Do Management Earnings Forecasts Matter in Loan Contracting?

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ABSTRACT

Management earnings forecasts (MEFs) may enhance the credibility of lenders' private information received from borrowers and therefore reduce information risk. Consistent with this idea, we find that among firms with a general policy of issuing MEFs, those providing MEFs within six months before loan origination with a forecast horizon beyond the origination date enjoy lower loan spreads. The frequency and precision of MEFs are also negatively associated with loan spreads. The associations are stronger when lenders' need for corroboration of their private information is expected to be greater. The associations are not driven by a firm's general information environment, signaling of managerial ability, or opportunistic disclosure. Moreover, the occurrence, frequency, and precision of MEFs are associated with loan amounts more spread out among participating lenders, suggesting that MEFs reduce information asymmetry within a loan syndicate. Our study provides insight into the role of publicly disseminated MEFs in private loan markets.

JEL Classification: D82, G21

Keywords: voluntary disclosure; management earnings forecasts; debt contracting; loan spreads.

1. Introduction

As the most common type of corporate voluntary disclosure, management earnings forecasts (MEFs) have played a prominent role in the U.S. equity markets. For example, Ball and Shivakumar (2008) find that MEFs are more important than earnings announcements in conveying new information to equity markets. Beyer, Cohen, Lys, and Walther (2010, p.300) conclude that in the decade leading up to their study, MEFs provided about 55% of the accounting information available to equity investors. Baginski and Rakow (2012) and Li and Zhuang (2012) report that MEFs reduce information asymmetry between a firm and its equity investors and thus lower the cost of equity capital. Findings about MEFs in equity markets, however, may not generalize to debt markets because debt holders have different informational needs than equity investors.

It is important to know whether MEFs matter in loan markets. Loans are the principal source of external funds to U.S. firms. Over 90% of the funds raised in the U.S. capital markets are in the form of debt (Gomes and Phillips 2012; Armstrong, Guay, and Weber 2010, p.212). Among funds raised in debt markets, private loans nearly double the dollar amount of corporate bonds (Bharath, Sunder and Sunder 2008). For example, \$2.7 trillion of syndicated loans (i.e., loans provided by a group of lenders) were originated in the U.S. in 2017, whereas only \$1.6 trillion of corporate bonds were issued that year.[1] Approximately 80% of all U.S. publicly listed firms have loans, but only 15-20% have bonds (Nini, Smith, and Sufi 2009).

A few studies have examined the role of MEFs in loan markets but reached different conclusions. Dhaliwal, Khurana, and Pereira (2011) find that firms with MEF activity in the three-year period before debt issuance are more likely to use public debt than private debt; Lo (2014) reports that firms increase their MEF activity to attract public funds. Both studies suggest that private lenders have less need for MEFs than public lenders. Ali, Fan, and Li (2018) document that the issuance of MEFs in the 12 months before loan origination has no effect on loan spreads (i.e., the difference between the effective interest rate and LIBOR).

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[1] See Thomson Reuters' *Global Syndicated Loan Review* for 2017 and the Securities Industry and Financial Markets Association's website at https://www.sifma.org/resources/research/us-corporate-bond-issuance/.

In contrast, Hsieh, Song, Wang, and Wang (2019) find that the issuance of MEFs in the nine months *before the beginning of the quarter of loan origination* is associated with lower loan spreads and attribute this effect to managers' opportunistic disclosure of good news. Demerjian, Donovan, and Jennings (2019) find that the accuracy of *realized* MEFs issued in the three years before loan origination is negatively associated with loan spreads and argue that forecast accuracy signals managerial ability.

We advance this burgeoning literature by proposing that MEFs may reduce private lenders' information risk by corroborating their private information. Lenders face both information risk and default risk (collectively known as credit risk). Default risk is inherent in borrowers' operations and investments (Duffie and Lando 2001; Bharath et al. 2008). Lenders have substantial access to borrowers' private information, such as strategies, budgets, financial projections, and investment plans (Armstrong et al. 2010, p.214). The cash flow news contained in MEFs may be communicated privately to lenders. Thus, if private communication is credible, MEFs should not offer additional information on borrowers' default risk.[2]

