The Informational Role of the Media in Private Lending

Robert M. Bushman
Kenan-Flagler Business School, University of North Carolina-Chapel Hill
Chapel Hill, North Carolina 27599
Bushman@unc.edu

Christopher D. Williams
Ross School of Business, University of Michigan
Ann Arbor, MI 48109
williacd@umich.edu

Regina Wittenberg-Moerman
The University of Chicago Booth School of Business
Chicago, Illinois 60637
rwitten1@chicagobooth.edu

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In this paper, we empirically examine the informational role of the business press in the private debt market. We find that media content prior to loan origination is significantly associated with interest spreads on syndicated loans, with more positive content leading to lower spreads. Consistent with lenders learning from the media rather than pricing information accessed from other sources, we find that the association between media content and spreads is significantly stronger when news dissemination is higher. We further show that the sensitivity of loan spreads to media content differs between relationship and non-relationship lenders. When media content is positive, the sensitivity of spreads to media content is lower for relationship than for non-relationship lenders, while for negative media content the sensitivity does not differ across lender types. This evidence is consistent with relationship lenders exploiting their information advantage to extract rents by not fully reflecting positive news in interest spreads. Finally, we document that positive media content is associated with an increased probability of an outside (non-relationship) lender winning a loan. This relation is magnified by the dissemination of positive media content, suggesting that highly disseminated media coverage serves to level the competitive playing field between incumbent and outside lenders.

1. Introduction

Information asymmetries play a central role in the design of loan contracts and in lenders' decisions about whether or not to compete for a borrower's loan business. Such asymmetries can exist between borrowers and lenders, and also between incumbent lenders and potential outside lenders.[1] Incumbent lenders' information advantage can create a threat of adverse selection that weakens competition from prospective lenders for a borrower's loans. The differential availability of borrower-specific information across potential lenders, if substantial, may provide incumbent lenders with an information monopoly, significantly affecting a borrower's access to debt capital and its pricing (e.g., Rajan, 1992). To address information asymmetry issues, banks incorporate a diverse information set derived from both public and private sources when assessing borrowers' creditworthiness and structuring loan contracts.

A potentially important source of public information about firms is the business press. The business press produces articles on a wide range of potentially relevant topics to lenders, including information about products, customers, competitors, executive teams, governance, strategic plans, acquisitions, labor markets, regulation, and legal issues, among many others. Our objective in this paper is to investigate whether the publication and dissemination of business press articles about a borrower convey credit-relevant information to lenders that influences loan spreads and reduces the information advantage of relationship lenders relative to other lenders.[2]

While there is little direct evidence on the role of the business press in private debt markets, a growing body of research shows that it plays an important role in detecting accounting fraud,

[1]Incumbents have ongoing access to private borrower-specific information not available to new lenders. This information is gathered by lenders in the process of pre-loan due diligence activities and the post-loan monitoring of borrowers. The idea that incumbent banks may have an information advantage is well established in the literature (e.g., Kane and Malkiel, 1965, Fama, 1985, Greenbaum, Kanatas, and Venezia, 1989, Sharpe, 1990, Rajan, 1992, Petersen and Rajan, 1994, 1995, and Dell'Ariccia and Marquez, 2004).

[2] We use the terms "incumbent lender" and "relationship lender" interchangeably. We discuss this further in Section 2 of the paper.

shaping firms' corporate governance choices, and in both reducing information asymmetry and influencing the pricing of securities in equity markets.[3] Miller (2006) shows that the media serves as a watchdog for accounting fraud, by rebroadcasting information from other information intermediaries and by undertaking original analysis that provide new information to investors. Several papers show that the media pressures firms to alter their governance structures and business strategies, such as the structure of CEO compensation and resource allocations (e.g., Dyck and Zingales, 2002, Bednar et al., 2012, Kuhnen and Niessen, 2012, and Joe, Louis and Robinson, 2009). Media articles that reveal improprieties or that pressure firms to alter their governance or strategic choices can plausibly convey new information to lenders about the integrity of a firm's executives, litigation risk, strategic direction, or changes in managerial incentives. There is also substantial evidence that the business press provides information about firm fundamentals to equity market participants, incremental to information provided by other information intermediaries and accounting data (e.g., Tetlock et al., 2008, Fang and Peress, 2009, Bushee et al., 2010, and Boudoukh et al., 2012). In particular, Tetlock et al. (2008) suggest that media content captures otherwise hard-to-quantify aspects of firms' fundamentals.

It is thus plausible that the media can also impact private lending markets by providing information useful for assessing a borrower's future prospects and mitigating information asymmetries across lenders. In particular, borrowers in the syndicated loan market, which is the focus of our study, tend to be large complex organizations operating in fluid economic environments that continuously expose them to significant changes in fundamentals, raising lenders' information needs. However, private lenders are sophisticated users of financial information with extensive experience in processing borrower-related information and access to

[3] In a recent paper, Bonsall et al. (2013) address the role of media in the public debt market by exploring whether business press monitors credit rating agencies' public bond ratings.

multiple information sources. Therefore, whether the media serves as an important information intermediary in the private debt market is ultimately an empirical question.[4]

In this paper, we execute a series of empirical analyses designed to explore three fundamental questions. Does media coverage convey information to lenders that influences their loan pricing decisions? Does media coverage differentially influence the loan pricing decisions of relationship and non-relationship lenders? Does media coverage reduce the information advantage of relationship lenders and increase the intensity of competition they face from non-relationship lenders? To examine these questions, we consider two aspects of media coverage: media content and dissemination. Media content quantitatively measures the informational characteristics of media-initiated press articles about a borrower. Using data from RavenPack News Analytics, we construct a media content measure that captures the average sentiment (positive vs. negative) across all borrower-specific articles published in the period preceding loan origination.[5] This media content variable is not simply a binary measure of positive or negative sentiment, but augments positive or negative sentiment by reflecting RavenPack's quantitative assessment of the directional strength of a given news story. We measure dissemination as the number of distinct articles about a borrower in the period preceding loan origination. We use this measure to proxy for the extent to which news about a borrower reaches prospective lenders.

We first examine whether media content transmits borrower-specific information that is reflected in banks' loan pricing decisions. We find that interest spreads are inversely associated

[4] Bushee et al. (2010) define an information intermediary as an agent that provides information that is new and useful to other parties, either because it has not been publicly released or widely disseminated.

[5] RavenPack employs a variety of textual analysis algorithms to quantify the extent of positive or negative sentiment in news articles. The term sentiment is being used here to simply capture the nature (i.e., positive or negative) and the strength of the news contained in the article. This use of the term is distinct from the notion of investor sentiment, which generally refers to beliefs not supported by prevailing fundamentals. For example, Tetlock (2007) defines investor sentiment as the level of noise traders' beliefs relative to Bayesian beliefs. See also Baker and Wurgler (2006) for an extensive discussion of investor sentiment.

with media content, with more positive news significantly reducing spreads.[6] However, while spreads are sensitive to media content, this finding does not speak to whether lenders are directly learning from the media or simply pricing information accessed from other sources. To address this issue, we examine whether the association between media content and interest spreads is magnified by dissemination. If the media is a source of information to lenders and dissemination captures the extent to which information reaches lenders, we predict that the sensitivity of spreads to media content will increase in dissemination. On the other hand, if media content simply reflects information available to lenders from other sources, its effect on interest spreads should not vary with dissemination. We find that the association between media content and spreads is significantly stronger when dissemination is higher.

While the results of dissemination-based tests are consistent with lenders learning from media, we acknowledge that they could alternatively be a consequence of dissemination reflecting more the importance of news rather than its reach to lenders. In this regard, it is important to emphasize that we directly control for the average importance of news across borrower-specific articles with RavenPack's sentiment strength assessments embedded in our media content measure and that media content is basically uncorrelated with dissemination ($\rho = -0.006$, $p>.10$). We further seek to isolate learning from information importance by splitting the sample into rated and non-rated firms. We posit that there should be no difference in the information and reach properties of dissemination across rated and non-rated firms. However, rated and non-rated firms should generally differ significantly with respect to the level of ex ante uncertainty about a firm's economic fundamentals, where greater uncertainty implies greater scope for learning. Thus, we expect the impact of dissemination on the sensitivity of spreads to

[6] Economically, the effect of media content on loan pricing is comparable to the effect of key credit risk measures, such as interest coverage, leverage and Altman's Z-score.

media content to be greater for non-rated firms, where greater ex ante uncertainty creates greater scope for learning by lenders.[7] Consistent with this prediction, we find that the amplification effect of dissemination on media content is more pronounced for non-rated borrowers.[8]

Having shown that media content is associated with interest spreads and that the strength of this association increases with dissemination, we next explore whether media content influences the extent of information asymmetries between incumbent lenders and outsiders. If relationship lenders enjoy an information advantage, the spreads on their loans should be relatively less sensitive to media content than are the spreads on non-relationship loans. In the models of Rajan (1992) and Hauswald and Marquez (2003, 2006) an incumbent bank uses its ability to distinguish between good and bad credit risks to opportunistically structure its lending strategy to bid on good loans and avoid bad loans. The information advantage of an incumbent therefore exposes less informed outside lenders to adverse selection risks. Since they face the risk of getting stuck with bad loans, outside lenders temper the aggressiveness with which they bid for loans. The net result is that incumbent lenders extract rents from borrowers deemed to be of high quality by exploiting their informational advantage over competitors to capture some of the upside from successful projects. Building on these models and positing that positive media content is positively associated with incumbents' assessments of credit quality, we predict that relationship lenders will not fully incorporate positive media content into interest spreads as they exploit their information advantage to extract rents, but will more fully incorporate negative media content into spreads to avoid underpricing loans. Consistent with this hypothesis, we

[7] A lack of credit rating is generally associated with greater opacity and ex ante uncertainty about economic fundamentals relative to rated firms (e.g., Sufi, 2007, Bharath et al., 2009, and Lim et al., 2013). To clarify the relation between uncertainty and scope for learning, assume that the variance of the distribution over fundamentals is larger for firm 1 (non-rated) than firm 2 (rated). Then, if an information signal of equal precision is released for each firm, the posterior mean of firm 1's fundamentals will be more sensitive to it than will that of firm 2.
[8] In all specifications, we include abnormal stock returns over the same period in which media content is measured to further control for cross-sectional differences in the importance of overall news arrival from all sources.

disaggregate media content into positive and negative components and find that spreads on non-relationship loans are sensitive to both positive and negative content, while spreads on relationship loans are sensitive only to negative content.

While the previous result suggests that relationship lenders extract rents from their information advantage, our earlier results raise the possibility that dissemination will decrease incumbents' information advantage and thus their ability to extract rents. That is, relationship lenders may have a larger information advantage when dissemination is low, allowing them to underreact to positive content, while high dissemination weakens their advantage and pressures them to more fully price positive news. We do not, however, find that spreads on relationship loans are more sensitive to positive media content when dissemination is high. We conjecture that this occurs because any reduction in information advantage driven by the dissemination of positive news serves to level the playing field between incumbent and outside lenders and manifests in borrowers more frequently switching to non-relationship lenders.

