Does Media Sentiment Influence Bank Supervision? ⋆

David Aldama-Navarrete[a,**], Filippo Curti[a], Anne Lundgaard Hansen[a], Sophia Kazinnik[a]

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Abstract

This paper explores the impact of media sentiment on bank supervision, focusing on the supervisory ratings of bank holding companies assigned by the Federal Reserve System. We uncover a significant impact of media sentiment on supervisory ratings by employing a robust instrumented differences-in-differences strategy. We show that the effect is predominantly driven by negative media articles, suggesting an inherent negativity bias. The effect is moderated by examiner experience and exam duration.

Keywords: Media Sentiment, Bank Holding Companies (BHCs), Bank Supervision, Supervisory Ratings, Financial News, Natural Language Processing (NLP)

JEL Classification: G18, G21, G28, G32

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**Corresponding author. Tel: +1 (704) 358-2556. Address: 530 East Trade Street, Charlotte, NC 28202

Email addresses: david.aldamanavarrete@rich.frb.org (David Aldama-Navarrete), filippo.curti@rich.frb.org (Filippo Curti), anne.hansen@rich.frb.org (Anne Lundgaard Hansen), sophia.kazinnik@rich.frb.org (Sophia Kazinnik)

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1. Introduction

The collapses of Silicon Valley Bank (SVB) and First Republic Bank have drawn massive attention to the regulatory standards of the Federal Reserve System (FRS) from the media, the legislative branches of the US government, and the general public.[1] In the review following the demise of SVB, Michael S. Barr, the Federal Reserve Vice Chair of Supervision, acknowledged that the regulatory standards for SVB had been less than ideal: *"Overall, the supervisory approach at Silicon Valley Bank was too deliberative and focused on the continued accumulation of supporting evidence in a consensus-driven environment"* (Board of Governors of the Federal Reserve System, 2023). This statement, among others from the review, highlights the importance of the informational environment faced by bank supervisors.

In this paper, we address whether exogenous shocks to the informational environment *unrelated to economic fundamentals* impact supervisory outcomes. We capture the informational environment by quantifying the sentiment of new articles published by major news media outlets. In terms of supervisory outcome, we focus on the supervisory ratings assigned by the FRS to bank holding companies (BHCs), a central element of its regulatory framework. Weaker supervisory ratings are accompanied by higher scrutiny and supervisory actions that may constrain the ability of bank management to operate freely, i.e., take on risk with the expectation of profit.

Our results show that media sentiment significantly impacts the risk management ratings of BHCs. Specifically, more negative articles are accompanied by weaker ratings, even after controlling for BHC and year fixed effects as well as several time-varying BHC-level controls. These results shed light on the broader question of

[1] Notable examples are: *"Fed Slams Its Own Oversight of Silicon Valley Bank in Post-Mortem."*, The New York Times (Smialek, l 28); and *"US regulation after SVB's collapse: What regulators can do and where Congress needs to act."*, Reuters (Engler, 2023).

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whether banking regulators consistently assess bank risk (Agarwal et al., 2014). This question is important, as bank supervision outcomes impact bank performance (see Cowhey et al., 2022, Hirtle et al., 2020, and Peek and Rosengren, 1995, among others); any systematic heterogeneity in the oversight of banks might lead to capital misallocation if orthogonal to bank fundamentals.

As media sentiment itself covaries with BHC performance and economic conditions, we rely on an instrumented differences-in-differences (DD-IV) strategy to unveil the causal link between media sentiment and supervisory outcomes. The method of identification is analogous to that used in Duflo (2001) and Abdulkadiroğlu et al. (2016), and relies on exploiting difference-in-differences (DiD) type variation in an instrument, mediated by a treatment-intensity variable, to recover exogenous variance in assignment to treatment (Hudson et al., 2017). Specifically, our estimation relies on local media mergers as an instrument. Merger activity — in which, typically, small media outlets are acquired by national conglomerates — is likely to shift news-coverage priorities as well as the slant of coverage. Although the locations of media mergers are not random, they are likely to be orthogonal to relevant omitted variables. Merger activity thus satisfies both the relevance and exogeneity conditions for a valid instrument.[2]

Our analysis shows that the influence of media tone on risk management ratings is mainly driven by the most negative articles. This result is consistent with the concept of *negativity bias* (Rozin and Royzman, 2001), postulating that individuals are more likely to remember and be impacted by things of a more negative nature (Kahneman and Tversky, 1984). We find that this effect is moderated by heightened media attention and when the articles are more quantitative in nature. The length

[2]All analyses in our paper are presented following such strategy but are robust to employing regular Ordinary Least Squares (OLS) estimation.

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of the bank exam and the experience of the examiner in charge also impact the identified effect: longer exam duration and more extensive supervisor experience reduce the impact of media sentiment on the risk management ratings. Thus, our results suggest that more experienced examiners and more thoughtful examinations lead to less biased supervisory outcomes.

Finally, we corroborate our results by investigating how media sentiment impacts other supervisory outcomes. First, we look into the sub-components of the risk management rating.[3] We find consistent results for three out of four components. The exception is the management information sub-component, which is the most quantitative element within this component, and is thus less likely to be affected by the media narrative. Second, we look into the confidential supervisory findings that FRS examiners communicate to the BHCs and that may require the attention of BHC boards.[4] We find that media sentiment impacts only the number of supervisory findings that do not require immediate attention (MRAs), i.e., findings with lower priority, and only those findings that are categorized as operational risk, legal or consumer-related. Higher priority findings (MRIAs) require a more thoughtful consideration, support, and represent a little more than 10% of all supervisory findings. We conjecture that the process around issuing higher priority findings involves more experienced examiners; the result is therefore consistent with the finding that more examiner experience reduces the potential bias coming from the media narrative.

We proceed as follows: Section 2 reviews the literature. We describe the data in Section 3 and present our empirical strategy in Section 4. We report our results in Section 5, and discuss potential implications for policy in Section 6. Finally, Section

[3]See Board of Governors of the Federal Reserve System (2004) for a detailed explanation of the RFI(C)D rating system and its sub-components.

[4]See Board of Governors of the Federal Reserve System (2013) for a detailed explanation of supervisory findings.

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7 concludes.[5]

2. Literature Review

We contribute to several strands of literature. We add to the body of work focusing on the economic aspects of bank supervision, a topic investigated by Eisenbach et al. (2016) and further detailed in Hirtle and Kovner (2022) and Cowhey et al. (2022). We also contribute to the understanding of how media sentiment impacts economic results. We examine a novel channel – bank supervision – through which sentiment might influence the economy, beyond those traditionally considered, such as the stock market (e.g., Tetlock, 2007 and García, 2013) or consumer confidence (e.g., Shapiro et al., 2022). Further, our paper adds to the literature which seeks to differentiate bias from skill in "expert" domains, ranging from grant evaluation (Li, 2017), to lending decisions (Fisman et al., 2017), to monetary-policy determination (Hansen et al., 2014).

Our primary contribution, however, is to the literature on the informational content of bank supervision, which has documented empirical relationships between supervisory ratings and a range of firm outcomes, such as equity returns (Berger et al., 2000, DeYoung et al., 2001), accounting variables (Kupiec et al., 2017), and bank failures (Cole and Gunther, 1995). Recent work in this literature uses NLP techniques to parse the informational content of supervisory sentiment (Cowhey et al., 2022). NLP has also recently been used to analyze other aspects of banking; for example, Cookson et al. (2023) use NLP to analyze the role of social media in bank runs.

Our approach is novel in the sense that we seek to draw a causal link between

[5]In Appendix A we provide a thorough description of the textual-analysis techniques we use to parse, structure, and score the news data we use; Appendix B lists our sample of BHCs; and Appendix C details the news sources.

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public information and supervisory outcomes, with the former as a causal primitive. Most previous literature, in contrast, focuses on the propagation of information from the supervisory to the public sphere; for instance, Berger and Davies (1998) analyze stock-market reactions to CAMEL ratings.

We believe that our results have the potential to help policymakers in designing a more effective and consistent bank supervisory framework. We document the influence of mass media as one channel which may lead to bias or inconsistency in supervisory activity; in this sense, we contribute to the conversation on supervisory variability to which Agarwal et al. (2014) and Eisenbach et al. (2016) speak. In documenting that media shapes supervisory outcomes, we also speak to an older literature which debates the marginal contribution, in an informational sense, of bank supervisory assessments over information present in market prices; e.g, Cargill (1989), who use certificate of deposit (CD) rates as bank risk-proxies as compared to CAMELS ratings, or Flannery and Houston (1999), who look at price-to-book ratio variation in response to bank examinations.

3. Data

We rely on several comprehensive sets of data related to supervisory outcomes, news articles, and media mergers. This section provides background and details on variable construction for each data set. We provide all variable definitions in Table 1:

[Insert Table 1 about here]

3.1. Supervisory Data

The supervision of BHCs in the United States is predominantly performed by the FRS.[6] The FRS supervisory framework is executed through various monitoring and

[6]Specifically, in the United States, three primary federal agencies perform bank supervision: the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation

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oversight activities, carried out by dedicated FRS personnel. The primary goal of these activities is to assess and maintain the "safety and soundness" of supervised firms. Actions taken include periodic issuance of supervisory ratings, providing guidance on regulatory expectations, and demanding corrective actions for bank policies and procedures that are deemed risky. While supervisory activity is tied closely to bank regulation, it is distinct in its nature. Regulation is statutory, setting a static standard of expectations for firms. Supervision, in contrast, is dynamic and relational, carried out by human agents. Thus, bank examiners play a crucial role in bank supervision.

FRS bank examiners specialize in particular "supervisory portfolios," i.e., firm categories based on size and operational complexity. Our study primarily covers firms in the Large and Foreign Banking Organizations (LFBOs) and Large Institution Supervision Coordinating Committee (LISCC) portfolios.

The LISCC portfolio covers the largest and most complex firms. LISCC supervisory activity is performed by dedicated supervisory teams (DSTs) and is overseen by the LISCC itself, a LISCC Operating Committee, and an Office of the Operating Committee (OOC). The second tier in size and complexity within the FRS's supervisory portfolios is represented by the LFBO firms. LFBO firms are also assigned DSTs that conduct several examinations throughout a typical year. These firms are also subject to periodic "horizontal" examinations, which involve coordinated examinations across multiple banks in the portfolio. Supervisory ratings are assigned to LFBOs annually based on examination results, perceived progress in addressing supervisory findings, and other information gathered through "continuous monitoring."

In this paper we characterize supervisory activity through the aggregate "roll-

(FDIC), and the FRS.