MEFs, however, may help reduce lenders' information risk. First, MEFs can corroborate the private information that lenders, as a group, receive from a borrower and enhance the credibility of the private information. Private communication of forward looking information has an inherent credibility problem when lenders and borrowers have a conflict of interest. As public disclosures to a vast range of audiences, MEFs are subject to the scrutiny of various stakeholders and are thus more credible than private communication (Bushman, Chen, Engel, and Smith 2004). Lenders can use MEFs to corroborate their private information. Second, MEFs may reduce information asymmetry within a loan syndicate. The lead arranger of a syndicate is charged with collecting information from a borrower and assessing its true credit quality, but contributes only a portion of the loan amount. The information asymmetry and moral hazard problems discourage other lenders from pooling their resources. MEFs can corroborate private information

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[2] Shivakumar, Urcan, Vasvari, and Zhang (2011) were one of the first to examine the role of MEFs in debt markets. The authors find that the premium of credit default swap (CDS) that references a sample firm responds to the firm's MEF news. This finding suggests that MEFs provide cash flow news about a firm's ongoing default risk to *CDS traders*, who typically do not have private access to borrowers. The finding does not apply to loan markets because private lenders have private access to borrowers.

that is shared by the lead arranger with syndicate participants, or simply reduce the lead arranger's information advantage by making relevant information available to all participants. We expect lenders to require lower loan spreads as information risk decreases.

Our study differs from Hsieh et al. (2019) both conceptually and empirically. They focus on the default risk component of credit risk and argue that managers influence lenders' cash flow assessments by providing MEFs opportunistically. In contrast, we focus on the information risk component of credit risk. Using improved empirical strategies, we find no evidence that managerial opportunism explains the lower loan spreads. Our study also differs from Demerjian et al. (2019). They examine MEFs that are already realized before the loan origination date, whereas we examine MEFs that are still outstanding at the loan origination date. These two types of MEFs contain different types of information to lenders. Realized MEFs contain historical information about managers' forecasting ability; outstanding MEFs contain publicly disseminated forward looking information that may reduce lenders' uncertainty about the credibility of their contemporaneous private information about the proposed loan. We examine a new role of MEFs in loan markets.

We use three improved empirical strategies to examine the role of MEFs in loan contracting. The first improvement addresses the selection bias regarding a firm's MEF disclosure policy. We require a sample firm to have issued at least one MEF within the 24 months before loan origination to avoid comparing firms with different MEF disclosure policies. Firms with a general policy of providing MEFs could be distinctly different from firms with a policy of not providing MEFs (Ajinkya, Bhojraj, and Senguta 2005; Houston, Lev, and Tucker 2010). Such differences in firm characteristics may bespeak different risk profiles to lenders. Ali et al. (2018) and Hsieh et al. (2019) use all firms regardless of their existing MEF policy. Recognizing the selection issue, Vashishtha (2014) requires that his sample firms provide at least one MEF during his sample period of 13 years and then examines the relationship between loan covenant violations and subsequent MEF issuance.[3] We shorten Vashishtha's window to 24 months before loan origination to ensure that our sample firms have a *current* policy of providing MEFs.

The second improvement is that we examine MEF activity in the six months before loan origination. We refer to this period as the "loan negotiation stage" and determine this period based on our conversations with loan officers and the literature (Bushman, Williams, and Wittenberg-Moerman 2017). Focusing on this window allows us to reduce confounding events that are likely to occur in a long window. In contrast, Ali et al. (2018) and Hsieh et al. (2019) examine a period of about 12 months. The third improvement is that we examine exclusively *outstanding* MEFs. Except for managerial ability signaling, all arguments for the role of MEFs in loan contracting assume that MEFs are forward looking information not yet realized by the time of loan origination. Once earnings for the forecasted period are reported, MEFs lose their value in conveying timely cash flow information or reducing lenders' information risk. Prior studies fail to distinguish between realized and outstanding MEFs.

We collect data for loans originated by U.S. firms between 1998 and the first quarter of 2017. For each firm-loan observation, we obtain the occurrence, frequency, and precision of MEFs (collectively referred to as "MEF properties") issued by the sample firm in the negotiation stage. In other words, all our sample firms have a general policy of providing MEFs but vary in MEF activity in the *loan negotiation stage*. After controlling for firm characteristics (e.g., accruals quality), loan characteristics, and macroeconomic factors, we find that MEF properties in the loan negotiation stage are significantly negatively associated with loan spreads. The economic effects are material. For example, firms that provide an outstanding MEF in the negotiation stage pay loan spreads 11.0 basis points (bps) lower, on average, than firms that do not. This difference in loan spreads translates into $0.475 million of savings in annual interest payments for the average sample firm. Our findings are robust to entropy balancing, which further

[3] Kim, Song, and Stratopoulos (2018) take the same approach as Vashishtha (2014) and address the selection concern by requiring both treatment and control firms to have appeared in the annual *InformationWeek* list of reputable information-technology firms at least once during their sample period of 10 years.

addresses the concern of selection on observables, and to changes analyses, which address the concern of omitted correlated time-invariant variables, including selection on unobservables.