We examine this proposition by exploring the extent to which media content and dissemination are associated with the probability of non-relationship lenders originating loans. Rajan (1992) shows that good news public signals about a firm's prospects increase the aggressiveness with which outside lenders bid for a loan, increasing the probability of an outsider winning the loan. In contrast, bad news signals decrease the bidding aggressiveness of outside lenders for a borrower's loan due to heightened adverse selection concerns. Consistent with Rajan (1992), we find that positive media content significantly increases the probability of an outside lender winning the loan. We also show that dissemination magnifies the association between positive media coverage and the probability of a non-relationship loan, consistent with dissemination helping to break down an incumbent's information advantage. The effect of positive media content on the probability of a loan being issued by a non-relationship lender doubles with high dissemination. In contrast, negative media content has only a marginal effect on the probability of a non-relationship loan, and this effect does not vary with dissemination.

Our study contributes to the literature along several dimensions. First, we extend the growing body of empirical literature on the role played by the business press in capital markets by providing new evidence consistent with the media serving as an important information intermediary in the private debt market. We document that media content is associated with interest spreads where the strength of this association increases with dissemination. While suggestive rather than definitive, these findings are consistent with lenders directly learning from the media rather than simply pricing information accessed from other sources.

Second, we contribute to the extensive research on the consequences of relationship lending. Petersen and Rajan (1994, 1995), Boot and Thakor (1994), Berger and Udell (1995) and Brahrath et al. (2009), among others, demonstrate the benefits to borrowers from an established banking relationship. However, Sharpe (1990) and Rajan (1992), among others, emphasize a dark side where borrowers become “locked in” due to information asymmetry, allowing incumbent lenders to extract rents via opportunistic loan pricing. We extend the literature by utilizing media coverage to explore the possibility that relationship lenders enjoy an information advantage in setting loan spreads. Consistent with the implications of Rajan (1992) and Hauswald and Marquez (2003, 2006), we document that relationship lenders do not fully incorporate positive news into interest rate spreads, while more fully incorporating negative news, suggesting that they exploit their information advantage to extract rents.

Finally, we contribute to the empirical literature on relationship lending and bank competition. We provide evidence consistent with the business press fundamentally altering the information structure and the nature of competition in the loan market by undermining the private information advantage of incumbent lenders. Consistent with the analysis in Rajan (1992) showing that public release of positive news increases the aggressiveness with which outside lenders compete for a loan, we document that positive media content significantly increases the probability of an outside lender winning a loan. This relation is magnified by the dissemination, suggesting that highly disseminated positive media coverage serves to level the competitive playing field between incumbent and outside lenders.

The remainder of the paper is organized as follows. Section 2 presents the prior research that motivates our analyses. Section 3 describes the sample and data. Section 4 reports our main results and section 5 concludes the paper.

2. Motivation and Related Literature

2.1. The role of the business press in capital markets

A fundamental premise of our paper is that business press conveys information to lenders about a firm's credit quality and that this information influences lenders loan pricing decisions and the aggressiveness with which they compete with other lenders for a firm's loan. While there is little evidence on the role of media in private debt markets, a growing body of research shows that the business press has a significant impact on the information transparency and behavior of equity markets' participants, firms' corporate governance choices and the detection of accounting fraud. As we discuss next, this body of evidence provides support for the plausibility of our premise that the media can be informative to lenders and can influence lenders' behavior.

Miller (2006) investigates the press's role as a watchdog for accounting fraud. He finds that the press fulfills this role by rebroadcasting information from other information intermediaries and by undertaking original investigation and analysis that provide new information to the markets. In a related vein, a number of papers document that media articles pressure firms to alter governance structures. Dyck and Zingales (2002) provide evidence that media affects companies' environmental policies and the amount of corporate resources diverted to the advantage of controlling shareholders. Bednar et al. (2012) show that negative media coverage prompts firms to change their resource allocations, suggesting that media influences strategic choices. Kuhnen and Niessen (2012) find that following more negative press coverage of CEO pay, firms reduce option grants and increase less contentious types of compensation, such as salary, although overall compensation does not change. Joe et al. (2009) find that media exposure about board ineffectiveness pressures firms to take corrective actions that enhance shareholder wealth. Media articles that speak to fraud or that pressure firms to alter governance or strategic choices can plausibly convey new information to lenders about the integrity of a firm's executives, litigation risk or changes in managerial incentives. This information is likely to have significant implications for a firm's future prospects, which are an important aspect of the lenders' assessments of a borrower's credit risk.

To assess the underlying economic fundamentals of a firm, investors evaluating a firm's equity value and lenders evaluating its credit quality rely on information from a variety of sources. There is substantial evidence that the business press provides information about firm fundamentals to equity market participants over and above information provided by other information intermediaries and accounting data.[9] Bushee et al. (2010) demonstrate that the press influences a firm's information environment by reducing information asymmetry in the equity market, incremental to firm-initiated disclosure and disclosures by equity analysts. Fang and

[9] Engelberg and Parsons (2011) establish the causal impact of media in financial markets by comparing the behaviors of investors with access to different media coverage of the same information event. For all earnings announcements of S&P 500 Index firms, they find that *local* media coverage strongly predicts local trading, after controlling for earnings, investor, and newspaper characteristics (see also Dougal et al. (2012) on causal relations).

Peress (2009) show that stocks with no media coverage earn significantly higher future returns than stocks with high media coverage. Tetlock et al. (2008) finds that the fraction of negative words in firm-specific news stories forecasts low firm earnings and that equity prices quickly respond to the information embedded in negative words. They suggest that linguistic media content captures otherwise hard-to-quantify aspects of firms' fundamentals. Further, using a textual analysis approach designed to distinguish business press articles that reflect relevant news from those that do not, Boudoukh et al. (2012) find a strong relation between news and stock price changes.[10] Overall, this literature provides substantial evidence that the media informs market participants by providing information on hard-to-quantify aspects of firms' fundamentals and mitigates information asymmetries in the equity market.[11] It is thus plausible that the media can also impact private lending markets by providing information on hard-to-quantify aspects of firms' fundamentals useful for assessing credit quality and by mitigating information asymmetries across lenders with differential access to a borrower's private information.

Because a vast range of information can impact stock prices, the literature often takes a computational linguistics approach that quantifies language from a wide swath of firms' media coverage rather than focusing on specific categories of news. As noted by Tetlock et al. (2008), by quantifying language, researchers can examine the directional impact of a very wide variety of events, rather than focusing on a particular event type, such as earnings announcements, mergers, or analysts' recommendations. It is also the case that a wide range of information can be informative with respect to lenders' assessments of a borrower's credit risk, including information about products, competitors, customers, industry growth potential, top executive

[10] In contrast to the result in Roll (1988) showing little relation between stock prices and news, Boudoukh et al. (2012) find using their refined news measures that market model (four-factor model) R-squares are now significantly lower on news versus no news days.

[11] See also Kothari et al. (2009) and Rogers et al. (2013). In contrast, a number of recent papers suggest that media coverage might exacerbate information asymmetry and inefficient trading behavior (e.g., Frankel and Li, 2004, Green et al., 2012, and Soltes et al., 2013).

teams, governance, strategic plans, acquisitions, labor markets, regulation, and legal issues, among many others. Our media content measure quantifies the overall sentiment of media coverage as positive or negative, and its strength.

2.2. Relationship lending and asymmetric information

While a growing literature examines the role of the media in equity markets, private lending markets operate differently than equity markets do and involve substantially different asymmetric information issues. The private lending process allows incumbent lenders to access private borrower-specific information not available to outside lenders.

Hauswald and Marquez (2003) posit two countervailing forces bearing on the degree of asymmetric information between relationship lenders and potential lenders as a lending relationship evolves: increased information-processing capacity and information spillover effects. As a relationship deepens, enhanced information-processing capacity increases asymmetric information between lenders and prospective lenders by improving the relationship bank's capacity for gathering, processing, and interpreting firm-specific information. Hauswald and Marquez (2003) argue that banks become better at processing borrower-specific information over time, leading to higher information collection efforts, which further enhance their information advantage. In contrast, information spillovers reduce information asymmetry between lending and non-lending banks. When a lender grants its current borrower a loan renewal, increasing relationship intensity, some firm-specific information is transmitted to non-lending banks (e.g., observing a loan renewal reveals information).

Schenone (2010) argues that for low relationship intensity, spillovers are likely to dominate information-processing capacity as, for example, non-lenders would likely learn more from observing a first loan renewal than they would from the tenth renewal. Also, lenders are at an early stage in learning about the firm and how to enhance the processing of the firm-specific information. For greater relationship intensity, the relationship bank's information-processing capacity is likely to dominate spillover effects as the bank has gathered firm-specific expertise over the course of the relationship, allowing it to become an efficient information acquirer.

Prior literature recognizes potential costs to relationship lending (e.g., Rajan, 1992, and Petersen and Rajan, 1994, 1995). Incumbent lenders' information advantage can create adverse selection threats, weakening competition from prospective lenders and thereby affecting a borrower's access to debt capital and loan pricing. This problem is illustrated by Rajan (1992), who examines competition between an informed (inside) bank that is already lending to a risky firm and an uninformed (outside) bank not currently lending to the firm. The inside bank knows whether the firm will succeed or fail, while the outside bank only knows that the firm has a certain probability of success. Under these conditions, the outside bank is at a disadvantage in bidding to lend to the firm. Rajan (1992) shows that incumbent lenders exploit their private information to extract rents from borrowers that they know will succeed, while not bidding for loans to borrowers that they know will fail. In response to adverse selection concerns, an uninformed lender tempers the aggressiveness with which it competes for a loan, allowing the inside bank space to extract rents from borrowers with successful projects by capturing some of the upside from the project. The incumbent opportunistically prices loans to high quality borrowers, knowing that they will win the loan and receive high profits whenever the uninformed lender fails to bid. The incumbent bank's information advantage thus gives it limited monopoly power over the borrower (see also Hauswald and Marquez, 2003, 2006).

The empirical literature on this issue has produced mixed results. Petersen and Rajan (1994), using data from the National Survey of Small Business Finances, find that borrowing costs are *unrelated* to the length of the lending relationship. However, if lending costs decrease with relationship length, Petersen and Rajan's evidence suggests that banks extract rents from captured borrowers. Degryse and Van Cayseele (2000), using data from small businesses in Belgium, report that interest rates *increase* with the length of the lending relationship, suggesting that banks exploit their information advantage. Using a sample of U.S. syndicated loans, Santos and Winton (2009) examine Rajan's (1992) hypothesis that the hold-up power of an incumbent bank increases with a firm's risk of failure, positing that banks with exploitable information should be able to raise their rates in recessions by more than is justified by borrower risk alone. They compare the loan pricing for bank-dependent borrowers to the loan pricing for borrowers with access to public debt markets. They find that loan spreads rise in recessions, but bank-dependent borrowers pay higher spreads and their spreads rise relatively more in recessions, consistent with the existence of hold-up problems. While Schenone (2010) shows that interest spreads on relationship loans are lower for low levels of relationship lending intensity, she finds that relationship loans become more expensive at high intensity levels. These findings are consistent with the information-processing capacity effect dominating the information spillover effect at high levels of relationship intensity, allowing relationship lenders to extract rents.

In contrast, using National Survey of Small Business Finances data, Berger and Udell (1995) focus on lines of credit and find that firms with longer lending relationships pay *lower* interest rates than do firms with shorter relationships. They conclude that banks share the benefits of their privileged information with their clients. In a related vein, Bharath et al. (2009) use a large sample of syndicated loans to show that repeated borrowing from the same lender results in spreads that are lower by 10 and 17 basis points over their sample period of 1986-2003.