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up" rating assigned to bank holding companies. Prior to 2019, the "roll-up" rating assigned to all BHCs was the RFI/C(D) rating. This aggregate assessment was typically issued annually but could be downgraded following targeted examinations due to perceived high idiosyncratic risk for a particular BHC or industry-level stresses. In 2019, a new ratings system, the Large Financial Institution (LFI) system, was introduced, to which the largest firms in our sample are now subject. Unlike the RFI/C(D) system, LFI ratings components carry no granular subcomponents. Hence, to allow for cross-sectional comparisons, as well as to enable bank assessments within granular risk dimensions, our sample ends in the fourth quarter of 2019.

Besides aggregate ratings, we also consider another important set of supervisory outputs: matters requiring attention (MRA) and matters requiring immediate attention (MRIAs). These confidential supervisory actions require banks to take corrective actions and have been formalized since 2013 to improve the consistency and clarity of written communication from FRS supervisors to banks. MRIAs are issues of significant importance and urgency that the FRS requires banking organizations to address immediately, including matters that pose significant risk to the safety and soundness of the banking organization. MRAs, on the other hand, are important issues that a banking organization is expected to address over a reasonable period of time. For the firms in our sample, MRAs and MRIAs form a significant part of the "regulatory package" they face.

3.1.1. Variable Construction

As discussed, we start with the data on "roll-up" BHC ratings, which consist of several components. First, the Risk Management Practices (R) component evaluates the ability of the BHC's board of directors and senior management, as appropriate for their respective positions, to identify, measure, monitor, and control risk. This component is rated on a 1 to 5 scale in ascending order of supervisory concern. The

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Risk Management variable represents this component using the above scale in our estimation framework.

Then, we consider the Board and Senior Management Oversight sub-component of the Risk Management Practices component. This sub-component evaluates the adequacy and effectiveness of board and senior management's understanding and management of risk inherent in the BHC's activities, as well as general management capabilities, including consideration of management's ability to identify, understand, and control risks undertaken by the institution, to hire competent staff, and to respond to changes in the institution's risk profile or innovations in the banking sector. The Board and Senior Management Oversight sub-component is rated on a 1 to 5 scale in ascending order of supervisory concern. The *Board Oversight* variable represents this sub-component in our estimation framework.

Next, the *Policies* variable represents the Policies, Procedures and Limits sub-component of the Risk Management rating and evaluates the adequacy of a holding company's policies, procedures, and limits given the risks inherent in the activities of the BHC. This analysis includes consideration of the adequacy of the institution's accounting and risk disclosure policies and procedures. The Policies, Procedures and Limits sub-component is rated on a 1 to 5 scale in ascending order of supervisory concern.

The *Information Systems* variable represents the Risk Monitoring and Management Information Systems sub-component of the Risk Management rating and assesses the adequacy of a holding company's risk measurement and monitoring, and the adequacy of its management reports and information systems. The Risk Monitoring and Management Information Systems sub-component is rated on a 1 to 5 scale in ascending order of supervisory concern.

The *Internal Control* variable represents the Internal Control sub-component of

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the Risk Management rating and evaluates the adequacy of a holding company's internal controls and internal audit procedures, including the accuracy of financial reporting and disclosure and the strength and influence, within the organization, of the internal audit team. The Internal Controls sub-component is rated on a 1 to 5 scale in ascending order of supervisory concern.

We then turn our attention to MRAs and MRIAs. We construct several variables based on this data. First, *MRIA Op* represents the number of unresolved confidential supervisory findings that require immediate attention within the operational risk, legal, or consumer categories. *Non-MRIA Op* represents the number of unresolved confidential supervisory findings that require attention and provisions within the operational risk, legal, or consumer categories. *MRIA Other* represents the number of unresolved confidential supervisory findings that require immediate attention *not* categorized as operational risk, legal, or consumer-related issues. Finally, *Non-MRIA Other* represents the number of unresolved confidential supervisory findings that require attention and provisions that are not categorized as operational risk, legal, or consumer-related issues.

We next construct a set of transformations based on these variables to improve their interpretability: *Ln(MRIA Op)* is a natural log transformation of *MRIA Op*, defined as *Ln(MRIA Op + 1)*. We similarly construct *Ln(Non-MRIA Op)*, *Ln(MRIA Other)*, and *Ln(Non-MRIA Other)* as a natural log transformations of *Non-MRIA Op*, *MRIA Other*, and *Non-MRIA Other*, respectively.

Next, we turn to data on examinations: *Exam Length* represents the number of days that pass between the start and the end of an exam from which a risk management rating is derived; *Examiner In Charge Experience* represents the number of years since the examiner leading the exam has first led, or reviewed, an exam; *Examiner In Charge First Exam* is an indicator variable taking the value of one if

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it is the first time that the examiner in charge has led an exam and zero otherwise; *Examiner In Charge-BHC Tenure* represents the number of years since the examiner leading the exam has been in charge of the examined BHC, and *Reviewer In Charge Experience* represents the number of years since the reviewer in charge has first led, or reviewed, an exam.

We perform log transformations of these variables analogous to those performed on the aforementioned regulatory-outcome variables: *Ln(Exam Length)* is a natural log transformation of *Exam Length*. *Ln(Examiner In Charge Experience)*, *Ln(Examiner In Charge-BHC Tenure)*, and *Ln(Reviewer In Charge Experience)* are constructed similarly.

We provide summary statistics for these variables in Table 2, Panel A:

[Insert Table 2 about here]

3.2. News Articles

We rely on financial news articles to capture sentiment, as financial news arguably both influence and reflect the overall sentiment of the financial world. This sentiment, in turn, informs expectations and collective perceptions of economic agents, thus driving economic trends. In essence, financial news articles provide valuable perspectives on the perception of economic conditions, and have proven to be a vital tool for capturing the prevailing sentiment in the financial sphere.[7]

We collect a comprehensive set of news articles published by the largest financial news sources from January 1st, 2000 to December 31st, 2019. The news articles are retrieved from the Dow Jones Factiva Analytics product (Factiva hereafter). The

[7]For instance, studies have demonstrated how news can uncover essential business information (Boudoukh et al., 2013), measure economic uncertainty (Baker et al., 2016), anticipate market risk and returns (Calomiris and Mamaysky, 2019), and capture underlying relationships between banks (Kazinnik et al., 2021).

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appendix discusses the source groups and the composition of all news outlets. We limit our sample to only those articles that discuss BHCs in our sample; this gives us a little over 600,000 news articles in total.

We use this sample of news articles to proxy for the informational environment by quantifying the article sentiment, as well as creating additional variables to proxy for article readability, emotional resonance, and numerical content. We also capture intensity of media attention, and a characterization of how the coverage distribution skews towards positive or negative sentiment. These parameters provide a comprehensive understanding of how media perception and representation of BHCs is structured. In the following, we describe how these parameters are constructed.

3.2.1. Variable Construction

Our main explanatory variable, *Media Sentiment*, is constructed using the dictionary proposed in Loughran and McDonald (2011) (henceforth, LM) at the BHC-quarter level. For each article, we run a sentiment analysis algorithm that evaluates the emotional polarity embedded within a provided text. It performs this task by cross-referencing the terms in the text with the LM dictionary that assigns emotional valences to different words. We also consider lexical context, encompassing multiple terms adjacent to each analyzed word, such as negators and modifiers. We consider the influence of specific modifiers that could potentially augment or mitigate the sentiment of the associated word. In cases where the algorithm encounters unrecognized terms or words absent in its reference dictionary, it assigns them a neutral emotional score. The sentiment scale is such that a higher value indicates a more favorable media outlook towards the BHC, while a lower value denotes a negative perception.

Article Readability measures the average readability of all articles covering a specific BHC in the prior year. We break down the text into its constituent tokens—individual words or units of meaning, and then use a measure known as Type-

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Token Ratio (TTR), which quantifies the diversity of vocabulary used in the text. The TTR measure essentially calculates the ratio of unique words (types) to the total number of words (tokens), offering a statistical perspective on the range of vocabulary utilized. This variable provides an overview of the complexity of the coverage the BHC has received. *Article Emotional Load* is the average emotional load of all equally weighted articles focusing uniquely on a BHC in the prior year. The average emotional load of media coverage is assessed through the use of the Emotional Load (EL) metric. Specifically, we evaluate the emotional polarity embedded within a provided text. It performs this task by cross-referencing the terms in the text with a pre-compiled dictionary that assigns emotional valences to different words. *Article Numeric Characters* is the average ratio of numeric characters to all characters measured by equally weighting all articles focusing uniquely on a BHC in the prior year.

Media Attention is the average number of sentences from all article focusing uniquely on a given BHC evaluated in the prior year. The measure of media attention directed towards a BHC within the preceding year is approximated by the average number of sentences across all articles specifically written about the BHC. This metric gives an indication of the amount of detailed coverage dedicated to the institution. We also consider the distribution of this measure by considering the following: the *Tail Frequency - Bottom N%* variable represents the number of articles with a *Media Sentiment* below the n-th percentile of the unconditional distribution. These articles represent the most negative articles in our sample. *Tail Frequency - Above N%* is the number of articles with *Media Sentiment* above the n-th percentile of the unconditional distribution. These articles represent the most positive articles in our sample. We provide summary statistics for these variables in Table 2, Panels B and C.

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3.3. Media Mergers

To construct our instrumental variable, we hand-collect data on acquisitions of local TV stations and the coverage of these stations to Designated Market Areas (DMAs), as defined by Nielsen Media Research in its annual Nielsen Station Index Directory and Nielsen Station Index US Television Household Estimates publications, for all years between 2000 and 2020.

Once we have assembled a list of market areas exposed to M&A activity during our sample period, we extract county names from DMAs as coded by Nielsen, and perform fuzzy string matching to merge this data with the Census Bureau county FIPS database. We are particularly interested in identifying counties exposed to acquisitions by Sinclair Broadcast Group (Sinclair), a large media conglomerate. We detail the reasons behind this in the Section 4. We code a county as "treated" if Sinclair acquired a station during our sample period in a DMA which (completely or partially) includes this county. Treated counties are coded as such for the year in which the acquisition was completed, and all successive years. All counties in the Census database for which we do not identify a Sinclair acquisition in associated DMAs are coded as "pure control" counties.

Once we have constructed yearly lists of treatment and control counties, we merge these with Summary of Deposits (SoD) data from the Federal Deposit Insurance Corporation (FDIC). From this data, we calculate the proportion of branches for a given firm located in each county, out of all domestic branches. The vector product of county-level treatment and firm-county branch proportions yields the proportion of branches treated for a firm in a given year, which produces our key instrumental variable, *Media Consolidation*.

