model for each sub-sample:

$$\begin{aligned} \text{Toneambiguity}_{it-1} = & \beta_0 + \beta_1 \text{DLLPs}_{it-1} + \beta_2 \text{EC}_{it-1} \\ & + \beta_3 \text{DLLPs}_{it-1} \times \text{EC}_{it-1} + \gamma \text{X}_{it-1} \\ & + \text{BankFE} + \text{YearFE} + \varepsilon_{it-1}, \quad (11) \end{aligned}$$

where Tone ambiguity is either Moderate modal, Uncertain or Managerial ambiguity. Tone ambiguity is measured at the same point in time as DLLPs for two reasons. First, we expect earnings management to lead to more ambiguous annual reports and not the other way around. Second, managers are more likely to camouflage their abnormal loan loss provisions with

Table 5. Earnings management and tone ambiguity

Variables	High LPC			Low LPC		
	Moderate modal (1)	Uncertain (2)	Managerial ambiguity (3)	Moderate modal (4)	Uncertain (5)	Managerial ambiguity (6)
DLLPs	0.023*** (4.95)	0.037* (1.88)	0.198** (2.19)	-0.006 (-0.94)	0.010 (0.44)	0.039 (0.40)
EC	-0.010 (-0.42)	-0.015 (-0.95)	-0.069 (-0.95)	0.003 (0.37)	-0.013 (-0.34)	-0.107 (-0.56)
DLLPs × EC	-0.023*** (-4.77)	-0.024 (-0.92)	-0.117 (-1.16)	-0.003 (-0.37)	-0.036 (-1.26)	-0.191* (-1.75)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,440	3,440	3,440	3,462	3,462	3,462
Adjusted R ²	0.658	0.653	0.643	0.649	0.625	0.658
p-value ($\beta_1 + \beta_3 = 0$)	0.88	0.64	0.47	0.15	0.27	0.11

This table presents panel regression results for a sample of 6,981 bank-year observations with filing dates from 1997 to 2021. The dependent variable is Moderate modal in models 1 and 4, Uncertain in models 2 and 5, and Managerial ambiguity in models 3 and 6. Models 1–3 refer to the high- (above-median) LPC banks. Models 4–6 refer to the low- (below-median) LPC banks. Refer to Table B1 in the Internet Appendices for detailed variable definitions. All continuous variables are winsorized at the 1% and 99% level. T-statistics (in parentheses) are based on standard errors with firm and year clustering. The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively, using a two-tail test.

ambiguous words in the same fiscal year than 1 year later.

We report the results of this analysis in Table 5. Columns 1–3 present results for high-LPC banks, while columns 4–6 present results for low-LPC banks. Furthermore, the coefficient of DLLPs shows the effect of earnings management on tone ambiguity during recessions. To evaluate its effect during expansions, we use the marginal associations ($\beta_1 + \beta_3$) at the end of the table. Our results indicate that during recessions, there is a positive and statistically significant relationship between DLLPs and Tone ambiguity for high-LPC banks. Then, the statistical significance of this relationship disappears in expansionary periods and for the sub-sample of low-LPC banks.

Collectively, the results are in line with our expectations. During bad times, managers of poorly diversified banks use more ambiguous language to camouflage the higher-than-expected loan loss provisions. Another interesting insight from the analysis is that they do not behave similarly during expansions. One potential explanation for this difference is that during bad times, managers can more easily mask their poor performance by attributing their lack of confidence to the worsening macroeconomic environment.

Tone ambiguity and stock price crash risk

What is the relationship between managerial tone and stock returns? Bloomfield (2002) argues that opportunistic managers may bury value-relevant negative information through ambiguous disclosures to avoid a negative market response. In the non-financial sector, there is supporting evidence for this argument, as firms

with more ambiguous reports are more vulnerable to price crashes (Ertugrul *et al.*, 2017).

So far, our results suggest that during recessions, banks with poorly diversified loan portfolios record higher DLLPs, especially if they operate in competitive markets. At the same time, we find that these banks also have more ambiguous annual reports. Therefore, it is reasonable to assume that tone ambiguity may reflect managerial efforts to conceal poor portfolio diversification. In this case, we would expect a positive relationship between tone ambiguity and future crash risk. To test this assumption, we estimate the following regression model:

$$\begin{aligned} \text{Crashrisk}_{it} = & \beta_0 + \beta_1 \text{Toneambiguity}_{it-1} + \beta_2 \text{EC}_{it-1} \\ & + \beta_3 \text{Toneambiguity}_{it-1} \times \text{EC}_{it-1} \\ & + \gamma \mathbf{X}_{it-1} + \text{BankFE} + \text{YearFE} + \varepsilon_{it}. \end{aligned} \quad (12)$$

To address our research question, we conduct a sub-sample analysis, where we estimate Equation (12) for four sub-samples: (1) high competition and high LPC, (2) high competition and low LPC, (3) low competition and high LPC, and (4) low competition and low LPC. To be consistent with the interpretation of our findings, we expect our results to be evident mostly in the first sub-sample.