In addition to the interest spread effects of relationship lending, prior research also focuses on the benefits of greater access to credit, particularly for credit-constrained borrowers (Rajan and Zingales, 1998). Petersen and Rajan (1994) use data from the National Survey of Small Business Finances to show that a key benefit of building close ties with a lender is greater availability of financing. Petersen and Rajan (1995) further show that relationship lending is especially beneficial to young, more credit rationed firms. Bolton et al. (2013) rely on credit register information for Italian banks before and after the Lehman Brothers' default and demonstrate that while relationship banks charge higher interest spreads in normal times, they offered continuation lending at more favorable terms during the crisis.

Most pertinent to our study are two recent papers that exploit significant changes in a firm's information environment to identify whether banks price their informational monopoly. Hale and Santos (2009) examine how loan pricing changes following bond IPOs. During the IPO process, firms publicly reveal significant new information about their creditworthiness, potentially reducing any information monopoly. They find that firms pay lower spreads on their loans after they undertake a bond IPO, with more pronounced interest savings for firms identified as more creditworthy at the time of the IPO. Schenone (2010), mentioned above, studies changes in bank loan pricing around initial public offerings of equity. Consistent with public information undermining relationship lenders' information advantage and increasing competition, she finds that interest rates decrease in relationship intensity following an IPO.

Hale and Santos (2009) and Schenone (2010) focus on loan spreads before and after significant information events to identify the effects of banks' information advantage. In contrast, we complement and extend the literature by focusing on how loan spreads set by relationship and non-relationship lenders are differentially influenced by business press articles in the period prior to the closing of a syndicated loan. We employ two distinct dimensions of press coverage. Our media content measure captures the average positive or negative tenor of the overall flow of borrower-specific articles leading up to a loan, thus reflecting the strength of the news sentiment. Second, we use the number of articles published about the firm to capture article dissemination and its effect on the firm's overall visibility and exposure to prospective lenders.

Following Hauswald and Marquez (2003) and Schenone (2010), we use the intensity of a lending relationship to proxy for the magnitude of an incumbent bank's private information advantage over other lenders. We classify loans as relationship lending transactions if the lender has syndicated a majority of a borrower's prior loan deals by volume over the five year period preceding the loan issuance date. To identify the impact of informational capture, we exploit the idea that spreads set by relationship lenders with pricing power should be less responsive to new information than spreads set by non-relationship lenders. Building on Rajan (1992) and Hauswald and Marquez (2003, 2006), we hypothesize that conditional on winning a loan deal, high intensity relationship lenders extract rents from borrowers by capturing some of the upside from successful projects. Specifically, we predict that the spreads on relationship loans will be less responsive to positive than to negative media content, as relationship lenders will resist lowering spreads in response to good news in order to extract rents, but will fully react to negative news to avoid underpricing the loan.

However, while relationship lenders may earn rents conditional on winning a loan deal, media content can also undermine a relationship lender's information advantage and decrease its probability of winning a loan. In Rajan (1992), the incumbent bank has private information and knows for sure whether the firm will succeed or fail, while the outside bank only knows that the firm has a certain probability of success. Rajan (1992) shows that the release of public good news signals about a firm's prospects increases outside lenders' assessments of a firm's credit quality, which mitigates their risk of getting stuck with a bad loan. This lower adverse selection risk increases the aggressiveness with which an outside lender bids against a relationship lender for a loan, increasing the probability of a relationship lender losing the loan to an outside lender. In contrast, bad news signals decrease the bidding aggressiveness of outside lenders for a loan due to heightened adverse selection concerns. Building on Rajan (1992), we examine the extent to which positive and negative media content are associated with the probability that a loan is made by a non-relationship lender, and whether such effects differ with dissemination.

Finally, it is useful to contrast our analysis using positive and negative media content with the extant literature on the impact of the media on equity markets. Tetlock (2007) and Tetlock et al. (2008) find that negative media content has a stronger impact on equity market outcomes than does positive content. For example, Tetlock (2007) finds that negative words have a much stronger correlation with stock returns than do other words. Tetlock et al. (2008) notes that this is consistent with a large body of literature in psychology—for example, Baumeister et al. (2001) and Rozin and Royzman (2001)—that argues that negative information has more impact and is processed more thoroughly than positive information is, across a wide range of contexts. In contrast, in our study, distinguishing between positive and negative media content is important because of the differential effects each generates on loan pricing and competition.

3. Sample, Data and Descriptive Statistics

3.1. Data sources and sample selection

We employ the DealScan database provided by the Thomson Reuters Loan Pricing Corporation (TRLPC) to obtain loan-specific characteristics. Media coverage and media content scores are from RavenPack News Analytics, which covers all news disseminated via Dow Jones

Newswires. RavenPack employs a variety of advanced textual analysis techniques to create news sentiment scores for business news stories. We obtain firm characteristics from COMPUSTAT. Firms' senior debt ratings, watchlist and outlook data (at the firm level) are retrieved from the S&P historical database. For borrowers with no rating data from the S&P database, we collect the S&P, Moody's and Fitch ratings from the Internet-based version of TRLPC.

Table 1 summarizes the sample selection process. For the period 2000 to 2012, DealScan reports 31,974 facilities outstanding to U.S. public firms and issued in U.S. dollars (we previously linked DealScan to Compustat using the borrower's name, industry and location). We focus on this time period to align DealScan with the availability of media data from RavenPack. Merging this sample with firms covered by RavenPack leaves us with 25,518 facilities. Next, we exclude facilities with insufficient loan data; this restricts the sample to 12,397 facilities. We also require borrowers in the sample to have sufficient COMPUSTAT data for estimating borrower characteristics and sufficient RavenPack data for estimating media coverage measures prior to loan issuance. We estimate borrower characteristics in the quarter prior to the loan issuance and media coverage over the 180 days prior to the loan issuance.[12] We limit media data to full-size articles, excluding news flashes (news articles composed only of a headline and no body text), news articles composed of a headline and mostly tabular data and firm-initiated press releases. We further restrict our sample to full-size articles with a relevance score of 75 and above. The relevance score is assigned by RavenPack to indicate when the firm is strongly related to the underlying news story. The scores range from 0 (low relevance) to 100 (high relevance). Our final sample contains 7,244 facilities related to 2,031 firms.

[12] We focus on the 180 days prior to the loan issuance to allow a sufficient time period prior to the start of the syndication process, which typically takes around 3 months. Our findings and inferences do not change if we estimate media coverage over 90 or 60 days prior to the loan issuance.

3.2. Descriptive statistics

Table 2 presents the descriptive statistics. Our main variable of interest, *Media Content*, is estimated as the average news content over the 180 days prior to a loan origination date. We are utilizing RavenPack's Composite Sentiment Score (CSS), which represents the news sentiment of a given story by combining various sentiment analysis techniques.[13] In contrast to prior research on sentiment, we do not assume that *Media Content* captures beliefs about future cash flows and/or discount rates that are not supported by the fundamentals (Baker and Wurgler, 2006). Instead, our *Media Content* variable simply reflects the nature (i.e., positive or negative) and the strength of the news in the articles. CSS scores range between 0 to 100, with a score above 50 indicating positive news; scores equal to 50, neutral news; and scores below 50, negative news. We apply a linear transformation to the CSS score and define *Media Content = (CSS-50)/50*, so that the *Media Content* ranges from -1 to 1, with zero being equivalent to neutral content. The mean (median) value of *Media Content* is -0.0046(0.0000), suggesting that news content is typically neutral over the 180 days prior to a loan announcement. The mean (median) value of the number of full-size articles (*#Articles*) over this period is 25.6 (13.0); there is a substantial variation in this variable, as reflected by a standard deviation of 60.87.

[13] CSS combines 5 sentiment scores (PEQ, BEE, BMQ, BCA and BAM), while insuring that there is no sentiment disagreement amongst these scores. The PEQ score represents the news sentiment of a given news item according to the PEQ classifier, which specializes in identifying positive and negative words and phrases in articles about firms with publicly traded equity. The BEE score represents the news sentiment of a given story according to the BEE classifier, which specializes in news stories about earnings evaluations. The BMQ score represents the news sentiment of a given story according to the BMQ classifier, which specializes in short commentary and editorials on global equity markets. The BCA score represents the news sentiment of a given news story according to the BCA classifier, which specializes in reports on corporate action announcements. The BAM score represents the news sentiment of a given story according to the BAM classifier, which specializes in news stories about mergers, acquisitions and takeovers. PEQ and BEE classifiers are dictionary-based measures, while BMQ, BCA and BAM classifiers are based on the Bayesian learning approach. It is important to clarify that in the above descriptions of the sentiment scores "specialize" means that the score was originally developed and tested using different samples of media articles. For example, the BEE score was developed based on the earnings-related articles and BMQ score was developed based on the articles about global equity markets. All five of the sentiment scores are applied to the media article when evaluating its CSS score.

The average interest rate spread (*Spread*) is 159.5 basis points, which is typical for the DealScan population (all variables are described in detail in Appendix B). In untabulated analysis, we find that *Spread* is significantly and negatively correlated with *Media Content* (Pearson correlation is -0.09 at the 1% significance level). Sample loans have, on average, a size (*Amount*) of $167.0M and a maturity (*Maturity*) of 47.9 months. 71.4 percent of the sample loans have performance pricing provisions (*PP*), 63.9 percent are secured (*Collateral*) and loans have, on average, 2.3 financial covenants (*#Covenants*). The majority of the loans in the sample are revolvers (62.3 percent) and 29 percent are term loans B and below (these loans are typically issued to non-bank institutional investors and have a back-end-loaded repayment structure).

We also present firm-specific characteristics. The average ratio of earnings before extraordinary items to total assets (ROA) is 0.85% and the average interest coverage ratio (*Interest coverage*) is 10.5. Sample firms have an average Altman's (1968) bankruptcy score (*Z-score*) of 2.24 (a higher score indicates a lower credit risk) and an average *Leverage*, measured as the ratio of total liabilities to total assets, of 0.25. These firms are relatively large, with a mean value of total assets of $1,411M. The average market-to-book ratio is 3.01. Sample borrowers experience, on average, a 2.2% abnormal return over the 180 days prior to the loan issuance.

4. Empirical Results

4.1. The association between media content on loan pricing

We start our analyses by testing the relation between the interest rate spread and the content of media articles in the 180 days prior to the loan issuance, controlling for the number of articles over the same time period, firm characteristics and loan characteristics that are likely to be associated with the spread. We estimate the following OLS model:

$$Spread = \alpha_0 + \beta_1 Media\ Content + \beta_2 \#\ Articles + \beta_3 Loan\ Controls + \beta_4 Firm\ Controls + \varepsilon, \qquad (1)$$

where *Spread* is the logarithm of the interest rate spread in basis points above LIBOR. Our primary variable of interest, *Media Content*, is the average news sentiment over the 180 days prior to a loan origination date. We predict a negative coefficient on this variable. *#Articles* is the number of full-size articles over the same period. We control for a variety of firm- and loan-specific characteristics that prior research suggests significantly affect loan spreads (e.g., Booth, 1992, Beatty et al., 2002, Asquith et al., 2005, Zhang, 2008, Costello and Wittenberg-Moerman, 2011, and Lim et al., 2013). We also control for a borrower's abnormal stock returns over the 180 days prior to a loan's issuance to proxy for the borrower-specific news over the same period during which media content is measured. Finally, all the analyses include loan purpose, industry and year fixed effects and we cluster the standard errors at the firm and calendar quarter levels.