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3.4. Other Variables

We also exploit data on specific financial characteristics of BHCs, including assets, leverage, return on assets, the ratio of non-interest income to interest income, and operational losses. We discuss how these variables are constructed below.

We start with *Ln(Assets)*, the natural log transformation of a BHC's assets in millions of U.S. Dollars. This transformation aids in controlling for the skewness of large-scale financial data and allows for better interpretation and comparison. *Leverage* is BHC total assets divided by the book value of equity. *RoA* is BHC return on assets measured in the previous year, a key indicator of the BHC's profitability relative to its total assets. *NII-to-II* is the ratio of BHC non-interest income to interest income. *Ln(OpLoss)* is the natural log transformation of *OpLoss*, defined as *OpLoss* + 1. *OpLoss* measures operational losses that occur at a BHC averaged over the prior year in millions of U.S. Dollars. This transformation, similar to the one used for assets, improves the interpretability of this risk-related metric.

Asset size (*Ln(Assets)*) is included in our regressions to hold constant variation in firm risk profiles associated with asset volume documented in the literature (Curti et al., 2022), as well as to control for supervision intensity related to firm size (Eisenbach et al., 2016). Leverage, profitability, and income mix are controlled for given evidence in the literature of associations between bank supervision and accounting variables (see, for instance, Chortareas et al. (2012)). Lastly, bank operational losses are included to proxy for firms' general risk tolerance, management practices, and culture; strong links between these variables have been documented by, among others, Abdymomunov and Mihov (2019). Data on operational losses for this purpose has been drawn from the FR Y-14(Q) report, submitted on a quarterly basis to the FRS by all BHCs with total consolidated assets of $50 billion or more.

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4. Empirical Strategy

In this section, we describe our identification procedure, which is predicated on instrumenting our (patently endogenous) regressor of interest, bank-specific sentiment. We first describe, however, a naive ordinary-least-squares version of our analysis.

4.1. OLS Estimation

To test our hypothesis that media sentiment influences supervisory outcomes, we estimate the following OLS equation:

$$SupOutcome_{i,t} = \alpha_i + \delta_t + \beta MediaSentiment_{i,[t-4,t]} + \Gamma \mathbf{X} + \varepsilon_{\mathbf{i,t}} \tag{1}$$

where *SupOutcome* is a vector with entries corresponding to each of the assessed ratings sub-components, *Ln(MRIA Op)*, and *Ln(Non-MRIA Op)*, α_i is a bank-level fixed effect, δ_t is a yearly fixed effect, $MediaSentiment_{i,[t-4,t]}$ is the average sentiment of articles focusing uniquely on a BHC over the prior calendar year, and $\mathbf{X}$ is a vector of bank controls. The specification presented in Equation (1) clearly suffers from endogeneity, as media sentiment and supervisory outcomes will be jointly determined by bank behavior. We therefore rely on an instrumental variables strategy, described next.

4.2. Instrumental Variables Strategy

To establish causality, we rely on an instrumented differences-in-differences (DD-IV) strategy, a method of identification analogous to that used in Duflo (2001) and Abdulkadiroğlu et al. (2016). Our estimation relies on local media mergers as an instrument. The reasoning behind this strategy is that merger activity – in which, typically, small media outlets are acquired by national media conglomerates – is likely to shift news-coverage priorities, as well as the slant of coverage. However, it is also likely to be orthogonal to relevant omitted variables.

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In particular, we focus on local network television M&A activity, and more granularly, on acquisitions by Sinclair Broadcast Group, Inc., one of the most active corporate parties over the past two decades in media merger activity. Sinclair is now the second-largest owner of local TV stations in the United States, controlling a total of 193 stations, which grant it coverage over around 40% of American households (Levendusky, 2022). A unique feature of Sinclair is its strong editorial slant, which favors viewpoints coded as "conservative" in the American political lexicon (Hedding et al., 2019, Martin and McCrain, 2019). However, not only the tone but also the content presented by Sinclair-owned stations is distinct from that of competitors. Stations owned by this media group favor national news themes more than similar stations, with around 25% more national news coverage being presented (Martin and McCrain, 2019), and topics on the national political agenda being prioritized at the expense of other news topics (Hedding et al., 2019).

Sinclair's unique business model has had profound effects on the media landscape, which have been documented in the literature: text-based measures of ideological slant shift rightward in content produced by Sinclair-acquired stations following acquisition, relative to other stations in the same market (Gentzkow and Shapiro, 2010, Martin and McCrain, 2019); Sinclair-acquired stations decrease coverage of local news, such as the local crime beat (Mastrorocco and Ornaghi, 2022).

Our working hypothesis in this paper is that Sinclair market presence, *ceteris paribus*, dampens news coverage critical of banks. We believe this pattern to be consistent with observed behavior, documented in the literature: (i) Sinclair affiliates focus on news topics in the national political agenda at the expense of other news coverage, and (ii) Sinclair's ideological stance is consistent with pro-business priors. Furthermore, we assume that the news coverage of local network television impacts that of printed media, as captured by *Media Sentiment*.

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In Figure 1, we plot county-level exposure to Sinclair broadcasting over time. Shaded counties are those within a Sinclair-affiliated station coverage area in the 2000-2020 period; darker shading denotes earlier exposure to this broadcaster. A few stylized patterns may be discerned from this figure: first, Sinclair coverage does not appear to covary with population density, nor the presence of metropolitan areas. Second, Sinclair presence straddles multiple geographical regions of the United States, with all four Census Bureau regions (Northeast, Midwest, South, and West) being represented in Sinclair-coverage areas. Lastly, earlier coverage is not confined to a narrow portion of the United States: from the beginning of our sample period, treated localities appear in multiple regions. We believe these patterns of variation to be favorable to our contention that our instrument is successful in isolating exogenous variation in sentiment.

[Insert Figure 1 about here]

Exploiting local media-merger activity introduces a source of variation (cross-sectional, across localities) into our estimation that is not present in our "target" reduced-form Equation (1). Hence, to recover an IV estimate of our coefficient of interest, we first interact a county-level treatment indicator with a bank-time-location "exposure" measure, and then sum up across locations.[8] This procedure effectively makes our first-stage estimation, Equation (2), a generalized differences-in-differences:

$$MediaSentiment_{i,[t-4,t]} = \alpha_i + \delta_t + \phi \left(\sum_l Exposure_{i,l,t-4} \times Treatment_{l,t-4} \right) + \varepsilon_{i,t} \tag{2}$$

[8]This measure is defined as the proportion of branches of bank i (out of its national branch network) located in l at time t.

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Figure 2 illustrates this "second component" in our IV construction. In this plot, the difference in (cross-BHC) mean branch concentration from years 2000 to 2020 is shown. As both ex-ante and ex-post county branch totals are scaled by total number of branches at bank level, this analysis is insensitive to the general trend of branch closures during this time-span. It is apparent from a comparison of this figure with Figure 1 that aggregate variation in branch network presence in our sample is largely orthogonal to Sinclair expansion. We believe this strengthens our contention that our proposed instrument is "as good as randomly assigned" to treatment units (BHCs).

[Insert Figure 2 about here]

In Equation (2), $MediaSentiment_{i,[t-4,t]}$ is again the (backward-looking) four-quarter average sentiment of articles focusing on bank i, α_i is a firm-level fixed effect, and δ_t a year fixed effect. $Exposure_{i,l,t-4}$ is the number of branches of bank i in location l, at time t-4; $Treatment_{l,t-4}$ is an indicator variable which is equal to one if county l is coded as treated (i.e., exposed to a Sinclair acquisition) at time t-4. In our results, we refer to the term $\sum_l Exposure \times Treatment$, our IV, as *Media Consolidation*.

Naturally, the reader might question the relevance of our chosen instrument. To allay concerns of this nature, we carry out two sets of exercises: first, we present results (in Table 3) for a number of variations of our first-stage specification, Equation (2). In this Table, Columns (1)-(4) report results for alternative first-stage specifications, with varying controls and fixed-effects schemes: even-column regressions are saturated with both bank-level and year fixed effects, while odd-column ones are not; Column (4) reports results for our preferred regression specification, which will be used for our main results. In Column (5), a robustness-check regression is reported, in which the construction of the media consolidation variable is based on deposit shares, rather than branch shares. Columns (6)-(8) report the results of

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differences-in-differences regressions, where "treatment" is defined by *Media Consolidation* exceeding, respectively, 20%, 30%, and 40% thresholds. To cleanly separate treatment times, these regressions only include treatment onsets that occur at least five quarters apart, and the sample only includes observations within four quarters of treatment assignment (pre- and post).

[Insert Table 3 about here]

Second, as is standard, we present evidence of a strong association between our instrument and our target endogenous regressor, *Media Sentiment*, in our main results table (Table 4), in the form of an F-test of the global significance of our first stage regression.

We interpret the results presented in Table 3 as robust evidence of a strong association between exposure to media consolidation and bank-specific sentiment, as expressed in written media. This empirical link appears orthogonal to both time-invariant bank characteristics and a wide battery of time-varying ones. Moreover, this relation is arguably *causal*: DiD regressions show that a shock to media consolidation leads to a significant improvement in media-coverage sentiment. In Figure 3, we graphically show that this result is not driven by pre-trends; this figure plots the 30% threshold case. Lastly, this effect is monotonically increasing in shock intensity.[9]

[Insert Figure 3 about here]

In our second stage, we regress the elements of the supervisory action vector *SupOutcome* on fitted values derived from the first stage regression:

$$SupOutcome_{i,t} = \alpha_i + \delta_t + \zeta \widehat{MediaSentiment}_{i,[t-4,t]} + \varepsilon_{i,t} \tag{3}$$

[9]We believe this shock intensity to be driven mainly by media M&A events, for two reasons: (i) the geographic footprint of bank-branch networks does not vary much at quarterly frequency; (ii) the fixed effects and controls in our DiD specifications will strip out much of the variation in bank geography due to business-model idiosyncrasies.

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We interpret the entries of the coefficient vector ζ as our desired "treatment effects".

A number of further concerns might exist regarding our identification strategy. First, why focus on local TV markets for the construction of our instrument? This may seem like an odd choice, given that (i) our target sentiment measure is derived from print media, and (ii) BHCs are often covered by nation-wide media outlets. There are two reasons for this, one substantive, and one of data availability.

For one, local television remains a key purveyor of new information into the news ecosystem, and thus a key gateway for news-content selection (Pew Research Center, 2010). Hence, by focusing on local TV market merger activity, we are proxying for local shocks to the global news ecosystem. Further, in spite of mass disruption by new forms of electronic media, local TV news remains the most trusted news source by Americans (Enten, 2018); hence, news selection effects stemming from editorial decisions by local newsrooms might be of particular importance. Also, as television M&A activity is subject to FCC jurisdiction, data on local TV station consolidation is far simpler to assemble than data on print media.