Table 6 presents the results of this analysis. Our findings confirm our predictions. More precisely, for the first sub-sample, the variables of interest (Moderate modal, Uncertain or Managerial ambiguity) enter the regressions with positive and statistically significant

Table 6. *Tone ambiguity and stock price crash risk*

Panel A: High competition	High LPC						Low LPC					
	NSkew (1)	Duval (2)	NSkew (3)	Duval (4)	NSkew (5)	Duval (6)	NSkew (7)	Duval (8)	NSkew (9)	Duval (10)	NSkew (11)	Duval (12)
Moderate modal	1.373*** (2.85)	0.945*** (3.01)					−0.298 (−0.64)	−0.306 (−1.25)				
Moderate modal × EC	0.484 (0.74)	0.130 (0.32)					1.186* (1.95)	0.615 (1.68)				
Uncertain			0.435*** (2.19)	0.229* (1.78)					0.033 (0.27)	0.024 (0.31)		
Uncertain × EC			−0.366 (−1.27)	−0.183 (−0.97)					0.175 (0.96)	0.096 (0.79)		
Managerial ambiguity					0.095*** (2.97)	0.064*** (2.87)					−0.007 (−0.24)	−0.008 (−0.50)
Managerial ambiguity × EC					−0.013 (−0.26)	−0.014 (−0.42)			0.070* (1.90)		0.037 (1.68)	
EC	−0.614** (−2.33)	−0.295* (−2.07)	−0.017 (−0.05)	−0.033 (−0.15)	−0.447*** (−2.84)	−0.252*** (−7.39)	−0.694** (−2.73)	−0.373** (−2.27)	−0.500* (−2.01)	−0.278 (−1.58)	−0.297*** (−3.61)	−0.166** (−2.54)
p-value ($\beta_1 + \beta_3 = 0$)	0.02	0.02	0.80	0.79	0.12	0.15	0.11	0.33	0.19	0.31	0.08	0.12

Table 6. (Continued)

Variables	High LPC						Low LPC					
	NSkew (1)	Duval (2)	NSkew (3)	Duval (4)	NSkew (5)	Duval (6)	NSkew (7)	Duval (8)	NSkew (9)	Duval (10)	NSkew (11)	Duval (12)
Moderate modal	0.300 (0.70)	0.289 (1.16)					-1.012** (-2.62)	-0.690** (-2.62)				
Moderate modal × EC	-0.208 (-0.49)	-0.079 (-0.29)					0.704 (1.45)	0.781*** (3.01)				
Uncertain			0.132 (1.16)	0.098 (1.42)					0.014 (0.14)	-0.084 (-1.10)		
Uncertain × EC			0.025 (0.15)	-0.023 (-0.21)					-0.193 (-0.87)	-0.017 (-0.12)		
Managerial ambiguity					0.023 (0.94)	0.020 (1.40)					-0.030 (-1.25)	-0.034* (-1.99)
Managerial ambiguity × EC					-0.004 (-0.11)	-0.005 (-0.25)					0.005 (0.11)	0.030 (1.14)
EC	0.068 (0.43)	-0.085 (-0.71)	-0.040 (-0.16)	-0.080 (-0.45)	-0.004 (-0.04)	-0.110 (-1.56)	-0.655*** (-3.07)	-0.735*** (-3.22)	-0.129 (-0.38)	-0.422 (-1.70)	-0.394*** (-5.05)	-0.461*** (-2.81)
p-value ($\beta_1 + \beta_3 = 0$)	0.84	0.42	0.35	0.43	0.56	0.41	0.50	0.73	0.36	0.34	0.48	0.81

This table presents panel regression results for a sample of 6,981 bank-year observations with filing dates from 1997 to 2021. In all models, the dependent variable is either NSkew or Duval. Models 1–6 (7–12) refer to the above- (below-) median LPC banks. All models include the baseline controls and bank- and year-fixed effects. Refer to Table B1 in the Internet Appendices for detailed variable definitions. T-statistics (in parentheses) are based on standard errors with firm and year clustering. The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively, using a two-tail test.

coefficients at the 5% level or better.¹² For the remaining sub-samples, there is no consistency in the results, with most of the textual proxies (along with their interactions with EC) being statistically insignificant.