We present our primary findings in Panel A of Table 3. We find that the interest spread is inversely associated with media content, with more positive news reducing the interest spread. In terms of economic significance, a one standard deviation change in *Media Content* translates into a 7.3 basis point increase in the spread. While this effect is relatively modest, it is similar to the effect of a one standard deviation change in other key credit risk measures, such as *Interest Coverage* (3.3 basis points), *Leverage* (9.6 basis points) and *Z-score* (10.5 basis points).[14] Surprisingly, the number of articles is not significantly related to the interest spread. As the

[14] The Raven Pack database also includes an Event Sentiment Score (ESS), which represents the news sentiment of a main event discussed in the story (this measure is based on a Bayesian learning approach). ESS is estimated only for stories matched to RavenPack's event categories, such as earnings, analysts' rating, credit rating agencies' actions, mergers and acquisitions, and insider trading activities. In contrast to CSS, which represents the news sentiment of the entire article, ESS is restricted to the sentiment of the article's headline only. While Raven Pack documents ESS's efficiency in predicting immediate trading responses to the publication of a news story, we view this measure as less appropriate for our paper's setting, which utilizes media sentiment over the long term horizon. In any case, we replicate our tests for a sub-sample of borrowers whose media coverage includes at least one article with an available ESS score. While the ESS score is positively and significantly related to the interest spread, this measure loses its economic and statistical significance when CSS is also incorporated into the interest rate model.

higher number of articles is likely to be associated with a firm's more transparent information environment, we would expect to find a negative relation between *#Articles* and the spread.[15]

The coefficients on control variables are generally consistent with prior research. Larger loans and loans with performance pricing provisions are associated with lower spreads (Booth, 1992, and Asquith et al., 2005). We do not find a significant relation between the interest rate and maturity. Longer maturity is typically associated with more uncertainty, but lenders may be willing to issue longer term loans to more creditworthy borrowers. Due to the endogenous determination of contractual terms, we observe a positive relation between the interest spread and both *Collateral* and *#Covenants* (Berger and Udell, 1990, and Bradley and Roberts, 2004).[16] While concurrently endogenizing all loan terms is beyond the scope of our paper, in untabulated analyses we estimate the interest rate model without controlling for loan-specific characteristics; our findings are unchanged. We find that revolvers (Term Loans B and below) are priced at lower (higher) rates (Harjoto et al., 2004, Zhang, 2008, Nandy and Shao, 2010, and Lim et al., 2013). We also report a negative relation between the interest rate and a borrower's profitability, Z-Score, size and market-to-book ratios, consistent with higher values of these variables being associated with higher creditworthiness. As predicted, interest rate increases with leverage.[17]

Interestingly, we find a positive coefficient on the *Return* variable. One explanation for this positive coefficient is that returns are capturing aspects of a borrower's riskiness. Stock returns can be decomposed into two components: changes in cash flow expectations or cash flow news,

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[15] This result does not change if we substitute #Articles with an indicator variable reflecting high versus low news dissemination or when we include in the model a logarithm of the number of articles.

[16] Agency theory suggests that there is a trade-off between restrictions imposed by the loan contract and the interest spread (Jensen and Meckling, 1979, Myers, 1977, and Smith and Warner, 1979). However, because more risky borrowers are likely to have higher spreads and lenders may simultaneously impose a higher number of covenants and/or require them to provide collateral, empirical tests typically reveal a positive relation between these variables.

[17] While liquidity, measured by the interest coverage ratio, should decrease the spread, we find the opposite result. The correlation between these variables is negative and significant; the positive relation in the multivariate tests may be attributed to multi-collinearity due to a high correlation (0.37) between the interest spread and profitability.

and changes in discount rates, or expected return news (e.g., Vuolteenaho, 2002). To the extent that *Media Content* captures cash flow news, returns may pick up primarily discount rate news, which is associated with risk. The positive relation between the interest rate and *Return* does not change if we utilize size-adjusted abnormal returns or abnormal returns based on the Fama-French three factor model. In untabulated tests, we also find that the relation between *Media Content* and the spread is not affected by including return volatility as an additional control.

In Panel B of Table 3, we present robustness analyses. In Column 1, using a sub-sample of borrowers who issued firm-initiated press releases prior to loan issuance, we examine whether the releases' content subsumes the *Media Content* effect.[18] We augment Equation (1) with the *Press Release Content* variable, which is estimated as the average news content in firm initiated press releases over the180 days prior to a loan origination date. We also control for the number of firm initiated press releases over this period. We report that *Media Content* continues to be significantly associated with the interest spread, controlling for the content and number of firm-initiated press releases. This result suggests that our *Media Content* variable is not simply picking up the rebroadcast of firm-initiated news. Further, controlling for *#Press Release Articles* helps alleviate a concern that borrowers may be influencing media coverage by originating more firm-initiated news prior to the loan issuance.[19]

In Columns 2 through 4 of Panel B, we focus on a sub-sample of borrowers with available credit rating data. The mean S&P credit rating for our sample is BB+ (we convert Moody's and Fitch ratings to an equivalent S&P rating). In addition to controlling for credit rating (*Credit Rating*) and credit rating *changes (ΔCredit Rating),* we also control for whether the firm is on a

[18] To ensure that we are capturing firm-initiated press releases, we impose a more stringent relevance criterion and require a relevance score of 90 or greater. Press releases with the relevance score above 75 and below 90 often relate to cases where the firm is mentioned in the press releases of other firms.
[19] Ahern and Sosyura (2013) find that by issuing a substantially higher number of press releases, bidders in stock mergers influence their stock price after the start of merger negotiations, but before the public announcement, thus substantially affecting the takeover price.

credit watch list at the time of a loan issuance or over the 180 days prior to the issuance, as *Media Content* may simply capture credit watch related news. We find *Credit Rating*, *Current Watch* and *Prior 180 Watch* to be strongly associated with the interest spread, but the relation between the spread and news content continues to be significant. In untabulated tests, we also control for whether a borrower has experienced a change in its long-term credit rating outlook over the 180 days prior to the loan issuance; we find that the results are robust to this control.[20]

To provide further evidence supporting the association between media content and the interest spread, in Panel C of Table 3 we re-estimate Equation (1) for two sub-samples based on the firm's credit riskiness. Because lenders are more sensitive to information when there is a higher probability of default (e.g., Easton et al., 2009, De Franco et al., 2009, and Dang et al., 2012), we expect media content to have a greater impact on the spreads of more risky firms. As credit ratings are available for only around 60 percent of our sample loans, we classify loans into information sensitivity sub-samples based on the Altman's Z-score. We follow the frequently used cutoff of a Z-score of 3 or below to identify more risky borrowers, labeling this group as 'information-sensitive' borrowers. Borrowers with a Z-score above 3 are classified as 'information-insensitive'. Our findings reveal that the effect of the media on loan pricing is concentrated in the high information sensitivity sub-sample: the coefficient on *Media Content* is negative and highly significant in Column 2. A one standard deviation increase in *Media Content* decreases the interest spread by 7.86 basis points (for comparison, the effect on the spread of a one standard deviation change in *Interest Coverage* (*Leverage*) is 3.3 (12.7) basis points).[21]

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[20] For 10.6% of the loans in Columns 2 and 3, credit ratings are obtained from the Internet-based version of TRLPC. For these loans, we do not have information about watch list and outlook changes. However, our results are unchanged when we exclude from the analyses loans without watch list and outlook data.

[21] It is important to note that we do not analyze the effect of *Media Content* on the spread across RavenPack's event categories (e.g., earnings, analysts' rating, credit rating agencies' actions, mergers and acquisitions and insider trading activities). The classification into the event categories is based primarily on the articles' headline and therefore is rather coarse. More importantly, event categories do not reflect the entirety of the article's content and

To summarize, the analyses presented in Table 3 reveals that the interest spread is sensitive to *Media Content.* However, it is plausible that *Media Content* simply reflects information already available to lenders that is not captured by the firm characteristics and loan controls included in the analyses. Because private lenders intensively collect and analyze soft and hard-to-quantify information, the pricing effect that we show does not speak to whether the media is the source of the information for lenders or whether the media content is simply picking up lenders' pricing of information that they have already obtained through their private sources. We address this issue in the next section.

4.2. The Interactive Effect of Media Content and Media Dissemination

In Table 4, Panel A, we re-estimate our spread model from Equation (1) and distinguish between the low and high dissemination of media articles. We classify a loan as high dissemination if, over the 180 days prior to a loan's issuance, the borrower's media coverage falls into the top quintile of the media coverage distribution for our sample. If the media is a source of information to lenders and dissemination captures the extent to which information reaches lenders, we predict that the sensitivity of spreads to media content will increase in dissemination. On the other hand, if media content simply reflects information available to lenders from other sources, its effect on interest spreads should not vary with dissemination.

We see in Table 4, Panel A that the coefficient on *Media Content* for the high dissemination sub-sample is substantially higher than it is for the low dissemination sub-sample. These two coefficients are significantly different at the 1 percent level, suggesting that dissemination amplifies the impact of media content. In a high dissemination environment, the

often omit hard-to-quantify information analyzed in the article. For example, the Wall Street Journal article related to the Sprint Corp. and Nextel Communications merger, classified into the mergers and acquisitions category, contained an extended discussion of industry trends and the latest technology developments, including interviews with various customers and business owners, and their potential implications for the merged firm's future prospects.

economic significance of *Media Content* is much higher than what we report for the entire sample. A one standard deviation increase in *Media Content* decreases the interest spread by 17.9 basis points, which is comparable to the 19.0 basis point decrease in the spread due to a one standard deviation increase in *Z-score* (the effect of a one standard deviation change in interest coverage and leverage is much smaller – 5.3 and 2.4 basis points, respectively).[22]

The previous result is consistent with lenders learning from media, but they could alternatively be a consequence of dissemination reflecting the importance of news rather than its reach to lenders. Although we directly control for the average importance of news with RavenPack's sentiment strength assessments and, empirically, media content and dissemination are uncorrelated (ρ=-0.006, p-value>0.10), to further isolate learning from information importance we split the sample into rated and non-rated firms. While there should be little difference in the properties of dissemination between rated and non-rated firms, there is greater ex ante uncertainty about economic fundamentals of non-rated firms (e.g., Sufi, 2007, Bharath et al., 2009, and Lim et al., 2013). Thus, we expect the impact of dissemination on the sensitivity of spreads to media content to be greater for non-rated borrowers, where greater ex ante uncertainty creates greater scope for learning by lenders.

The results reported in Table 4, Panel B provide supporting evidence for our predictions. For both rated and non-rated firms, the effect of *Media Content* on *Spread* is more pronounced when dissemination is high, but this effect is significantly larger for non-rated firms. Specifically, the coefficient on *Media Content* of -3.6455 for the non-rated partition (Column 4) is significantly higher (p-value < 0.05) than the coefficient of -1.639 on *Media Content* for the

[22] In untabulated tests, we classify loans into the high dissemination group if a borrower's media coverage is above the sample median or falls in the top tercile or quartile of the media coverage distribution. We continue to find that the effect of media coverage on the interest rate is significantly higher for the high dissemination partition, but the economic significance of the *Media Content* for this partition becomes slightly smaller.

rated partition (Column 2). However, when dissemination is low, the effect of *Media Content* is similar for rated and non-rated firms (the coefficients on *Media Content* in Columns 1 and 3 are not statistically different from each other). It is also important to point out that the amplification effect of high dissemination on the impact of *Media Content* is more pronounced for more opaque firms, as the difference in the coefficients between Columns 1 and 2 is significantly smaller (p-value < 0.05) relative to the difference in the coefficients between Columns 3 and 4. This evidence is consistent with lenders learning from the media rather than media dissemination reflecting the importance of the news. Taken together, the results of dissemination-based tests support our proposition that the media is informative to private lenders.