One might also question whether our instrument satisfies the exclusion restriction. We believe that if our endogenous regressor of interest, *Media Sentiment*, is interpreted as a sufficient statistic for broad media sentiment, then this is a tenable assumption.[10] Lastly, concern might exist about our instrument violating exclusion through its location component: county locations in which banks choose to operate are certainly not chosen at random, and Sinclair presence might co-vary with these determinants of banks' footprint. However, there is evidence in prior literature that Sinclair expansion is driven by the availability of acquisition targets, being

[10]We interpret the significant covariance of media sentiment with consumer confidence documented by Shapiro et al. (2022) to be evidence in this regard. Coincidentally, Uhl (2012) documents that television news-media sentiment also co-varies closely with the University of Michigan Index of Consumer Sentiment, the workhorse measure of consumer confidence; this strengthens the case for the validity of our instrumental variable.

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only marginally related to county population, and largely uncorrelated to other local demographic characteristics (Kaviani et al., 2021). Incidentally, these prior results appear to be validated by the pattern of variation in Sinclair coverage apparent in Figure 1.

5. Results

5.1. Main results

Table 4 presents the main results of our analysis. Columns (1) through (4) report the estimated coefficients of OLS regressions of risk-management ratings on media sentiment, at the quarterly frequency. Column (1) reports a specification without fixed effects; Columns (2) and (3) report specifications with only bank-level and yearly fixed effects. Column (4) reports our preferred specification, which is saturated with both bank and year fixed effects. All specifications include bank-quarter controls, such as log assets, leverage ratio, return on assets, net-interest-to-interest-income ratio, and log operational losses. In Columns (5) and (6), we report the first- and second-stage results of our DD-IV strategy. Both of these specifications are fully saturated and include the bank controls mentioned above.

[Insert Table 4 about here]

All substantive specifications in this table (Columns 1-4 and 6) report negative and significant coefficients on media sentiment, consistent with our working hypothesis that media tone influences supervisory outputs. Specifically, increasingly negative media sentiment impacts supervisory outcomes by weakening (increasing) risk management ratings. In terms of magnitude, the risk management rating increases by one as negative media sentiment increases by approximately two standard deviations. The estimated coefficients are uniformly significant at the 99% confidence level. In

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our DD-IV specification, the estimation of our first stage yields an F-statistic of 88.88, far above the level required by Stock and Yogo (2002).

5.2. Asymmetry across the distribution of sentiment

We investigate the relative contribution of different loci of the sentiment distribution to the effect reported in the main results. For this analysis, we consider specifications where the independent variables are (bank-quarter) counts of articles that belong to the p-th percentile of the sentiment distribution, scaled by the sum of all articles covering a bank during the quarter in question. The dependent variable, as before, is the risk management rating for the firm-quarter in question.

Table 5 reports the results from this analysis, which shows a notable asymmetry. Specifically, the loadings are negative for the right tail of the sentiment distribution and positive for the left tail. These results are as expected: risk management ratings weaken, i.e., increase, following negative news coverage whereas positive media sentiment has the opposite effect on ratings. We note, however, that only the left tail loadings are significant at the 5% level. The effect of media sentiment on supervisory ratings is therefore driven by negative news coverage.

[Insert Table 5 about here]

5.3. Interactions

Next, we analyze heterogeneity in the baseline effect derived from examiner exposure to differential article structure and syntax. For this analysis, Table 6 reports the results of tests in which we interact media sentiment with article characteristics. All specifications reported in this table are fully saturated with fixed effects and include the usual controls.

[Insert Table 6 about here]

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In Column (1), *Media Sentiment* is found to load negatively and significantly (at 99% confidence), as in the baseline specification. However, both *Media Attention* and the interaction of *Media Sentiment* and *Media Attention* load positively and significantly (at 90% and 99% confidence levels, respectively). The interpretation of this pattern of coefficients is clear: heightened media attention tempers the influence of media tone on regulatory action, and more so conditional on positive news coverage. A similar pattern is found for *Article Numeric Characters*, a count variable which tallies the incidence of numerical characters in an article: the presence of numbers in article text seems to mitigate the influence of tone on examiner actions: the term *Media Sentiment* $\times$ *Article Numeric Characters* loads positively and significantly, at 90% confidence.

We also consider heterogeneity stemming from variation in supervisory style or focus. Table 7 reports results of tests in which media sentiment is interacted with examiner characteristics, i.e., the length of the exam and the experiences of the examiner and reviewer in charge. Like before, all reported specifications contain bank- and year-level fixed effects, as well as the bank controls discussed before.

[Insert Table 7 about here]

Column (2) reports results of a test in which the assessed risk management rating is regressed on the interaction of *Media Sentiment* and *Examiner-in-Charge Experience* in years, together with factorial terms. As in the baseline regression, *Media Sentiment* loads negatively and significantly, but the *Media Sentiment* and *Examiner-in-Charge Experience* interaction does so with positive sign (at 90% confidence). Like the presence of more "objective" information – proxied by the presence of numerical characters – examiner experience appears to temper examiner subjectivity, leading to a decreased sentiment effect.

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In Column (4), a similar effect, both qualitatively and quantitatively, is reported for *Examiner In Charge-BHC Tenure*. The *Media Sentiment* and *Examiner In Charge-BHC Tenure* interaction term loads positively and significantly at 95% confidence, suggesting that a similar "experience" channel is at play. The aforementioned result carries over. Column (5) reports results for a test in which the regressor of interest is the interaction between *Media Sentiment* and *Reviewer-in-Charge Experience*. Again, a similar effect is found both qualitatively and quantitatively: the experience level of an examination reviewer appears to lessen the effect of sentiment.

5.4. Testing alternative supervisory outcomes

Table 8 reports regression specifications in which the risk component of RFI/C(D) ratings is broken down into its constituent subcomponents: (i) Board Oversight, (ii) Policies, (iii) Information Systems, and (iv) Internal Controls. Each column in this table reports the result of the estimation of a regression specification in which a subcomponent measure appears as the dependent variable, and the regressor of interest is *Media Sentiment*. All specifications contain BHC- and year fixed effects, and BHC controls described above.

[Insert Table 8 about here]

This analysis serves a dual purpose. First, it elucidates from which sub-components the covariance between the Risk Management rating and Media Sentiment stems. Second, and particularly for the specification involving the Information Systems rating, the analysis facilities a "placebo test": Information System examinations are largely (i) conducted by subject-matter specific examiners and (ii) based on a series of tight criteria around what constitutes prudent risk management. Hence, we would expect *Media Sentiment* to have less of an effect on this ratings stripe, if any.

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Columns (1), (2), and (4) of Table 8 present regressions in which Board Oversight, Policies, and Internal Controls ratings appear as dependent variables. All subcomponents load negatively and significantly in these specifications (at 90%, 95%, and 95% confidence, respectively). However, in line with our prior, the coefficient on *Information Systems* is not significant; indeed, its calculated p-value is quite large, at 0.921. In our view, this result strengthens the contention that the presence of "objective" evidence crowds out subjectivity in supervisory activity.

Table 9 presents tests that use the quarterly issuance of MRIAs, MRAs and lesser supervisory admonishments as dependent variables. We split our sample of supervisory findings into MRIAs and "all other" for the purpose of these tests; we also analyze supervisory findings with Operations, Legal, or Consumer Protection scope separately from all others.

[Insert Table 9 about here]

The table shows that only the coefficient on *Non-MRIA* variable for the Operations/Legal/Consumer category loads significantly (at 95% confidence) with the expected negative sign. The coefficient on *Non-MRIA* variable with "Other" scope does not load at conventional significance, but the calculated p-value is low enough to make it of note (0.105); in quantitative terms, it is similar in both sign and magnitude to the aforementioned coefficient on *Non-MRIA/Operations/Legal/Consumer* variables.

We interpret these results as follows. *Media Sentiment* retains influence on examiner actions for those supervisory findings that draw less scrutiny; namely, non-MRIA issuance. This is more so the case for findings in which examiner judgment might play a greater role in assessing bank risk-taking and/or compliance with regulation or previous supervisory guidance. This influence disappears for supervisory actions

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subject to review or more scrutiny such as MRIAs (especially those relating to readily measurable aspects of banks' performance).

5.5. Testing media sentiment by topic

Table 10 reports results of tests in which media sentiment is constructed in an alternative way – using only articles from within each of the following Factiva subject-matter categories: (i) Performance & Earnings, (ii) Management, (iii) Corporate, (iv) Legal & Fraud, (v) Political & Regulatory, (vi) Analysts Recommendation, (vii) Markets, and (viii) Economy. This allows us to understand which data categories drive our identified effects.

[Insert Table 10 about here]

The results obtained are somewhat surprising: categories (i), (ii), and (v) above load significantly (see corresponding columns (1), (2) and (5); significance occurs at 95%, 95%, and 90% respectively), with the expected negative signs. However, specifications (3) through (8) (i.e., Corporate News, Legal and Fraud, Political and Regulatory, Analyst Recommendations, Markets, and Economy) do not yield significance. Categories (6)-(8) likely present less firm-specific information, and thus are less relevant to examiners' "learning" about the firm; categories (3) and (4), however, likely do present heavily firm-specific detail.

Taking a closer look at these categories, however, reveals that the coefficient estimated on category (iv) is quite close to conventional significance (calculated p-value of 0.166). Category (v) remains puzzling, although we conjecture that it is likely to consist of news items presenting more "objective information" than more general discussions on firm management and performance, which are likely categorized in categories (i)-(iii).

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6. Policy Implications

We believe our previously presented results shed some light on potential avenues for improvements in the current supervisory framework and specifically can help policymakers in designing a more consistent one.

First, our basic results suggest that media framing significantly influences supervisory outcomes, even when orthogonal to bank fundamentals. This suggests a source of bias in bank examination; however, many other sources are plausible, and indeed, have been recognized as potential pitfalls by regulatory authorities in many jurisdictions.[11] We believe that incorporating "de-biasing" materials, with basis in behavioral science, into examiner training might go a long way in helping supervisors become aware of latent bias they might harbor, and correct biased judgment in the course of their activity.

Our findings also suggest that more experienced examiners and longer exams improve consistency in ratings. Expanding the oversight committees with more decision-making abilities, more senior examiners, and more time commitment seems to be a potential avenue to mitigate biases in ratings.