Overall, the results of the sections ‘Poor managerial performance and earnings management’, ‘Earnings management and tone ambiguity’ and ‘Tone ambiguity and stock price crash risk’ could be summarized as follows. During economic downturns, poorly diversified banks in competitive markets are more likely to record high DLLPs. Furthermore, these banks are also more likely to use ambiguous tone in their annual reports, and, consequently, they are more prone to stock price crashes. Collectively, our findings are supportive of *H2b*. Finally, we observe that our results are highly dependent on the state of the economy, suggesting that *H2a* is not fully supported.

A quasi-natural experiment

In our empirical setting, endogeneity may emerge for three main reasons: (1) reverse causality, (2) omitted variable bias, and (3) measurement error. To mitigate reverse causality issues, we have relied on a lead–lag relationship between crash risk and our independent variables of interest, and we also include the lagged value of NSkew in all our models to capture persistency in stock price crashes.¹³ Furthermore, the inclusion of bank and year fixed effects in our regressions helps to account for omitted variable bias (Al Mamun *et al.*, 2024). Nonetheless, our results may be subject to important caveats owing to measurement error bias. The main potential source of measurement error comes from the use of textual variables as proxies of managerial behaviour (Bushman, Hendricks and Williams, 2016; Lang and Stice-Lawrence, 2015). For instance, higher uncertainty in an annual report might reflect concerns regarding the macroeconomic environment rather than the manager’s attempt to misrepresent the bank’s prospects. However, similar arguments could apply to the use of LPC as a proxy for poor managerial performance or of DLLPs as a proxy for earnings management.

To address such endogeneity concerns, we examine whether and to what extent the EGRRCPA, an exogenous regulation that occurred in the last years of our examination period, may have influenced managers’ tendency to conceal bad news through ambiguous

disclosures. To understand how EGRRCPA may serve as a quasi-natural experiment in our setting, we first discuss the pre-EGRRCPA regulatory environment.

Following the global financial crisis of 2007–2008 (GFC), President Obama signed the DFA on 21 July 2010. One of the Act’s most prominent provisions is the introduction of two asset-size cut-offs, \$10 billion and \$50 billion. Banks with assets between \$10 and \$50 billion in assets were considered as medium-sized banks, while banks that exceeded the \$50 billion threshold were considered as large systemically important financial institutions (SIFIs). Under the DFA, large SIFIs were subject to extensive scrutiny, along with increased prudential, capital and liquidity standards (Leledakis and Pyrgiotakis, 2022). More relevant to our research question, SIFIs were also subject to advanced reporting requirements, such as credit risk exposure reports and living wills. As a result of these regulations, Akhigbe, Martin and Whyte (2016) show that bank risk for SIFIs substantially declined after the enactment of the DFA.

On 24 May 2018, President Trump signed the EGRRCPA, a deregulatory piece of legislation that removed many of the strict DFA regulations on large banks. Most notably, the act raised the asset-sized threshold for enhanced supervision of SIFIs from \$50 to \$250 billion. Accordingly, banks with assets between \$50 and \$250 billion (treated banks), which were considered large SIFIs under the DFA, are treated as medium-sized banks under the EGRRCPA. Therefore, treated banks are no longer subject to the same standard and reporting requirements as their larger counterparts. From the agency point of view, this regulatory relief would incentivize managers to engage in riskier behaviours and bad-news hoarding.

We expect treated banks to file more ambiguous reports after the EGRRCPA’s enactment for two reasons. First, treated banks were exempt from advanced disclosure requirements, such as credit exposure reports. Thus, managers have more leeway to exploit soft information to misreport information regarding the performance of their loan portfolio. Second, Chronopoulos, Wilson and Yilmaz (2023) show that in the post-EGRRCPA period, treated banks experience a significant increase in credit risk. Therefore, managers may be inclined to bury some of this unfavourable information in a difficult-to-interpret annual report. Hence, to test these conjectures, we employ a similar DD setting to in Chronopoulos, Wilson and Yilmaz (2023). More precisely, we estimate the following DD model over the period 2015–2021:

$$\begin{aligned} \text{Toneambiguity}_{it} = & \beta_0 + \beta_1 \text{Treated} + \beta_2 \text{EGRRCPA} \\ & + \beta_3 \text{Treated} \times \text{EGRRCPA} \\ & + \gamma X_{it-1} + \text{BankFE} + \text{YearFE} + \varepsilon_{it}, \end{aligned} \quad (13)$$

¹²Except in column 4, where *Uncertain* is statistically significant at the 10% level.