4.3. Media Content and Relationship Lenders' Information Advantage

Having shown that media content is associated with interest spreads and that the strength of this association increases with dissemination, we next explore whether media content affects the extent of information asymmetries between incumbent lenders and outsiders. We first use media coverage to explore the possibility that relationship lenders enjoy an information advantage in setting loan spreads by examining how the sensitivity of loan spreads to *Media Content* varies across relationship and non-relationship lenders. Then we examine whether the media alters the information structure and the intensity of competition in the loan market by undermining the private information advantage of incumbent lenders. Here we focus on the effect of *Media Content* on the probability that a loan is issued by a non-relationship versus a relationship lender.

4.3.1. Does the sensitivity of spreads to Media Content vary across relationship and non-relationship lenders?

Following prior research (e.g., Sufi, 2007, Bharath, 2008, and Bushman et al., 2010), we classify loans into relationship or non-relationship categories based on the lead arranger of syndication. To account for the intensity of the lending relationship (Hauswald and Marquez, 2003 and Schenone, 2010), we define a lead arranger as a relationship lender if it has syndicated more than 50 percent of a borrower's prior loan deals by volume over the five year period preceding the loan issuance date. In Panel A of Table 5, we estimate Equation (1) separately for relationship and non-relationship partitions. We find that the impact of *Media Content* on *Spread* is significantly larger for non-relationship than relationship lenders (the difference in coefficients on *Media Content* in Columns 1 and 2 is significant at the 5 percent level). The fact that the spreads set by relationship lenders are less responsive to public information provided by the media provides preliminary evidence in support of relationship lenders' information advantage, which protects them from competition.

We next distinguish between positive and negative content. Building on Rajan (1992) and Hauswald and Marquez (2003, 2006) as discussed earlier, we predict that relationship lenders will not fully incorporate positive media content into lower spreads as they exploit their information advantage to extract rents, but will more fully incorporate negative media content in spreads to avoid underpricing loans. To examine this prediction, we create two separate variables capturing positive (*Pos. Media Content*) and negative (*Neg. Media Content*) media content. As reported in Table 5, Panel B, spreads on non-relationship loans respond significantly to both the positive and negative content, while in contrast, spreads on loans from relationship lenders are sensitive only to the negative content. Comparing coefficients between the two partitions, we find that non-relationship lenders are significantly more sensitive to positive media content than relationship lenders are (the coefficients on *Pos. Media Content* in Columns 1 and 2 are significantly different from each other at the 5 percent level). However, the sensitivity to negative media news is not significantly different across the two relationship-based partitions.

Extrapolating from our findings in Table 4, Panel B, relationship lenders should have a larger information advantage when dissemination is low, allowing them to underreact to positive content, while high dissemination should weaken their advantage and pressure them to more fully price positive news, as the competitive pressure on relationship lenders is likely to increase with dissemination. If this is the case, when dissemination is low, spreads on relationship loans will respond significantly only to negative, not positive, media content, as the lack of dissemination preserves relationship lenders' information advantage. In contrast, when news is broadly disseminated, relationship lenders will price not only negative but also positive news sentiment, similar to non-relationship lenders.

We examine this prediction in Table 6. In the low dissemination environment, non-relationship lenders price both the positive and negative media content but relationship lenders do not. Specifically, for non-relationship lenders (Column 1), the coefficients on both *Pos. Media Content* and *Neg. Media Content* are significant. For relationship lenders (Column 2), only the coefficient on *Neg. Media Content* is significant. Although relationship lenders do not price *Pos. Media Content*, their reaction to *Neg. Media Content* is not significantly different from that of relationship lenders (the coefficients on *Neg. Media Content* are not significantly different from each other in Columns 1 and 2).

In a high media dissemination environment, non-relationship lenders, as expected, react strongly to *Neg. Media Content*. While the coefficient on *Pos. Media Content* is significant only at the 10% one-sided level, potentially due a small sample size of only 818 loans, its economic significance is large. Relationship lenders react similarly to non-relationship lenders with respect to *Neg. Media Content* (the coefficients on *Neg. Media Content* are not significantly different from each other in Columns 3 and 4). However, we find only weak support for our prediction regarding relationship lenders' reaction to *Pos. Media Content* – the coefficient on this variable is substantially higher in the high dissemination environment, but it remains insignificant.

What explains the finding that spreads on relationship loans are not more sensitive to positive media content when dissemination is high? We conjecture that this occurs because any reduction in information advantage driven by the dissemination of positive news serves to level the playing field between incumbent and outside lenders and manifests in firms more frequently switching to non-relationship lenders. This prediction is consistent with Rajan's (1992) model showing that good news public signals about a firm's prospects increase the aggressiveness with which outside lenders bid for the loan, increasing the probability of an outsider winning the loan. Indeed, out of the 665 loans in the high dissemination-relationship lender partition (Column 4), only 219 are issued when the news content is positive prior to a loan's issuance.[23] We examine this proposition next by exploring the extent to which media content and dissemination are associated with the probability of non-relationship lenders originating loans.

4.3.2. Does Media Content Affect the Probability of a Loan Being Issued by a Non-relationship Lender?

In Panel A of Table 7, we estimate a borrower's propensity to receive a loan from a non-relationship lender, using the following logistic regression:

$$\begin{aligned} Non-relationship = \alpha_0 + \beta_1 Pos.MediaContent + \beta_2 Neg.MediaContent + \\ \beta_3 \#Articles + \beta_4 LoanControls + \beta_5 FirmControls + \\ \beta_6 TightCreditSupply + \varepsilon, \end{aligned} \tag{2}$$

where *Non-relationship* is an indicator variable equal to 1 if a loan is issued by a non-relationship lender, and zero otherwise. We incorporate the loan and firm controls suggested by

[23] The dissemination of positive news is generally low relative to the dissemination of negative news. Green et al. (2012) document that while the number of good news events reported in the business press is very similar to the number of bad news events, bad news is more widely disseminated.

Gopalan et al. (2011) and Li et al. (2013) as potential determinants of the probability that a loan is issued by a non-relationship lender. We also control for the tightness of the credit supply in the economy as borrowers may be less likely to obtain credit from non-relationship lenders when the credit supply is tight (Bolton et al., 2013). We proxy for credit supply using changes in bank lending standards for mid-sized and large commercial loans, as reported in the Federal Reserve Board's quarterly Senior Loan Officer Opinion Survey on Bank Lending Practices (e.g., Bassett et al. 2012). The *Tight Credit Supply* variable takes the value of 1 if the change in lending standards in the quarter of a loan's origination is in the top quartile of the sample's distribution, and 0 otherwise. We restrict the analyses to the sub-sample of borrowers who issued at least one loan over the 5 year period prior to a current loan's origination date. 59 percent of the loans in this sample are issued by non-relationship lenders.[24]

The significant and positive coefficient on *Pos. Media Content* in Panel A of Table 7 indicates that positive news sentiment preceding loan issuance is associated with a higher probability of a non-relationship loan. In terms of economic significance, a one standard deviation increase in positive media content increases the probability that a loan is issued by a new lender by 2.1%. This effect is meaningful and substantially higher than the effect of a one standard deviation change in *Z-score* (0.8%) and *MTB* (0.3%), two other firm characteristics that we find to significantly affect a loan's probability of being issued by a new lender. We find that negative media content has a marginally positive effect on the probability of a non-relationship loan. This is not consistent with the Rajan (1992) result that bad news signals decrease the bidding aggressiveness of outside lenders for a borrower's loan due to heightened adverse selection concerns. It is possible that this result is a consequence of forces outside of the Rajan

[24] In light of Greene's (2004) criticism of the inclusion of fixed effects in non-linear models, we do not incorporate year and industry fixed effects into the lending relationship logistic regression.

(1992) model. One possibility involves the role of relationship lenders in providing *access* to loan capital when firms are in trouble (e.g., Rajan and Zingales, 1998). As discussed in section 2, Bolton et al. (2013) document that while relationship banks charge higher interest spreads in normal times, they offer continuation lending at more favorable terms during a crisis. Thus, it is possible that some firms receiving negative media coverage are being supported by their relationship lenders.

In terms of control variables, we find, surprisingly, that the coefficient on *#Articles* is negative and significant. When borrowers issue larger loans or loans with a longer maturity, they are less likely to obtain credit from non-relationship lenders. These results are consistent with higher information asymmetry between the borrower and non-relationship lenders potentially preventing these lenders from extending larger and longer term credit. Consistent with Gopalan et al. (2011) and Li et al. (2013), we do not find that loan type, estimated by the *Revolver* and *Term Loan B* indicator variables, affects the propensity of a non-relationship transaction. Similar to these studies, we also control for whether a firm's previous loan is still outstanding when the current loan is issued (*Outstanding*) and the time period between the current and the previous loan (*Time Between*). We find that these variables do not affect the probability of a non-relationship transaction.[25]

Similar to prior research, we show that many variables associated with a borrower's creditworthiness, such as leverage, interest coverage, profitability and size do not affect the probability of a loan of being issued by a non-relationship lender. Only a market-to-book ratio and Z-score are marginally related to this probability. To proxy for information opacity, we also

[25] We do not include other loan-specific characteristics, such as the interest spread and the number of financial covenants, which are determined during the negotiation process between a lead arranger and the borrower and therefore cannot affect the choice of the lender. In contrast, when a borrower approaches a potential lender, it typically has a good idea about the amount and tenure of the credit desired. In any case, we find that our results are robust to the inclusion of the interest spread, the number of financial covenants, and indicator variables reflecting whether a loan is secured or includes a performance pricing provision.

incorporate into the model an indicator variable reflecting whether a borrower is rated (*Rated*) and a variable reflecting the number of equity analysts covering the firm *(#Analysts*). The positive coefficient on *Rated* is consistent with more transparent firms being more likely to obtain credit from non-relationship lenders (e.g., Petersen and Rajan, 1994). However, similar to the association we document for the number of articles, the coefficient on the number of analysts is negative and significant (Gopalan et al., 2011, and Li et al., 2013, also find that the number of analysts is negatively related to the probability of a non-relationship transaction). With respect to the tightness of the credit supply, we do not find this variable to significantly affect the probability of a borrower obtaining credit from a non-relationship lender.[26]

We next examine whether the effect of positive media coverage on the probability of a non-relationship loan increases with dissemination. We predict that positive media content is more likely to undermine a relationship lender's information advantage when it is broadly disseminated, thus informing a wider range of potential lenders. We augment the lender choice model in Equation (2) with interaction terms between positive and negative media content and the high dissemination indicator variable. In Panel B of Table 7, we only present the coefficient and standard errors on our main variable of interest, although we include the same set of control variables as in the Panel A test. Control variable coefficients are similar to those previously presented and are omitted for brevity.