Lastly, our results suggest that ratings that are informed by quantitative data exhibit greater consistency. This suggests, in turn, that the widespread application of benchmark models to support ratings may help in mitigating supervisory bias. The benefits associated with quantitative benchmarking, as well as computational advances allowing for the harvesting and interpretation of data once thought of as non-amenable to quantitative analysis (text, audio, video), suggest that model-

[11] See, for instance, references to institutional initiatives meant to reduce "complacency, overconfidence, short-term focus, and lack of effective challenge" among Australian, Canadian, Irish, Dutch, and Singaporean bank regulators referenced in the Review of the Federal Reserve's Supervision and Regulation of Silicon Valley Bank (Board of Governors of the Federal Reserve System, 2023).

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derived ratings may be a reasonable aid for bank supervision even for dimensions that are, at first glance, more qualitative in nature, such as risk management.

7. Concluding Remarks

In light of recent episodes of bank stress, there is a pressing need to understand and address the sources of bias in bank supervision.[12]

In this paper, we document a novel channel of potential bias in bank supervision: media sentiment in the news coverage of banks. Our identification strategy allows us to focus on media sentiment that is unrelated to fundamentals driving supervisory outcomes.

We see our results as important for a variety of reasons. For one, prior literature has documented that bank performance is responsive to supervisory action. Thus, bias in supervisory outcomes might lead to capital misallocation, an antithetical outcome to the mandate of bank regulators. Second, if media sentiment significantly impacts supervisory outcomes, media might act as a regulatory "agenda setter," leading to a state of affairs tantamount to regulatory capture. Lastly, as the time series of media sentiment covaries with the business cycle, media-sentiment driven supervisory action might act as a cyclical amplifier. This procyclical amplification defeats the purpose of financial stability. The cyclical nature of sentiment might also interact perversely with media agenda setting. Recent work (Culpepper et al., 2023) documents how media coverage shapes popular demand for financial regulation, with a proclivity for harsher standards spiking immediately after corporate scandals, and waning afterward. This might lead to "risk-on/risk-off" boom-bust cycles, with negative welfare consequences.

[12]We take to heart Zingales (2015) "call to arms" for both regulators and finance academics to remain vigilant, helping ensure that regulatory agencies not devolve into "club[s] to consolidate the power of incumbents."

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Figures

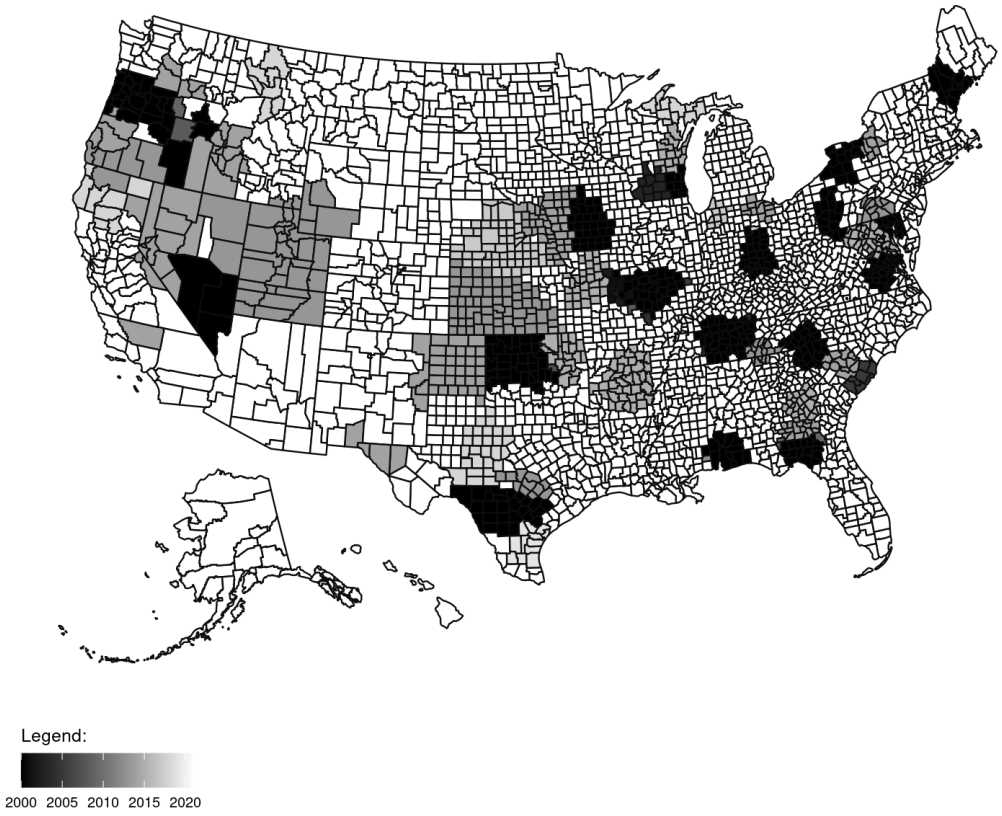


Figure 1: **County-level Exposure to Sinclair Broadcasting, 2000-2020**
This figure plots county-level exposure to Sinclair broadcasting over time. Shading encodes the onset of exposure to Sinclair coverage; counties shaded black are exposed from the onset of our sample period (2000), while lighter shades of gray signify later exposure onset, up to the year 2020. A county is defined as "Sinclair exposed" if it lies in the Nielsen Designated Market Area of a Sinclair-owned station in year t.

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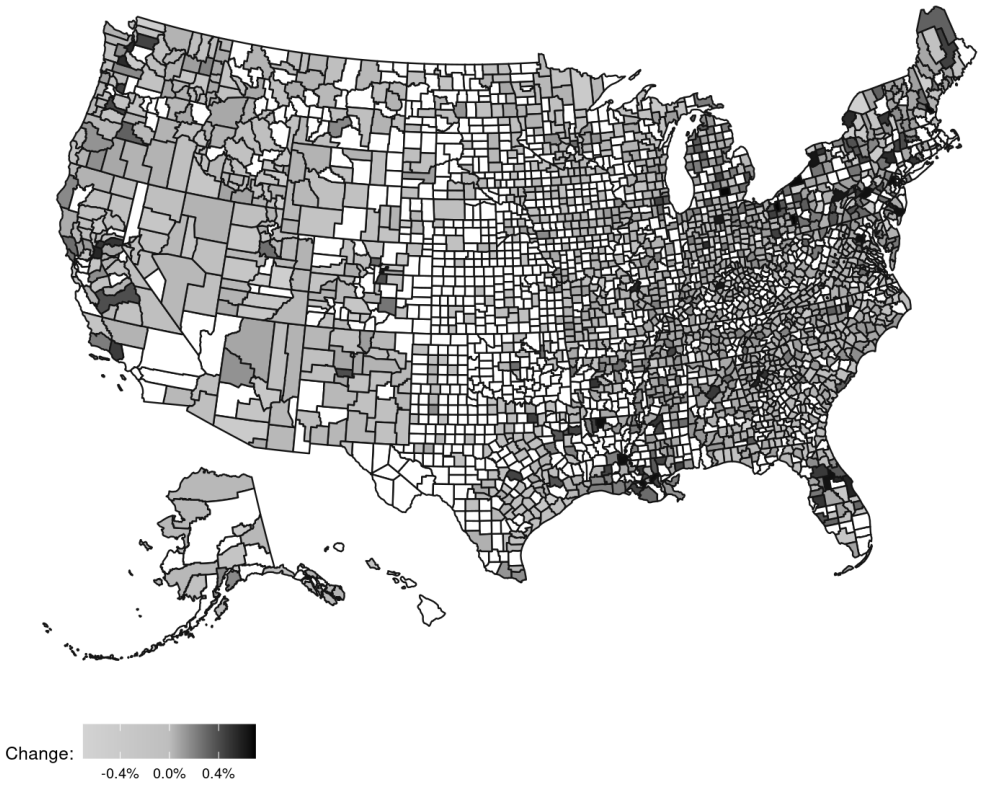


Figure 2: **County-level Changes in Mean Branch Concentration, 2000-2020**
The figure plots mean changes in scaled branch ratios from 2000 to 2020, at the county level. Darker shading encodes greater relative concentration in branch presence for banks operating in a given county.

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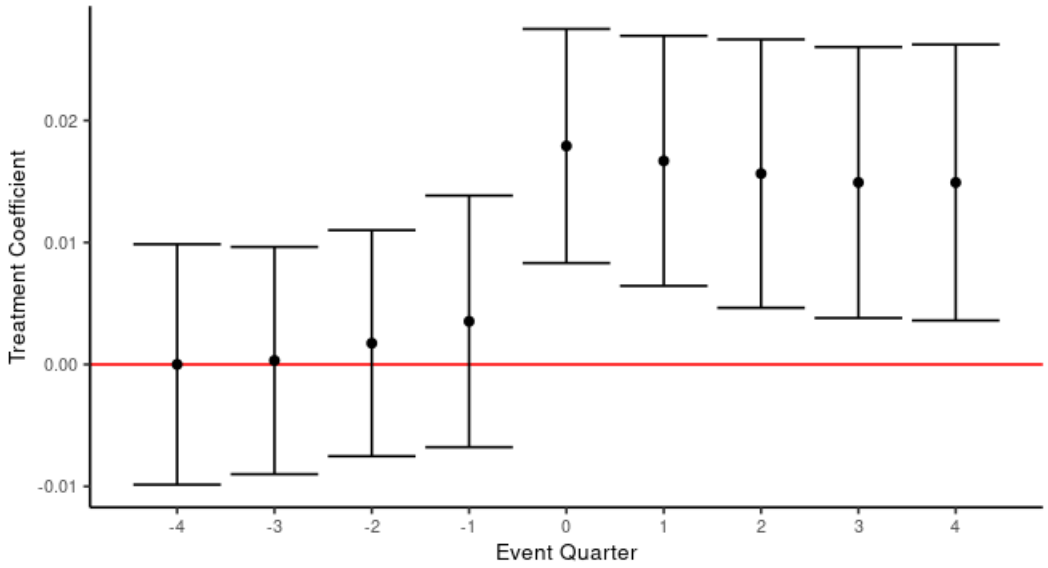


Figure 3: **Media Sentiment Dynamics around Media Consolidation Events**
This figure shows treatment coefficients and 95% confidence intervals from differences-in-differences regressions of media sentiment on media consolidation events. The first coefficient is normalized to zero. A firm is considered as treated by the media consolidation event if the proportion of branches located in counties affected by media mergers as defined in Section 3.3 exceeds 30%. To cleanly separate treatment times, the regressions only include treatments that occur at least 5 quarters apart, and the sample only includes quarters within 4 quarters before or after the treatment times. The regressions include controls and BHC×Year fixed effects as reported in Column (7) of Table 3. The error terms are clustered at the BHC×Year level.