¹³Furthermore, following Andreou, Andreou and Lambertides (2021), we changed the order of the two variables (Crash risk and Tone ambiguity). Specifically, we examine whether lagged values of crash risk are associated with future tone ambiguity. We do not find any significance, which reduces reverse causality concerns.

Table 7. Difference-in-differences

	Actual treatment			Pseudo-treatment		
	Moderate modal	Uncertain	Managerial ambiguity	Moderate modal	Uncertain	Managerial ambiguity
Panel A: Tone ambiguity	(1)	(2)	(3)	(4)	(5)	(6)
EGRRCPA	0.270** (2.28)	−0.225 (−0.50)	2.386 (0.84)	0.039 (1.48)	0.120 (0.48)	0.764 (0.90)
Treated	−0.018 (−0.56)	−0.237** (−2.01)	−1.092 (−1.39)	−0.065** (−2.12)	−0.326*** (−3.39)	−1.665*** (−3.01)
EGRRCPA × Treated	0.033*** (4.00)	0.072* (1.69)	0.632*** (2.74)	0.008 (0.78)	0.036 (0.88)	0.194 (0.96)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	398	398	398	509	509	509
Adjusted R ²	0.759	0.528	0.586	0.533	0.499	0.529

	Actual treatment		Pseudo-treatment	
	LPC	DLLPs	LPC	DLLPs
Panel B: LPC or DLLPs	(1)	(2)	(3)	(4)
EGRRCPA	0.345** (2.26)	−0.111 (−1.25)	0.027 (0.32)	−0.317 (−0.60)
Treated	0.101*** (7.11)	−0.384*** (−2.73)	−0.146*** (−8.27)	−0.427*** (−3.78)
EGRRCPA × Treated	0.020** (1.97)	0.061* (1.75)	−0.011 (−1.23)	0.033 (0.42)
Baseline controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	398	398	509	509
Adjusted R ²	0.929	0.432	0.900	0.387

	Actual treatment		Pseudo-treatment	
	NSkew	Duval	NSkew	Duval
Panel C: Crash risk	(1)	(2)	(3)	(4)
EGRRCPA	0.049 (1.05)	−3.184*** (−5.70)	−0.313*** (−2.70)	−0.173 (−1.04)
Treated	−0.197*** (−3.04)	−0.198*** (−2.94)	−0.154 (−1.50)	−0.121 (−1.28)
EGRRCPA × Treated	0.060** (2.08)	0.077** (2.18)	−0.020 (−0.43)	0.043 (0.92)
Baseline controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	398	398	509	509
Adjusted R ²	0.271	0.280	0.217	0.207

This table reports DD regressions. Panel A reports results where the dependent variable is one of the three employed tone-ambiguity proxies. Panel B reports results where the dependent variable is either LPC or DLLPs. Panel C reports results where the dependent variable is either NSkew or Duval. Actual treatment refers to the period between 2015 and 2021. Pseudo-treatment refers to the period between 1997 and 2006. For the actual treatment, EGRRCPA is a dummy that takes the value of 1 for observations after the passage of the Economic Growth, Regulatory Relief and Consumer Protection Act (EGRRCPA) on 24 May 2018. For the pseudo-treatment, EGRRCPA is a dummy that takes the value of 1 for observations after the pseudo-enactment year (2002), and 0 otherwise. Treated is a dummy that takes the value of 1 for BHCs with assets between \$50 billion and \$250 million dollars as of 2018Q1, and 0 for BHCs with assets between \$10 billion and \$50 million dollars as of 2018Q1. Refer to Table B1 in the Internet Appendices for detailed variable definitions. T-statistics (in parentheses) are based on standard errors with firm and year clustering. The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively, using a two-tail test.

where Treated is a dummy variable that equals 1 for banks with assets between \$50 and \$250 billion, and 0 for control banks with assets between \$10 and \$50 billion.¹⁴ EGRRCPA is a dummy variable that equals 1 for all bank-year observations with filing dates after the Act's enactment. For consistency, we include the same control variables and fixed effects as in our baseline models. Therefore, Treated $\times$ EGRRCPA is our DD estimator, and we expect it to be positive and statistically significant.