We find a positive and significant coefficient on the interaction term between *Pos. Media Content* and *High Dissemination*. Based on the Norton et al. (2004) adjustment for interaction terms in a non-linear model, the effect of positive media content on the probability of a loan

[26] The effect of *Media Content* on the interest spread is robust to incorporating alternative measures of the tightness of the supply of credit, such as the percentage of banks tightening standards for loans to large and middle-market firms, an indicator variable taking value of one if the percentage of banks tightening standards for loans to large and middle-market firms is above the sample median and the syndicated loan volume in the quarter of a loan's issuance. The results also do not change when we incorporate year fixed effects into the model.

being issued by a non-relationship lender doubles with high dissemination (Panel C, Column 1).[27] This suggests that positive media content, conditional on its broad dissemination, undermines relationship lenders' information advantage, causing them to lose some of their borrowers to competition from new lenders. In contrast, the interaction term between *Neg. Media Content* and *High Dissemination* is not significantly different from zero. The fact that positive media content has a greater impact on bank competition dynamics than negative content stands in stark contrast to prior research showing that negative media content has a stronger impact than positive news on equity market outcomes (e.g., Tetlock, 2007, and Tetlock et al., 2008).

The results in this section suggest that the media serves as an important information intermediary that influences the intensity of the competition relationship lenders face from non-relationship lenders. We find that the probability of a non-relationship lender originating a loan is increasing in the level of positive media content, and that this effect is enhanced by dissemination.

5. Summary

In this paper, we investigate whether the publication and dissemination of business press articles about a borrower influence loan spreads and reduce the information advantage of relationship lenders relative to other potential lenders. We consider two aspects of media coverage: media content and dissemination. Using data from RavenPack News Analytics, we construct a media content measure that captures the average sentiment strength across all borrower-specific articles published in the period preceding loan origination We measure dissemination as the number of distinct articles about a borrower in the period preceding loan origination to proxy for the extent to which news about a borrower reaches prospective lenders.

[27] Recent papers, such as Green (2010) and Kolasinski and Siegel (2010), dispute the need for this adjustment and suggest that it is correct to use just the interaction term in non-linear models.

We first examine whether media content transmits borrower-specific information that is reflected in banks' loan pricing decisions, finding that interest spreads are inversely associated with media content, with more positive news reducing spreads. We further examine whether the effect of media content on interest spreads is magnified by dissemination, noting that if media content simply reflects information available to lenders from other sources, its effect on interest spreads should not vary with dissemination. Consistent with lenders learning from the media, we find that the impact of media content on spreads is significantly higher when dissemination is higher.

We also examine whether the media affects the economics of relationship lending. Following the models of Rajan (1992) and Hauswald and Marquez (2003, 2006), we hypothesize that the spreads on relationship loans will be less responsive to positive than to negative media content, as relationship lenders will resist lowering spreads in response to good news in order to extract rents, but will fully react to negative news to avoid underpricing the loan. Consistent with this hypothesis, we find that spreads on non-relationship loans respond significantly to both positive and negative content, while, in contrast, spreads on relationship loans are sensitive only to negative content.

Finally, we examine whether media content decreases relationship lenders' information advantage and increases the level of competition from outside lenders for loans. We find that positive media content preceding a loan significantly increases the probability of a non-relationship lender making a loan, consistent with media coverage mitigating adverse selection problems and increasing the aggressiveness with which outside lenders bid against relationship lenders for a loan. We also show that the effect of positive media coverage on the propensity of a loan being issued by a non-relationship lender is enhanced by high dissemination, consistent with the media informing a wider range of lenders.

Our study contributes to the literature across several dimensions. First, we extend the growing body of empirical literature on the role played by the business press, providing new evidence suggesting that the media serves as an important information intermediary in the private debt market by expanding the information set available to lenders. Second, we contribute to the relationship lending literature by providing evidence suggesting that relationship lenders appear to exploit a private information advantage, extracting rents from borrowers by under-reacting to the arrival of positive news. Finally, we contribute to the literature on bank competition by providing evidence consistent with the business press fundamentally altering the information structure and the nature of competition in the loan market by undermining the private information advantage of incumbent lenders and increasing the aggressiveness with which outside lenders bid against relationship lenders for loans.

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Appendix A: Variable Definitions

Variable	Definition
Amount	The natural logarithm of the loan amount in US dollars. (DealScan)
Collateral	An indicator equal to 1 if the loan is secured, 0 otherwise. (DealScan)
Credit Rating	The numerical equivalent of the senior debt rating at the time of a loan's issuance. It is set as equal to 1 if the S&P senior debt rating is AAA, through 22 when the S&P senior debt rating is D. For firms not rated by S&P, we assign the Moody's senior debt rating, converted to an equivalent S&P rating. For firms not rated by S&P or Moody's, we assign the Fitch senior debt rating, converted to an equivalent S&P rating (DealScan and S&P historical database).
Current Watch	The variable equal to -1 (1) if a borrower is on a negative or developing (positive) credit watch list at a loan's issuance date. The variable is equal to 0 if a borrower is not on a credit watch at a loan's issuance date (S&P historical database).
High Dissemination	An indicator variable equal to 1 if over the 180 day period prior to a loan's issuance the borrower's media coverage falls into the top quintile of media coverage distribution for our sample (RavenPack).
Interest Coverage	Earnings before interest and tax divided by the interest expense, estimated in the quarter preceding a loan's issuance (Compustat).
Lev	Total liabilities divided by total assets, estimated in the quarter preceding a loan's issuance (Compustat).
Maturity	The number of months to maturity (DealScan).
Media Content	The average Composite Sentiment Score (CSS) over the 180 day period prior to a loan's issuance date for full-size articles, conditional on the article's relevance score above 75. Firm-initiated press releases are excluded from this estimation. CSS combines 5 sentiment scores (PEQ, BEE, BMQ, BCA and BAM), while insuring that there is no sentiment disagreement amongst these scores. The PEQ score represents the news sentiment of the given news item according to the PEQ classifier, which specializes in identifying positive and negative words and phrases in articles about global equities. The BEE score represents the news sentiment of a given story according to the BEE classifier, which specializes in news stories about

earnings evaluations. The BMQ score represents the news sentiment of a given story according to the BMQ classifier, which specializes in short commentary and editorials on global equity markets. The BCA score represents the news sentiment of a given news story according to the BCA classifier, which specializes in reports on corporate action announcements. The BAM score represents the news sentiment of a given story according to the BAM classifier, which specializes in news stories about mergers, acquisitions and takeovers.

CSS scores range from 0 to 100, with a score above 50 indicating positive news sentiment; equal to 50, neutral news sentiment; and below 50, negative news sentiment. We apply a linear transformation to the CSS score and define *Media Content = (CSS-50)/50*, so that the *Media Content* ranges from -1 to 1, with zero being equivalent to neutral sentiment (RavenPack).

MTB	The market value of equity divided by the book value of equity, estimated in the quarter preceding a loan's issuance (Compustat).
Neg. Media Content	Equal to the *Media Content* if *Media Content* is less than 0, and 0 otherwise.
(Non)Relationship	An indicator variable equal to 1(0) if a loan's lead arranger has syndicated less (more) than 50 percent of a borrower's prior loan deals by volume over the five year period preceding the loan issuance date (DealScan).
Outstanding	An indicator variable equal to 1 if the borrower's previous deals are still outstanding at the current loan's issuance date, 0 otherwise (DealScan).
Pos. Media Content	Equal to *Media Content* if *Media Content* is greater than 0, 0 otherwise.
Prior 180 Watch	The average of the *Current Watch* variable over the 180 day period prior to a loan's issuance date. *Credit Watch* is equal to -1 (1) if a borrower is on a negative or developing (positive) credit watch at a loan's issuance date. The variable is equal to 0 if a borrower is not on a credit watch at a loan's issuance date (S&P historical database).
Press Release Content	The average CSS for firm-initiated press releases with relevance score greater than 90, estimated over the 180 day period prior to a loan's issuance date (RavenPack).
PP	An indicator variable equal to 1 if the loan has a performance pricing provision, 0 otherwise (DealScan).

Rated	An indicator variable equal to 1 if the borrower has a senior debt rating from S&P, Moody's or Fitch, zero otherwise (DealScan and S&P historical database).
Revolver	An indicator variable equal to 1 if the loan is a revolving line of credit, 0 otherwise (DealScan).
Return	The firm's market-adjusted (value-weighted) cumulative return over the 180 day period prior to a loan's issuance date.
ROA	Return on assets, defined as earnings before extraordinary items divided by total assets and estimated in the quarter preceding a loan's issuance (Compustat).
Spread	The natural logarithm of the loan spread over LIBOR (DealScan).
Size	The natural logarithm of total assets, estimated in the quarter preceding a loan's issuance (Compustat).
Term Loan B	An indicator variable equal to 1 if the loan type is Term loan B or below (C, D, E and F), 0 otherwise (DealScan).
Tight Credit Supply	An indicator variable equal to 1 if the change in bank lending standards for mid-sized and large commercial loans, as reported in the Federal Reserve Board's quarterly Senior Loan Officer Opinion Survey on Bank Lending Practices, in the quarter of a loan's origination is in the top quartile of the sample's distribution, and 0 otherwise.
Time-Between	The number of days between the loan's issuance date and the previous deal (DealScan).
Z-Score	Altman's (1968) bankruptcy measure, estimated by the following model: $Z= 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$ where X_1 is defined as working capital (total current asset minus total current liabilities) divided by total assets. X_2 is defined as retained earnings divided by total assets. X_3 is defined as earnings before interest and taxes divided by total assets. X_4 is the market value of equity divided by total liabilities. X_5 is total sales divided by total assets. All measures are estimated in the quarter preceding a loan's issuance (Compustat).
#Article	The number of full-size articles, excluding firm-initiated press releases, over the 180 day period prior to the loan issuance date (RavenPack).
#Press Releases Articles	The number of firm-initiated press releases over the 180 day

	period prior to the loan issuance date (RavenPack).
#Analysts	The number of analysts that follow the firm (I/B/E/S).
#Covenants	The number of financial covenants (DealScan).

Table 1 – Sample Selection

This table presents the sample selection process.

Filters	Number of facilities
Syndicated loans to public U.S. borrowers, in U.S. dollars, issued over the period 2000-2012	31,974
After elimination of facilities of firms not covered by RavenPack	24,308
After elimination of facilities with missing loan data	12,397
After elimination of facilities with insufficient firm and media data	**7,244**

Table 2 – Descriptive Statistics

This table provides descriptive statistics (see Table 1 for the sample selection procedure). Variables are defined in Appendix A.