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Tables

Table 1: **Definitions**
This table presents variable definitions.

Dependent Variables: *Risk Management Measures*	
Risk Management	Represents the *Risk Management Practices* (R) component of the Federal Reserve's RFI rating system (first outlined in Board of Governors of the Federal Reserve System (2004)) which is an evaluation of the ability of the holding company's board of directors and senior management, as appropriate for their respective positions, to identify, measure, monitor, and control risk. The R component is rated on a 1 to 5 scale in ascending order of supervisory concern. More detailed information can be found at https://www.federalreserve.gov/supervisionreg/srletters/sr1904a2.pdf
Board Oversight	Represents the *Board and Senior Management Oversight* sub-component of the Risk Management Practices component and evaluates the adequacy and effectiveness of board and senior management's understanding and management of risk inherent in the holding company's activities, as well as the general capabilities of management. It also includes consideration of management's ability to identify, understand, and control the risks undertaken by the institution, to hire competent staff, and to respond to changes in the institution's risk profile or innovations in the banking sector. The *Board and Senior Management Oversight* sub-component is rated on a 1 to 5 scale in ascending order of supervisory concern.
Policies	Represents the *Policies, Procedures and Limits* sub-component of the Risk Management rating and evaluates the adequacy of a holding company's policies, procedures, and limits given the risks inherent in the activities of the consolidated organization and its stated goals and objectives. This analysis will include consideration of the adequacy of the institution's accounting and risk disclosure policies and procedures. The *Policies, Procedures and Limits* sub-component is rated on a 1 to 5 scale in ascending order of supervisory concern.
Information System	Represents the *Risk Monitoring and Management Information Systems* sub-component of the Risk Management rating and assesses the adequacy of a holding company's risk measurement and monitoring, and the adequacy of its management reports and information systems. This analysis will include a review of the assumptions, data, and procedures used to measure risk and the consistency of these tools with the level of complexity of the organization's activities. The *Risk Monitoring and Management Information Systems* sub-component is rated on a 1 to 5 scale in ascending order of supervisory concern.
Internal Control	Represents the *Internal Control* sub-component of the Risk Management rating and evaluates the adequacy of a holding company's internal controls and internal audit procedures, including the accuracy of financial reporting and disclosure and the strength and influence, within the organization, of the internal audit team. This analysis will also include a review of the independence of control areas from management and the consistency of the scope coverage of the internal audit team with the complexity of the organization. The *Internal Controls* sub-component is rated on a 1 to 5 scale in ascending order of supervisory concern.
Ln(MRIA Op)	A natural log transformation of *MRIA Op*, defined as *Ln(1 + MRIA Op)*. *MRIA Op* represents the number of unresolved confidential supervisory findings that require immediate attention within the operational risk, legal, or consumer categories.
Ln(Non-MRIA Op)	A natural log transformation of *Non-MRIA Op*, defined as *Ln(1 + Non-MRIA Op)*. *Non-MRIA Op* represents the number of unresolved confidential supervisory findings that require attention and provisions within the operational risk, legal, or consumer categories.
Ln(MRIA Other)	A natural log transformation of *MRIA Other*, defined as *Ln(1 + MRIA Other)*. *MRIA Other* represents the number of unresolved confidential supervisory findings that require immediate attention not categorized as operational risk, legal, or consumer-related issues.
Ln(Non-MRIA Other)	A natural log transformation of *Non-MRIA Other*, defined as *Ln(1 + Non-MRIA Other)*. *Non-MRIA Other* represents the number of unresolved confidential supervisory findings that require attention and provisions that are not categorized as operational risk, legal, or consumer-related issues.

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Key Independent Variables: *Media Sentiment Variables*	
Media Sentiment	The sentiment, measured following Loughran and McDonald (2011), of all articles focusing uniquely on a BHC, equally weighted within the previous year. A higher (lower) value reflects a more positive (negative) sentiment towards the BHC.
Media Consolidation	A measure of media consolidation. We aggregate the FIPS-level index at the BHC level using the relative presence of the BHC in the affected FIPS as weights. The vector product of county-level treatment and firm-county branch proportions yields the proportion of branches treated for a firm in a given year.
Tail Frequency - Bottom N%	The number of articles with a *Media Sentiment* below the N^{th} percentile of the unconditional distribution. These articles represent the most negative articles in our sample.
Tail Frequency - Above N%	The number of articles with a Media Sentiment above the N^{th} percentile of the unconditional distribution. These articles represent the most positive articles in our sample.
Other Variables: *BHC Controls, Article and Exam Characteristics*	
Ln(Assets)	A natural log transformation of a BHC's *Assets* in millions of U.S Dollars.
Leverage	BHC total assets divided by book value of equity.
RoA	BHC return on assets measured in the previous year.
NII-to-II	The ratio of BHC non-interest income to interest income.
Ln(OpLoss)	A natural log transformation of *OpLoss*, defined as *1 + OpLoss*. *OpLoss* measures operational losses that occur at a BHC averaged over the prior year in millions of U.S. Dollars.
Media Attention	The average number of sentences from all articles focusing uniquely on a BHC evaluated in the prior year.
Article Readability	The average article readability - measured as TTR (see Kincaid et al. (1975)) evaluated equally weighting all articles focusing uniquely on a BHC in the prior year.
Article Emotional Load	The average article emotional load - measured as EL (based on Mohammad and Turney (2013) dictionary), and evaluated equally weighting all articles focusing uniquely on a BHC in the prior year.
Article Numeric Characters	The average ratio of numeric characters to all characters measured equally weighting all articles focusing uniquely on a BHC in the prior year.
Ln(Exam Length)	A natural log transformation of *Exam Length*, defined as *1 + Exam Length*. *Exam Length* represents the number of days that pass between the start and the end of the exam where a risk management rating is assigned.
Ln(Examiner In Charge Experience)	A natural log transformation of *Examiner In Charge Experience*, defined as *1 + Examiner In Charge Experience*. *Examiner In Charge Experience* represents the number of years since the examiner leading the exam has first led, or reviewed, an exam.
Examiner In Charge First Exam	An indicator variable taking the value of one if it is the first time that the examiner in charge has led an exam and zero otherwise.
Ln(Examiner In Charge-BHC Tenure)	A natural log transformation of *Examiner In Charge-BHC Tenure*, defined as *1 + Examiner In Charge-BHC Tenure*. *Examiner In Charge-BHC Tenure* represents the number of years since the examiner leading the exam has been in charge of the examined BHC.
Ln(Reviewer In Charge Experience)	A natural log transformation of *Reviewer In Charge Experience*, defined as *1 + Reviewer In Charge Experience*. *Reviewer In Charge Experience* represents the number of years since the reviewer in charge has first led, or reviewed, an exam.

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Table 2: **Descriptive Statistics**
This table presents descriptive statistics of risk management ratings in Panel A, media sentiment measures in Panel B, and other variables used in our analyses in Panel C. The sample includes 1,516 quarterly observations of 30 large bank holding companies over the period [2002:Q1-2019:Q4]. Variable definitions are reported in Table 1.

Panel A: Dependent Variables

	N	Mean	Std	P25	P50	P75
Risk Management	1,516	2.503	0.580	2.000	2.000	3.000
Board Oversight	1,477	2.421	0.600	2.000	2.000	3.000
Policies	1,477	2.239	0.473	2.000	2.000	2.000
Information System	1,477	2.565	0.552	2.000	3.000	3.000
Internal Control	1,477	2.471	0.555	2.000	2.000	3.000
MRIA Op	1,240	0.454	1.270	0.000	0.000	0.000
Ln(MRIA Op)	1,240	0.204	0.483	0.000	0.000	0.000
Non-MRIA Op	1,240	1.890	6.516	0.000	0.000	0.000
Ln(Non-MRIA Op)	1,240	0.381	0.859	0.000	0.000	0.000
MRIA Other	1,240	5.419	5.933	0.000	4.000	8.000
Ln(MRIA Other)	1,240	1.389	1.026	0.000	1.609	2.197
Non-MRIA Other	1,240	40.320	32.288	15.000	32.000	60.000
Ln(Non-MRIA Other)	1,240	3.349	0.966	2.773	3.497	4.111

Panel B: Key Independent Variables

	N	Mean	Std	P25	P50	P75
Media Sentiment	1,516	-0.030	0.032	-0.051	-0.029	-0.009
Media Consolidation	1,516	0.167	0.198	0.032	0.128	0.221
Tail Frequency - Bottom 1%	1,516	0.009	0.016	0.000	0.000	0.012
Tail Frequency - Bottom 5%	1,516	0.040	0.040	0.009	0.028	0.057
Tail Frequency - Bottom 10%	1,516	0.078	0.065	0.029	0.064	0.113
Tail Frequency - Top 10%	1,516	0.133	0.107	0.065	0.108	0.173
Tail Frequency - Top 5%	1,516	0.070	0.073	0.027	0.053	0.090
Tail Frequency - Top 1%	1,516	0.014	0.022	0.000	0.007	0.019

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Panel C: Other Variables

	N	Mean	Std	P25	P50	P75
Assets	1,515	525.925	693.639	114.816	172.010	501.926
Ln(Assets)	1,516	5.558	1.123	4.733	5.147	6.202
Leverage	1,516	10.989	18.522	7.943	9.366	11.267
RoA	1,516	0.843	0.978	0.570	0.935	1.214
NII-to-II	1,516	2.145	10.008	0.547	0.781	2.192
OpLoss	1,516	116.401	254.957	7.661	22.107	102.418
Ln(OpLoss)	1,516	3.444	1.592	2.159	3.140	4.639
Media Attention	1,516	318.398	394.082	80.907	159.449	409.871
Article Readability	1,516	0.439	0.081	0.401	0.453	0.497
Article Emotional Load	1,516	16.959	17.582	7.526	11.142	17.925
Article Numeric Characters	1,516	2.882	0.959	2.216	2.647	3.362
Exam Length	1,516	96.792	77.118	50.000	88.000	120.000
Ln(Exam Length)	1,516	4.237	1.027	3.932	4.489	4.796
Examiner In Charge Experience	1,516	4.245	3.913	1.000	3.000	6.000
Ln(Examiner In Charge Experience)	1,516	1.372	0.794	0.693	1.386	1.946
Examiner In Charge First Exam	1,516	0.145	0.352	0.000	0.000	0.000
Examiner In Charge-BHC Tenure	1,516	1.945	2.606	0.000	1.000	3.000
Ln(Examiner In Charge-BHC Tenure)	1,516	0.793	0.733	0.000	0.693	1.386
Reviewer In Charge Experience	1,481	7.115	4.715	3.000	7.000	11.000
Ln(Reviewer In Charge Experience)	1,481	1.855	0.780	1.386	2.079	2.485