Panel A of Table 7 presents the results of the DD analysis. The results are consistent with our expectations. In fact, Treated $\times$ EGRRCPA is positive and statistically significant at the 1% level when Moderate modal is the dependent variable, and it is positive and statistically significant at the 10% level when Uncertain is the dependent variable. Furthermore, Treated $\times$ EGRRCPA is positive and statistically significant at the 1% level in the regression of Managerial ambiguity. Furthermore, to ensure that our DD estimator is valid, we examine whether the treated and control banks followed parallel trends prior to the treatment. Hence, to examine the validity of the parallel-trend hypothesis, we use data from a pre-treatment period as in Almeida *et al.* (2012). To avoid any confounding effects from the GFC and the DFA, we use the years 1997–2006 as the pre-treatment period, as we define the median year (2002) as the pseudo-treatment year. The results of the last three columns show that the parallel-trend hypothesis holds, as in all three cases the coefficient of Treated $\times$ EGRRCPA is statistically insignificant.

In Panel B of Table 7, we re-run our analysis by using LPC as the dependent variable. For the actual treatment period, the DD estimator is positive and statistically significant at the 5% level, while it loses any significance in the pseudo-treatment period. Hence, after the EGRRCPA, treated banks had myopically increased their loan portfolio concentration, a finding that complements the positive EGRRCPA effect on credit risk documented by Chronopoulos, Wilson and Yilmaz (2023). Furthermore, we re-run our DD regression using DLLPs as the dependent variable. The DD estimator is positive and statistically significant at the 10% level in the actual treatment period and statistically insignificant in the pseudo-treatment period. Thus, these findings indicate that treated banks are more likely to engage in earnings management practices post-EGRRCPA.

Collectively, our results indicate that after the passage of the EGRRCPA, treated banks increased their loan portfolio concentration, recorded higher DLLPs, and used a more ambiguous tone in their annual reports relative to control banks. Furthermore, treated banks faced higher competitive pressures during that period,

as the mean difference in Competition between treated and control banks is positive and statistically significant at the 10% level ($t = 1.68$).¹⁵ Therefore, according to our conjectures, treated banks should also be more prone to stock price crash risk. To test this assumption, we re-estimate Equation (13) using either NSkew or Duvol as the dependent variable. Panel C of Table 7 presents the results of this analysis. In the actual treatment period, the DD estimator is positive and statistically significant at the 5% level in both models, while in the pseudo-treatment period, its statistical significance disappears. The results are consistent with our expectations.¹⁶ Importantly, our findings can contribute to the ongoing debate on whether the EGRRCPA was at least partially responsible for the 2023 banking crisis. It is also worth mentioning that SBV is one of the treated banks in our DD setting.

Conclusion

In this study, we document a significant positive link between loan portfolio concentration, market competition and stock price crash risk in the US banking industry. Furthermore, we find that this positive link is channelled by managerial opportunistic behaviour, as measured by DLLPs and ambiguous annual reports. Furthermore, we show that our results are highly dependent on the state of the economy, a finding that is consistent with the countercyclical relationship between managerial risk appetite and bank risk.

Previous research indicates that high DLLPs lead to bank crashes during economic downturns, as managers opportunistically exploit these provisions to conceal their poor performance (Andreou *et al.*, 2017; Cohen *et al.*, 2014). In our study, we extend this literature by linking DLLPs to a dimension of poor managerial performance. In other words, we show that banks with poor loan portfolio diversification are more likely to record abnormally high loan loss provisions, especially if they operate in competitive states.

Besides recording extra provision expenses, managers can also utilize soft information to misrepresent their bank's performance and shape investors' expectations. In fact, we show that banks with high DLLPs have more ambiguous text in their annual reports, which leads to higher crash risk. We believe that the banking industry constitutes a unique case to test the relationship between soft information and crash risk, because its inherent opacity could enable managers to 'muddy the waters' by using ambiguous and hard-to-interpret annual reports.

¹⁵ Market competition is not endogenous in our setting, and thus we do not use it as a dependent variable in our DD regressions.

¹⁶ Altogether, the results of the DD analysis support both *H1a* and *H2a* because we do not condition for the state of the economy.

¹⁴For treated and control groups, assets are measured at the first quarter of 2018, as in Chronopoulos, Wilson and Yilmaz (2023).

As a concluding remark, we acknowledge that the use of word counts as managerial ambiguity measures could raise endogeneity concerns, such as measurement error. While we can never rule out such concerns, we have made extensive efforts to mitigate their impact on our results. Hence, we believe that our findings can be informative to market participants, regulators and policy makers, as they could serve as early warning signals of bank stock price crashes.

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Supporting Information

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