Variable	Mean	Median	StdDev
Media Content	-0.0046	0.0000	0.0386
#Articles	25.6275	13.0000	60.8675
Spread	5.0720	5.1648	0.7221
Amount	18.9334	19.1138	1.4854
Maturity	47.9482	57.0000	21.4141
PP	0.7143	1.0000	0.4519
Collateral	0.6392	1.0000	0.4802
#Covenants	2.3109	2.0000	1.0131
Revolver	0.6229	1.0000	0.4846
Term Loan B	0.1002	0.0000	0.3006
ROA	0.0085	0.0102	0.0253
Interest Coverage	10.5052	2.1228	40.9157
Z-Score	2.2403	1.6907	2.2198
Lev	0.2520	0.2373	0.1789
Size	7.2521	7.2688	1.6609
MTB	3.0102	2.0201	3.7461
Return	0.0558	0.0216	0.3121

Table 3 Media Content and Interest Spreads

This table presents the analysis of the association between media content on the interest spread (*Spread*). Panel A presents our main specification. Panel B presents robustness tests for the sample of firms with available firm-initiated press release data (Column 1) and rating data (Columns 2-4). Panel C presents robustness tests for sub-samples based on a loan's information sensitivity. We estimate each model with year and two digit industry fixed effects and cluster the standard errors at the firm level and calendar quarter levels. Standard errors are in parentheses. ***, **, and * indicates significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

Panel A: Main Specification

Variable	**Prediction**	**Dependent Variable: *Spread***
	(1)	(2)
Media Content	−	-1.1629***
		(0.1928)
#Articles	−	-0.0001
		(0.0001)
Amount	−	-0.0706***
		(0.0074)
Maturity	?	-0.0005
		(0.0004)
PP	−	-0.1161***
		(0.0224)
Collateral	?	0.5125***
		(0.0519)
#Covenants	?	0.0910***
		(0.0082)
Revolver	−	-0.0654***
		(0.0232)
Term Loan B	+	0.1868***
		(0.0382)
ROA	−	-3.3746***
		(0.4343)
Interest Coverage	−	0.0005**
		(0.0002)
Z-Score	−	-0.0288***
		(0.0066)
Lev	+	0.3277***
		(0.0502)
Size	−	-0.0396**
		(0.0169)
MTB	−	-0.0046*
		(0.0028)
Return	−	0.0437**
		(0.0194)
Fixed Effects		Year/Industry/Purpose
N		7,244
R^2		0.6826

Panel B: Robustness Analysis – Controlling for Firm-Initiated Press Releases and Rating-Related Data

Variables	**Dependent Variable:** ***Spread***			
	(1)	(2)	(3)	(4)
Media Content	-1.0556***	-0.9778***	-1.0319***	-0.9779***
	(0.2131)	(0.2426)	(0.2463)	(0.2425)
#Articles	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Amount	-0.0708***	-0.0458***	-0.0446***	-0.0458***
	(0.0076)	(0.0087)	(0.0088)	(0.0087)
Maturity	-0.0005	-0.0005	-0.0005	-0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
PP	-0.1125***	-0.0591***	-0.0616***	-0.0591***
	(0.0222)	(0.0209)	(0.0209)	(0.0209)
Collateral	0.5043***	0.2932***	0.2973***	0.2932***
	(0.0529)	(0.0336)	(0.0339)	(0.0336)
#Covenants	0.0921***	0.0661***	0.0666***	0.0661***
	(0.0085)	(0.0095)	(0.0094)	(0.0095)
Revolver	-0.0658***	-0.0431**	-0.0454***	-0.0431**
	(0.0241)	(0.0172)	(0.0175)	(0.0171)
Term Loan B	0.1815***	0.1326***	0.1309***	0.1326***
	(0.0386)	(0.0274)	(0.0276)	(0.0274)
ROA	-3.3414***	-0.9640**	-0.9713**	-0.9640**
	(0.5002)	(0.4397)	(0.4546)	(0.4399)
Interest Coverage	0.0005**	-0.0000	-0.0000	-0.0000
	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Z-Score	-0.0282***	-0.0003	-0.0013	-0.0003
	(0.0072)	(0.0061)	(0.0064)	(0.0061)
Lev	0.3332***	0.1130*	0.1081*	0.1130*
	(0.0532)	(0.0580)	(0.0581)	(0.0580)
Size	-0.0432**	0.0178	0.0168	0.0178
	(0.0171)	(0.0121)	(0.0122)	(0.0121)
MTB	-0.0046	-0.0080***	-0.0076***	-0.0080***
	(0.0028)	(0.0022)	(0.0022)	(0.0022)
Returns	0.0487**	-0.0110	-0.0199	-0.0111
	(0.0213)	(0.0297)	(0.0301)	(0.0299)
Press Release Content	-0.9152***			
	(0.2641)			
#Press Release Articles	0.0000			
	(0.0002)			
Current Watch		-0.1349***		-0.1335***
		(0.0294)		(0.0318)
Prior 180 Watch			-0.1216***	-0.0032
			(0.0406)	(0.0418)
Credit Rating		0.1273***	0.1258***	0.1273***
		(0.0079)	(0.0078)	(0.0079)
ΔCredit Rating		0.0025	-0.0033	0.0023
		(0.0111)	(0.0122)	(0.0114)
Fixed Effects	Y/I/P	Y/I/P	Y/I/P	Y/I/P
N	6,964	4,536	4,536	4,536
R^2	0.6829	0.7901	0.7886	0.7901

Panel C: Robustness Analysis – Tests for Sub-Samples Based on a Loan's Information Sensitivity

Variable	**Dependent Variable:** ***Spread***	
	Information-sensitive	**Information-insensitive**
	(1)	(2)
Media Content	-1.2470***	-0.3481
	(0.2274)	(0.4524) ❖❖❖
#Articles	-0.0000	-0.0002
	(0.0001)	(0.0002)
Amount	-0.0795***	-0.0402***
	(0.0103)	(0.0120)
Maturity	-0.0003	-0.0005
	(0.0005)	(0.0007)
PP	-0.1238***	-0.1144***
	(0.0269)	(0.0401)
Collateral	0.5360***	0.3710***
	(0.0573)	(0.0461)
#Covenants	0.0819***	0.1171***
	(0.0096)	(0.0168)
Revolver	-0.0622**	-0.0664**
	(0.0243)	(0.0286)
Term Loan B	0.1735***	0.1785***
	(0.0436)	(0.0378)
ROA	-3.2872***	-2.8159***
	(0.4890)	(0.9956)
Interest Coverage	0.0005	-0.0001
	(0.0005)	(0.0002)
Lev	0.4272***	0.1638
	(0.0501)	(0.1300)
Size	-0.0234	-0.1195***
	(0.0166)	(0.0193)
MTB	-0.0022	-0.0134***
	(0.0030)	(0.0036)
Return	-0.0018	0.1645***
	(0.0221)	(0.0591)
Fixed Effects	Year/Industry/Purpose	Year/Industry/Purpose
N	5,587	1,657
R^2	0.6777	0.7177

❖❖❖, ❖❖, ❖ indicates that the difference across Columns (1) and (2) is significant at the 1%, 5%, and 10% levels, respectively.

Table 4 – Media Content and Dissemination

This table presents the analysis of the impact of media content on the interest spread (*Spread*), conditional on dissemination. Panel A presents the analysis for the sub-samples based on media dissemination. We classify loans into the high dissemination group if, over the 180 days prior to the loan's issuance, the borrower's media coverage falls into the top quintile of media coverage distribution for our sample. Panel C extends the analysis presented in Panel B by performing the tests for rated and non-rated borrowers. We estimate each model with year and two digit industry fixed effects and cluster the standard errors at the firm level and calendar quarter levels. Standard errors are in parentheses. ***, **, and * indicates significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

Panel A: High versus Low Dissemination

	Dependent Variable: *Spread*	
Variable	**Low Dissemination**	**High Dissemination**
	(1)	(2)
Media Content	-0.8350***	-2.7523***
	(0.1904)	(0.7332)❖❖❖
Amount	-0.0721***	-0.0498***
	(0.0080)	(0.0167)
Maturity	-0.0004	-0.0010
	(0.0004)	(0.0008)
PP	-0.1283***	-0.1088***
	(0.0207)	(0.0365)
Collateral	0.4889***	0.5213***
	(0.0466)	(0.0695)
#Covenants	0.0837***	0.1817***
	(0.0082)	(0.0361)
Revolver	-0.0726***	-0.0370
	(0.0279)	(0.0354)
Term Loan B	0.1626***	0.2606***
	(0.0399)	(0.0647)
ROA	-3.1521***	-5.0013***
	(0.4027)	(0.9168)
Interest Coverage	0.0005*	0.0008
	(0.0002)	(0.0006)
Z-Score	-0.0257***	-0.0508***
	(0.0075)	(0.0128)
Lev	0.3751***	0.0818
	(0.0652)	(0.1609)
Size	-0.0482**	-0.0404
	(0.0212)	(0.0252)
MTB	-0.0037	-0.0060
	(0.0029)	(0.0054)
Return	0.0509**	0.0186
	(0.0220)	(0.0869)
Fixed Effects	Year/Industry/Purpose	Year/Industry/Purpose
N	5,796	1,448
R^2	0.6497	0.7592

❖❖❖, ❖❖, ❖ indicates that the difference across Columns (1) and (2) is significant at the 1%, 5%, and 10% levels, respectively.

Panel B: Does the Importance of News Dissemination Vary between Rated and Non-Rated Borrowers?

	Dependent Variable: *Spread*			
	Rated Borrowers		**Non-Rated Borrowers**	
Variable	**Low Dissemination**	**High Dissemination**	**Low Dissemination**	**High Dissemination**
	(1)	(2)	(3)	(4)
Media Content	-0.9354***	-1.6390***	-0.6102***	-3.6455***
	(0.2019)	(0.5914)	(0.2207)	(1.3953)❖❖
|Difference| (2)-(1);(4)-(3)	0.7036		3.0353♯♯	
Amount	-0.0707***	-0.0152	-0.0507***	0.0045
	(0.0095)	(0.0161)	(0.0103)	(0.0354)
Maturity	0.0020***	-0.0011	-0.0016***	-0.0022
	(0.0004)	(0.0008)	(0.0005)	(0.0020)
PP	-0.0851***	-0.0615*	-0.1361***	-0.1968***
	(0.0185)	(0.0323)	(0.0198)	(0.0710)
Collateral	0.6365***	0.7231***	0.4651***	0.2312***
	(0.0199)	(0.0354)	(0.0225)	(0.0701)
#Covenants	0.0887***	0.2064***	0.0696***	0.1422***
	(0.0081)	(0.0198)	(0.0093)	(0.0484)
Revolver	-0.0189	-0.0669**	-0.1396***	-0.1374**
	(0.0180)	(0.0328)	(0.0203)	(0.0638)
Term Loan B	0.1688***	0.2770***	0.2460***	0.7129***
	(0.0271)	(0.0558)	(0.0452)	(0.2000)
ROA	-2.2819***	-2.5806***	-1.0623***	-2.8207***
	(0.2500)	(0.4586)	(0.2074)	(1.0507)
Interest Coverage	0.0015***	0.0012**	0.0000	0.0000
	(0.0003)	(0.0005)	(0.0002)	(0.0005)
Z-Score	-0.0266***	-0.0624***	-0.0296***	-0.0371***
	(0.0059)	(0.0118)	(0.0041)	(0.0115)
Lev	0.1994***	-0.0375	0.2723***	-0.7068**
	(0.0572)	(0.1230)	(0.0680)	(0.2727)
Size	-0.0802***	-0.0372**	-0.0629***	-0.1062***
	(0.0097)	(0.0173)	(0.0120)	(0.0383)
MTB	-0.0081***	-0.0102***	0.0007	0.0094
	(0.0022)	(0.0031)	(0.0025)	(0.0066)
Return	0.0557**	-0.0617	0.0266	0.4346***
	(0.0239)	(0.0555)	(0.0252)	(0.1072)
Fixed Effects	Y/I/P	Y/I/P	Y/I/P	Y/I/P
N	3,287	1,247	2,509	199
R^2	0.6960	0.7422	0.7510	0.5787

❖❖❖, ❖❖, ❖ indicates that the difference across Columns (1) and (3) or (2) and (4) is significant at the 1%, 5%, and 10% levels, respectively.