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Table 3: **Media Sentiment and Media Consolidation**
This table reports coefficient estimates from Ordinary Least Squares regressions of media sentiment on media consolidation. The estimation sample comprises an unbalanced panel of 1,516 quarterly observations by 30 large U.S. bank holding companies (BHCs) over the period [2002:Q1-2019:Q4]. *Media Sentiment* measures the average sentiment, as per Loughran and McDonald (2011), of articles focusing uniquely on a BHC over the prior calendar year. *Media Consolidation* captures the exposure of a BHC to the consolidation in the media landscape measured in the year prior to the measurement of *Media Sentiment*. *Treatment* is a dummy variable that takes value one if *Media Consolidation* exceeds 20% in Column (6), 30% in Column (7), and 40% in Column (8). *Ln(Assets)* is a natural log transformation of a BHC's Total Assets. *Leverage* is measured as a BHC total assets divided by book value of equity. *RoA* is a BHC return on assets measured in the previous year. *NII-to-II* the ratio of a BHC non-interest income to interest income. *Ln(OpLoss)* is a natural log transformation of a BHC's operational losses averaged in the prior year. Columns (1) to (4) reports OLS coefficients under different fixed effects and control schemes, Column (5) reports the results when *Media Consolidation* is defined by deposit shares rather than branch shares, while Columns (6) to (8) report differences-in-differences regression results. To cleanly separate treatment times, these regressions only include treatments that occur at least 5 quarters apart, and the sample only includes quarters within 4 quarters before or after the treatment times. The error terms are clustered at the BHC×Year level; p-values are presented in parentheses.

	Media Sentiment							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Media Consolidation	0.039***	0.042***	0.025***	0.042***	0.027***			
	(0.005)	(0.011)	(0.008)	(0.000)	(0.007)			
Treatment						0.010***	0.023***	0.031***
						(0.003)	(0.005)	(0.008)
Ln(Assets)			0.009***	0.015***	0.016***	-0.001	-0.008	-0.023
			(0.002)	(0.004)	(0.005)	(0.005)	(0.010)	(0.020)
Leverage			0.000	0.000	0.000	0.002	0.003*	0.004**
			(0.000)	(0.368)	(0.000)	(0.001)	(0.002)	(0.002)
RoA			0.011***	0.005***	0.005***	0.005***	0.002	0.001
			(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
NII-to-II			-0.000	0.000	-0.000	0.000	0.000	-0.004*
			(0.000)	(0.449)	(0.000)	(0.000)	(0.000)	(0.002)
Ln(OpLoss)			0.011***	-0.006***	-0.006***	-0.004**	-0.000	0.004
			(0.001)	(0.000)	(0.002)	(0.002)	(0.003)	(0.004)
Intercept	-0.037							
	(0.002)							
BHC FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
N	1,516	1,516	1,516	1,516	1,516	1,029	543	291
Adj R^2	0.059	0.554	0.240	0.580	0.572	0.546	0.580	0.615

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

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Table 4: **Media Sentiment and Risk Management Ratings**
This table reports coefficient estimates from Ordinary Least Squares (OLS) and Two Stages Least Square (2SLS) regressions of risk management ratings on media sentiment. The estimation sample comprises an unbalanced panel of 1,516 quarterly observations by 30 large U.S. bank holding companies (BHCs) over the period [2002:Q1-2019:Q4]. *Risk Management* is a BHC risk management rating (R) as part of the RFI rating system. *Media Sentiment* measures the average sentiment, as per Loughran and McDonald (2011), of articles focusing uniquely on a BHC over the prior calendar year. *Media Consolidation* captures the exposure of a BHC to the consolidation in the media landscape measured in the year prior to the measurement of *Media Sentiment*. *Ln(Assets)* is a natural log transformation of a BHC's Total Assets. *Leverage* is measured as a BHC's total assets divided by book value of equity. *RoA* is a BHC's return on assets measured in the previous year. *NII-to-II* the ratio of a BHC's non-interest income to interest income. *Ln(OpLoss)* is a natural log transformation of a BHC's operational losses averaged in the prior year. Columns (1) to (4) reports OLS coefficients under different fixed effects schemes, Column (5) reports the first stage coefficients while Column (6) reports the second stage coefficients of the 2SLS regression with both BHC and year fixed effects. The error terms are clustered at the BHC×Year level. p-values are presented in parentheses.

	Risk Management Rating					
	OLS				2SLS	
	(1)	(2)	(3)	(4)	(5) I Stage	(6) II Stage
Media Sentiment	-2.627***	-3.211***	-5.807***	-5.275***		-16.106***
	(0.001)	(0.000)	(0.000)	(0.000)		(0.006)
Media Consolidation					0.042***	
					(0.000)	
Ln(Assets)	0.058	0.327***	-0.145***	-0.129	0.015***	0.046
	(0.171)	(0.000)	(0.002)	(0.160)	(0.004)	(0.741)
Leverage	-0.002**	-0.005	0.000	-0.002	0.000	0.000
	(0.039)	(0.161)	(0.834)	(0.274)	(0.368)	(0.654)
RoA	-0.126***	-0.121***	-0.160***	-0.190***	0.005***	-0.140***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
NII-to-II	0.004**	0.002	0.003***	0.001**	0.000	0.001
	(0.034)	(0.274)	(0.002)	(0.020)	(0.449)	(0.569)
Ln(OpLoss)	0.035	-0.006	0.171***	0.059**	-0.006***	0.005
	(0.269)	(0.824)	(0.000)	(0.042)	(0.000)	(0.912)
BHC FE	No	Yes	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
N	1,516	1,516	1,516	1,516	1,516	1,516
Adj R^2	0.147	0.433	0.349	0.537		
F-test					88.884	

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

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Table 5: **Extreme Media Sentiment**

This table reports coefficient estimates from Two Stages Least Square (2SLS) regressions of risk management ratings on tail media sentiment. The estimation sample comprises an unbalanced panel of 1,516 quarterly observations by 30 large U.S. bank holding companies (BHCs) over the period [2002:Q1-2019:Q4]. *Risk Management* is a BHC risk management rating (R) as part of the RFI rating system. *Media Sentiment* represents the number of articles with a *Media Sentiment* below the N^{th} percentile of the unconditional distribution. These articles represent the most negative articles in our sample. *Tail Frequency - Top* N^{th} represents the number of articles with a *Media Sentiment* above the N^{th} percentile of the unconditional distribution. These articles represent the most positive articles in our sample. All specifications include BHC and year fixed effects. Control variables (*Ln(Assets)*, *Leverage*, *RoA*, *NII-to-II*, *Ln(OpLoss)*) are included, but their coefficient estimates are omitted for brevity. The error terms are clustered at the BHC×Year level; p-values are presented in parentheses.

	Risk Management Rating					
	(1)	(2)	(3)	(4)	(5)	(6)
Tail Frequency - Bottom 1%	67.068**					
	(0.033)					
Tail Frequency - Bottom 5%		19.098**				
		(0.013)				
Tail Frequency - Bottom 10%			11.728**			
			(0.017)			
Tail Frequency - Top 10%				-11.374		
				(0.163)		
Tail Frequency - Top 5%					-23.830	
					(0.337)	
Tail Frequency - Top 1%						-64.522
						(0.433)
BHC Controls	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,516	1,516	1,516	1,516	1,516	1,516

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

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Table 6: **Article Characteristics**

This table reports coefficient estimates from Two Stages Least Square (2SLS) regressions of risk management ratings on tail media sentiment. The estimation sample comprises an unbalanced panel of 1,516 quarterly observations by 30 large U.S. bank holding companies (BHCs) over the period [2002:Q1-2019:Q4]. *Risk Management* is a BHC risk management rating (R) as part of the RFI rating system. *Media Sentiment* measures the average sentiment, as per Loughran and McDonald (2011), of articles focusing uniquely on a BHC over the prior calendar year. *Media Attention* represents the average number of sentences from all article focusing uniquely on a BHC evaluated in the prior year. *Article Readability* represents the average article readability, measured as TTR (Kincaid et al., 1975), evaluated equally weighting all articles focusing uniquely on a BHC in the prior year. *Article Emotional Load* represents the average article emotional load, as EL (based on Mohammad and Turney (2013) dictionary), evaluated equally weighting all articles focusing uniquely on a BHC in the prior year. *Article Numeric Characters* represents the average ratio of numeric characters to all characters measured equally weighting all articles focusing uniquely on a BHC in the prior year. All specifications include BHC and year fixed effects. Control variables (*Ln(Assets)*, *Leverage*, *RoA*, *NII-to-II*, *Ln(OpLoss)*) are included, but their coefficient estimates are omitted for brevity. The error terms are clustered at the BHC×Year level. p-values are presented in parentheses.

	Risk Management Rating			
	(1)	(2)	(3)	(4)
Media Sentiment	-14.830***	240.582	-55.497	-60.311**
	(0.009)	(0.327)	(0.132)	(0.047)
Media Attention	0.007*			
	(0.062)			
Media Sentiment * Media Attention	0.099*			
	(0.052)			
Article Readability		-14.036		
		(0.287)		
Media Sentiment * Article Readability		-549.262		
		(0.296)		
Article Emotional Load			0.116	
			(0.317)	
Media Sentiment * Article Emotional Load			3.051	
			(0.315)	
Article Numeric Characters				0.382
				(0.150)
Media Sentiment * Article Numeric Characters				18.874*
				(0.096)
BHC Controls	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,516	1,516	1,516	1,516

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

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Table 7: **Exam Characteristics**

This table reports coefficient estimates from Two Stages Least Square (2SLS) regressions of risk management ratings on tail media sentiment. The estimation sample comprises an unbalanced panel of 1,516 quarterly observations by 30 large U.S. bank holding companies (BHCs) over the period [2002:Q1-2019:Q4]. *Risk Management* is a BHC risk management rating (R) as part of the RFI rating system. *Media Sentiment* measures the average sentiment, as per Loughran and McDonald (2011), of articles focusing uniquely on a BHC over the prior calendar year. *Ln(Exam Length)* represents the number of days that pass between the start and the end of the exam where risk management rating is assigned. *Examiner In Charge Experience* represents the number of years since the supervisor leading the exam has first led, or reviewed, an exam. *Examiner In Charge First Exam* is an indicator variable taking the value of one if it is the first time that the examiner in charge has led an exam and zero otherwise. *Ln(Examiner In Charge-BHC Tenure)* represents the number of years since the supervisor leading the exam has been in charge of the examined BHC. *Reviewer In Charge Experience* represents the number of years since the reviewer in charge of the exam has first led, or reviewed, an exam. All specifications include BHC and year fixed effects. Control variables (*Ln(Assets)*, *Leverage*, *RoA*, *NII-to-II*, *Ln(OpLoss)*) are included, but their coefficient estimates are omitted for brevity. The error terms are clustered at the BHC×Year level. p-values are presented in parentheses.