♯♯ indicates that the difference in the coefficients between Columns (1) and (2) is significantly different from the difference in the coefficients between Columns (3) and (4) at the 5% level.

Table 5 – Media Content and Relationship Lending

This table presents the analysis of the impact of media content on the interest spread (*Spread*), conditional on whether the loan is issued by a relationship or non-relationship lender. We classify a loan as issued by a relationship lender if its lead arranger has syndicated more than 50 percent of a borrower's prior loan deals by volume over the five year period preceding the loan issuance date. Panel A presents the analysis based on the aggregate measure of media content (Media Content), while Panel B distinguishes between positive (*Pos. Media Content*) and negative (*Neg. Media Content*) media content. We estimate each model with year and two digit industry fixed effects and cluster the standard errors at the firm level and calendar quarter levels. Standard errors are in parentheses. ***, **, and * indicates significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

Panel A: The Sensitivity of Loan Spread to Media Content across Relationship and Non-Relationship Lenders

	Dependent Variable: *Spread*	
Variable	**Non-relationship**	**Relationship**
	(1)	(2)
Media Content	-1.4964***	-0.9281**
	(0.1951)	(0.4188)❖❖
#Articles	-0.0000	-0.0002
	(0.0001)	(0.0002)
Amount	-0.0592***	-0.0891***
	(0.0091)	(0.0108)
Maturity	-0.0002	-0.0016***
	(0.0004)	(0.0005)
PP	-0.1622***	-0.0817**
	(0.0239)	(0.0368)
Collateral	0.5675***	0.4741***
	(0.0452)	(0.0589)
#Covenants	0.0902***	0.0973***
	(0.0117)	(0.0111)
Revolver	-0.0982***	-0.0170
	(0.0301)	(0.0223)
Term Loan B	0.1428***	0.2544***
	(0.0381)	(0.0574)
ROA	-1.9001***	-2.2416**
	(0.3824)	(0.9083)
Interest Coverage	0.0000	-0.0001
	(0.0000)	(0.0001)
Z-Score	-0.0095**	-0.0061
	(0.0041)	(0.0078)
Lev	0.4004***	0.5259***
	(0.0803)	(0.0685)
Size	-0.0414**	-0.0274
	(0.0188)	(0.0194)
MTB	-0.0056	-0.0133***
	(0.0034)	(0.0045)
Return	0.0319	0.0373
	(0.0203)	(0.0396)
Fixed Effects	Year/Industry/Purpose	Year/Industry/Purpose
N	4,621	2,623
R^2	0.6558	0.7065

❖❖❖, ❖❖, ❖ indicates that the difference across Columns (1) and (2) is significant at the 1%, 5%, and 10% levels, respectively.

Panel B: The Effect of Positive versus Negative Sentiment

	Dependent Variable: *Spread*	
Variable	**Non-relationship**	**Relationship**
	(1)	(2)
Pos. Media Content	-1.7257***	0.1527
	(0.5931)	(0.8176)❖❖
Neg. Media Content	1.0259***	1.4217***
	(0.3729)	(0.4412)
#Articles	-0.0000	-0.0002
	(0.0002)	(0.0002)
Amount	-0.0593***	-0.0887***
	(0.0091)	(0.0110)
Maturity	-0.0002	-0.0016**
	(0.0004)	(0.0007)
PP	-0.1619***	-0.0820***
	(0.0238)	(0.0294)
Collateral	0.5687***	0.4734***
	(0.0448)	(0.0325)
#Covenants	0.0905***	0.0992***
	(0.0117)	(0.0134)
Revolver	-0.0977***	-0.0171
	(0.0298)	(0.0217)
Term Loan B	0.1439***	0.2529***
	(0.0381)	(0.0345)
ROA	-1.9161***	-2.2261***
	(0.3848)	(0.6922)
Interest Coverage	0.0000	-0.0001
	(0.0000)	(0.0001)
Z-Score	-0.0095**	-0.0064
	(0.0041)	(0.0075)
Lev	0.4001***	0.5225***
	(0.0811)	(0.0873)
Size	-0.0411**	-0.0266**
	(0.0187)	(0.0127)
MTB	-0.0055	-0.0133***
	(0.0035)	(0.0051)
Return	0.0293	0.0403
	(0.0200)	(0.0449)
Fixed Effects	Year/Industry/Purpose	Year/Industry/Purpose
N	4,621	2,623
R^2	0.6553	0.7070

❖❖❖, ❖❖, ❖ indicates that the difference across Columns (1) and (2) is significant at the 1%, 5%, and 10% levels, respectively.

Table 6 –Dissemination and Lenders' Sensitivity to Media Content

This table presents the analysis of the impact of positive and negative media content on the interest spread (*Spread*), conditional on whether the loan is issued by a relationship or non-relationship lender and on media dissemination. We classify a loan as issued by a relationship lender if its lead arranger has syndicated more than 50 percent of a borrower's prior loan deals by volume over the five year period preceding the loan issuance date. We classify loans into the high dissemination group if, over the 180 days prior to a loan's issuance, the borrower's media coverage falls into the top quintile of media coverage distribution for our sample. We estimate each model with year and two digit industry fixed effects and cluster the standard errors at the firm level and calendar quarter levels. Standard errors are in parentheses. ***, **, and * indicates significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

	Dependent Variable: *Spread*			
	Low Dissemination		**High Dissemination**	
Variable	**Non-relationship**	**Relationship**	**Non-relationship**	**Relationship**
	(1)	(2)	(3)	(4)
Pos. Media Content	-1.1669***	-0.1975	-2.8723	-1.4701
	(0.3896)	(0.6589)❖❖	(2.2755)	(2.1704)
Neg. Media Content	0.8857***	1.0959***	2.4081**	3.2274**
	(0.3158)	(0.4143)	(1.2130)	(1.6656)
Amount	-0.0588***	-0.0967***	-0.0460*	-0.0514**
	(0.0113)	(0.0122)	(0.0257)	(0.0202)
Maturity	-0.0003	-0.0013*	0.0002	-0.0032***
	(0.0004)	(0.0007)	(0.0013)	(0.0011)
PP	-0.1652***	-0.1007***	-0.1530***	-0.0535
	(0.0245)	(0.0316)	(0.0536)	(0.0440)
Collateral	0.5326***	0.4611***	0.5879***	0.4602***
	(0.0412)	(0.0320)	(0.0657)	(0.0657)
#Covenants	0.0836***	0.0852***	0.1699***	0.2172***
	(0.0098)	(0.0142)	(0.0313)	(0.0357)
Revolver	-0.0940***	-0.0260	-0.0689*	0.0283
	(0.0348)	(0.0232)	(0.0406)	(0.0501)
Term Loan B	0.1370***	0.2072***	0.1607**	0.3610***
	(0.0400)	(0.0349)	(0.0770)	(0.0741)
ROA	-1.6111***	-1.7624***	-4.3048***	-3.8241***
	(0.3987)	(0.6216)	(0.6728)	(1.2932)
Interest Coverage	0.0000	-0.0000	-0.0000	0.0003
	(0.0000)	(0.0000)	(0.0000)	(0.0010)
Lev	0.3790***	0.5394***	0.3876**	0.1602
	(0.0769)	(0.0854)	(0.1601)	(0.2078)
Z-Score	-0.0150*	-0.0043	-0.0020	-0.0476***
	(0.0079)	(0.0077)	(0.0040)	(0.0160)
Size	-0.0481**	-0.0301**	-0.0245	-0.0264
	(0.0215)	(0.0149)	(0.0318)	(0.0276)
MTB	0.0000***	-0.0054**	-0.0054	-0.0049
	(0.0000)	(0.0026)	(0.0043)	(0.0047)
Return	0.0218	0.0621	0.0991	-0.0471
	(0.0176)	(0.0429)	(0.1052)	(0.1031)
Fixed Effects	Y/I/P	Y/I/P	Y/I/P	Y/I/P
N	3,803	1,958	818	665
R^2	0.6245	0.6889	0.7692	0.7904

❖❖❖, ❖❖, ❖ indicates that the difference across Columns (1) and (2) or (3) and (4) is significant at the 1%, 5%, and 10% levels, respectively.

Table 7 –Media Content and Relationship Lending

This table presents the analysis of the impact of positive and negative media content on the propensity of a loan being issued by a non-relationship lender (*Non-relationship*). We classify a loan as issued by a non-relationship lender if its lead arranger has syndicated less than 50 percent of a borrower's prior loan deals by volume over the five year period preceding the loan issuance date. To properly measure the banking relationship, the analyses in this table are restricted to a sample of borrowers who had issued at least one loan over the 5 year period prior to a current loan's origination date. Panel A presents our main specification, while Panel B conditions on the media dissemination. In Panel C, we report the Norton et al. (2004) correction and the marginal effects for the main variables of interest. We classify loans into the high dissemination group if, over the 180 days prior to a loan's issuance, the borrower's media coverage falls into the top quintile of media coverage distribution for our sample. Standard errors are in parentheses. ***, **, and * indicates significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

Panel A: Positive versus Negative Media Content and Relationship Lending

Variable	**Prediction**	**Dependent Variable: Non-relationship**
	(1)	(2)
Pos. Media Content	+	5.8531**
		(2.6686)
Neg. Media Content	+	2.4192*
		(1.4083)
#Articles	+	-0.0004**
		(0.0002)
Amount	−	-0.1427***
		(0.0353)
Maturity	−	-0.0053***
		(0.0018)
Revolver	?	-0.0317
		(0.0659)
Term Loan B	?	0.1361
		(0.1111)
Outstanding	-	0.0538
		(0.0884)
Time-Between	+	0.0001
		(0.0001)
ROA	+	-1.7831
		(1.1998)
Interest Coverage	+	0.0007
		(0.0010)
ZScore	−	-0.0379**
		(0.0185)
Lev	−	-0.2488
		(0.2752)
Size	+	-0.0349
		(0.0409)
MTB	+	0.0103*
		(0.0056)
Rated	+	0.1576*
		(0.0905)
#Analysts	+	-0.0133*
		(0.0069)
Return	?	0.3080***
		(0.1099)
Tight Credit Supply	?	-0.0074
		(0.1005)
N		6,348

Panel B: Does High Dissemination Help Diminish the Relationship Lender's Information Advantage?

Variable	**Dependent Variable: Non-relationship**
*Pos. Media Content *High Dissemination*	8.3610**
	(4.1478)
Neg. Media Content High Dissemination*	3.7264
	(2.3218)
Pos. Media Content	2.6508
	(2.2558)
Neg. Media Content	1.2661
	(1.1389)
High Dissemination	-0.2609***
	(0.0820)
Control Variables	Yes
N	6,348

Panel C: Norton et al. (2004) Correction and Marginal Effects

	Marginal Effect	**Standard Error**	**Z-Statistic**	**P-Value**
Pos. Media Content High Dissemination*				
Mean	1.98	0.96	2.06	0.0394**
StdDev	0.18	0.10	0.07	
Neg. Media Content High Dissemination*				
Mean	0.89	0.55	1.63	0.1031
StdDev	0.09	0.06	0.06	