	Risk Management Rating				
	(1)	(2)	(3)	(4)	(5)
Media Sentiment	-82.457**	-28.285**	-7.455	-32.122**	-257.215
	(0.028)	(0.025)	(0.134)	(0.035)	(0.526)
Ln(Exam Length)	0.713**				
	(0.034)				
Media Sentiment * Exam Length	15.727*				
	(0.053)				
Ln(Examiner In Charge Experience)		0.464*			
		(0.050)			
Media Sentiment * Examiner In Charge Experience		15.371*			
		(0.082)			
Examiner In Charge First Exam			-0.702*		
			(0.083)		
Media Sentiment * Examiner In Charge First Exam			-25.177*		
			(0.097)		
Ln(Examiner In Charge-BHC Tenure)				0.740*	
				(0.083)	
Media Sentiment * Examiner In Charge-BHC Tenure				26.121	
				(0.103)	
Ln(Reviewer In Charge Experence)					3.163
					(0.554)
Media Sentiment * Reviewer In Charge Experience					122.084
					(0.553)
BHC Controls	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	1,516	1,516	1,516	1,516	1,481

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

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Table 8: **Risk Management Sub-components**
This table reports coefficient estimates from Two Stages Least Square (2SLS) regressions of risk management ratings on tail media sentiment. The estimation sample comprises an unbalanced panel of 1,516 quarterly observations by 30 large U.S. bank holding companies (BHCs) over the period [2002:Q1-2019:Q4]. *Board Oversight* represents the Board and Senior Management Oversight sub-component rating of the RFI rating system and evaluates the adequacy and effectiveness of board and senior management's understanding and management of risk inherent in the holding company's activities, as well as the general capabilities of management. *Policies* represents the Policies, Procedures and Limits sub-component rating of the RFI rating system and evaluates the adequacy of a holding company's policies, procedures, and limits given the risks inherent in the activities of the consolidated organization and its stated goals and objectives. *Information System* represents the Risk Monitoring and Management Information Systems sub-component rating of the RFI rating system and assesses the adequacy of a holding company's risk measurement and monitoring, and the adequacy of its management reports and information systems. *Information System* represents the Risk Monitoring and Management Information Systems sub-component rating of the RFI rating system and assesses the adequacy of a holding company's risk measurement and monitoring, and the adequacy of its management reports and information systems. *Internal Control* represents the Internal Control sub-component rating of the RFI rating system and evaluates the adequacy of a holding company's internal controls and internal audit procedures, including the accuracy of financial reporting and disclosure and the strength and influence, within the organization, of the internal audit team. *Media Sentiment* measures the average sentiment, as per Loughran and McDonald (2011), of articles focusing uniquely on a BHC over the prior calendar year. All specifications include BHC and year fixed effects. Control variables (*Ln(Assets)*, *Leverage*, *RoA*, *NII-to-II*, *Ln(OpLoss)*) are included, but their coefficient estimates are omitted for brevity. The error terms are clustered at the BHC×Year level; p-values are presented in parentheses.

	Risk Management Rating			
	Sub-Components			
	(1) Board Oversight	(2) Policies	(3) Information System	(4) Internal Controls
Media Sentiment	-10.516**	-20.209***	0.336	-20.835***
	(0.044)	(0.003)	(0.929)	(0.002)
BHC Controls	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,477	1,477	1,477	1,477

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

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Table 9: **Supervisory Findings**
This table reports coefficient estimates from Two Stages Least Square (2SLS) regressions of risk management ratings on tail media sentiment. The estimation sample comprises an unbalanced panel of 1,516 quarterly observations by 30 large U.S. bank holding companies (BHCs) over the period [2002:Q1-2019:Q4]. *Op-Legal-Consumer MRIA* represents the natural log transformation of unresolved confidential supervisory findings that require immediate attention within the operational risk, legal, or consumer categories. *Op-Legal-Consumer Non-MRIA* represents the natural log transformation of of unresolved confidential supervisory findings that require attention and provisions within the operational risk, legal, or consumer categories. *Other MRIA* represents the natural log transformation of of unresolved confidential supervisory findings that require immediate attention not categorized as operational risk, legal, or consumer-related issues. *Other Non-MRIA* represents the natural log transformation of unresolved confidential supervisory findings that require attention and provisions that are not categorized as operational risk, legal, or consumer-related issues. *Media Sentiment* measures the average sentiment, as per Loughran and McDonald (2011), of articles focusing uniquely on a BHC over the prior calendar year. All specifications include BHC and year fixed effects. Control variables (*Ln(Assets)*, *Leverage*, *RoA*, *NII-to-II*, *Ln(OpLoss)*) are included, but their coefficient estimates are omitted for brevity. The error terms are clustered at the BHC×Year level. p-values are presented in parentheses.

	Supervisory Findings			
	Op-Legal-Consumer		Other	
	(1) MRIA	(2) Non-MRIA	(3) MRIA	(4) Non-MRIA
Media Sentiment	-3.614	-16.847**	0.235	-15.648
	(0.429)	(0.041)	(0.977)	(0.105)
BHC Controls	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,240	1,240	1,240	1,240

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

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Table 10: **News Topic**

This table reports coefficient estimates from Two Stages Least Square (2SLS) regressions of risk management ratings on tail media sentiment. The estimation sample comprises an unbalanced panel of 1,516 quarterly observations by 30 large U.S. bank holding companies (BHCs) over the period [2002:Q1-2019:Q4]. *Performance & Earnings* represents the subset of articles that have as primary focus a BHC's financial performance earnings. *Management* represents the subset of articles that have as primary focus information about a BHC's board of directors, management, and their changes. *Corporate* represents the subset of articles that have as primary focus a BHC's corporate governance, corporate changes, and corporate actions. *Legal & Fraud* represents the subset of articles that have as primary focus a BHC's legal cases and fraud incidents. *Political & Regulatory* represents the subset of articles that have as primary focus the political and regulatory environment as related to a BHC. *Analyst Recommendation* represents the subset of articles that have as primary focus analyst recommendations targeting a BHC. *Markets* represents the subset of articles that have as primary focus markets - equity, bonds, commodities, etc... - as related to a BHC. *Economy* represents the subset of articles that have as primary focus the general economy - interest rates, monetary economics, economic growth etc... - as related to a BHC. *Media Sentiment* measures the average sentiment, as per Loughran and McDonald (2011), of articles focusing uniquely on a BHC over the prior calendar year. All specifications include BHC and year fixed effects. Control variables (*Ln(Assets)*, *Leverage*, *RoA*, *NII-to-II*, *Ln(OpLoss)*) are included, but their coefficient estimates are omitted for brevity. The error terms are clustered at the BHC×Year level; p-values are presented in parentheses.

	Risk Management Rating							
	News Topic							
	(1) Performance & Earnings	(2) Management	(3) Corporate	(4) Legal & Fraud	(5) Political & Regulatory	(6) Analysts Recommen-dation	(7) Markets	(8) Economy
Media Sentiment	-30.633**	-33.226**	-43.256	-86.669	-28.890*	-134.862	-177.126	305.457
	(0.033)	(0.030)	(0.168)	(0.515)	(0.053)	(0.496)	(0.603)	(0.772)
BHC Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,516	1,516	1,516	1,516	1,516	1,516	1,516	1,516

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

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Appendix A. Sentiment Analysis

Factiva has the capability to assign entity codes to each news article. Specifically, if a news article discusses a bank in sufficient detail, Factiva matches this article to the bank's entity code, enabling us to identify relevant articles based on bank's identity rather than a less precise method of text matching.[13]

Since we are dealing with BHCs, we have to consider their subsidiaries. Dow Jones integrates Dun & Bradstreet corporate family trees such that the news about subsidiaries of BHCs would also be captured as news of the parent company. In the case of mergers, the news articles are backdated to be captured at the current resulting merged entity (for example, Truist would capture historical BB&T and SunTrust news).

We consider each article as a unit of observation and decompose each article into a set of sentences. We then run our algorithm to derive a sentiment score for each sentence in that article, by considering both the presence of positive and negative terms, as well as amplifiers and negations in the neighborhood of each relevant term. Once we assign a sentiment score to each sentence, we aggregate the sentiment score to the article level. We then calculate a set of scores for bank-quarter level. This method yields bank-quarter level observations.

[13]One complication is that DFAST banks are often mentioned in the news in several variations, including known short names and acronyms. For example, JP Morgan Chase can be called JPMC, JPM, JPMorgan, JPMorgan Chase, and lower case variations lead to additional possible naming. However, Factiva's classification system is robust enough to recognize these variations as one entity.

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Appendix B. BHC Sample

Table B.11: List of Bank Holding Companies (Ticker/Bank Type).
The table provides a list of bank holding companies in our sample, along with their respective stock symbols.

Bank Name	Symbol
Ally Financial	Ally
American Express	Amex
BBVA Compass	BBVA
Bank of Montreal	BMO
BNP Paribas	BNP
BNY Mellon	BNY
Bank of America	BofA
Barclays Bank	BCS
Capital One	COF
Citigroup	Citi
Credit Suisse	CS
Discover Financial	DFS
Deutsche Bank	DB
Fifth Third Bank	FITB
Goldman Sachs	GS
Huntington Bank	HBAN
HSBC Bank	HSBC
JPMorgan Chase	JPMC
KeyCorp	KEY
Morgan Stanley	MS
M&T Bank	MTB
MUFG Union	MUFG
Northern Trust	NTRS
PNC Group	PNC
Regions Financial	RF
Santander Bank	SAN
State Street Corp	STT
Truist	TFC
TD Bank	TD
UBS Group	UBS
US Bancorp	USBC
Wells Fargo	WFC

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Appendix C. News Sources

Table C.12: List of News Sources

Panel D: Top News Sources

Sources
Reuters News
Dow Jones Institutional News
Dow Jones News Service
Business Wire
Associated Press Newswires
Dow Jones International News
Regulatory News Service
The Wall Street Journal
The Wall Street Journal Online
Dow Jones Business News
Dow Jones Newswires
Dow Jones Chinese Financial Wire
Dow Jones Capital Markets Report
Dow Jones News Service
ENP Newswire
MarketWatch
Dow Jones International News
Business Wire
Dow Jones Commodities Service
M2 Presswire
The New York Times
Associated Press Newswires
Dow Jones Newswires Chinese (English)
Dow Jones Global News Select

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