We conduct three cross-sectional analyses to better understand the mechanism behind the negative associations between MEFs and loan spreads. If MEFs truly reduce information risk in loan pricing, we expect this effect to be more pronounced when lenders have a greater need to substantiate their private information. We examine three situations: (1) borrowers are at high financial distress risk, (2) lenders have no prior lending relationship with the borrower, and (3) borrowers are undergoing restructuring. We find some evidence of stronger associations for non-relationship lending than for relationship lending among small firms and substantial evidence of stronger associations for firms at high distress risk or firms undergoing restructuring.

We address three alternative explanations. First, firms with richer information environments enjoy lower loan spreads because of lower information asymmetry *and* these firms are more likely to issue MEFs and provide more precise MEFs in the negotiation stage. After controlling for the richness of a firm's information environment, the negative associations between MEFs and loan spreads remain largely unchanged. Second, managers may provide accurate MEFs to signal their ability to execute future operation and investment plans *and* these capable managers are more likely to provide MEFs and more precise MEFs in the negotiation stage. We calculate the accuracy of MEFs that are realized in the 24 months before loan origination and find that a borrower's *outstanding* MEFs provide incremental explanatory power for loan spreads above and beyond that of the accuracy of its *realized* MEFs. Last, firms may be more likely to provide good-news MEFs than bad-news MEFs to induce lower loan spreads. We observe that borrowers are as likely to provide good-news MEFs as bad-news MEFs in the negotiation stage and that MEF news is not associated with loan spreads. Thus, the disclosure opportunism explanation is not supported by our data.

In our final analysis, we examine the relation of MEFs with information asymmetry between the lead arranger and other lenders in a syndicate. Sufi (2007) argues that this information asymmetry hinders other lenders from participating and holding larger proportions of the loan. We find that MEF properties in the loan negotiation stage are associated with a smaller proportion of loan amount held by the lead arranger and with the loan amount more spread out among syndicate participants. The evidence suggests that MEFs reduce information asymmetry within a syndicate, consistent with the idea that MEFs reduce lenders' information risk.

We make two contributions to the literature. First, our study provides new insights into the role of accounting information in debt contracting. Most prior research focuses on realized accounting information. Controlling for the quality of a firm's financial reporting, we find that the occurrence, frequency, and precision of outstanding MEFs in the negotiation stage have incremental effects on loan pricing. These effects cannot be explained by managerial ability signaling and opportunistic disclosure—explanations that have been provided by prior research. The effects are consistent with the idea that outstanding MEFs can reduce lenders' information risk by corroborating their private information and reducing information asymmetry both between borrowers and lenders and among lenders in a syndicate.

Second, our study contributes to the research on the confirmation effects of accounting information.[4] This stream of research started with realized accounting information, which becomes available to investors only in the last stage of the financial reporting cycle (Gigler and Hemmer 1998; Ball and Shivakumar 2008; Ball, Jayaraman, and Shivakumar 2012). The argument for the confirmation role of realized financials is that, although not very timely, they can confirm the information that investors have collected from other, more timely sources. Corporate governance research expands the probe of the confirmation role of accounting information to public corporate disclosure in general. Duchin, Matsusaka, and Ozbas (2010) and Armstrong, Core, and Guay (2014) suggest that corporate disclosure improves board monitoring by corroborating outside directors' private information obtained from board meetings and managers. We extend this stream of research by exploring the corroboration role of MEFs in loan markets.

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[4] "Confirmation" is stronger than "corroboration." To "confirm" means to remove all doubt about something, whereas to "corroborate" means to lend support to something.

Our study has two caveats. The first caveat applies to most prior research on the confirmation role of accounting information: we cannot provide *direct* evidence on the corroboration role of MEFs in loan contracting because private information is not observable to researchers. Second, we document a benefit of MEFs but do not examine the costs of providing MEFs. One such cost is perhaps the inadvertent revelation of proprietary information to other stakeholders, especially competitors, who may take action against the disclosing firm. Disclosure costs can be one reason why not every firm provides MEFs to secure lower loan spreads. The findings we document represent a partial equilibrium, not a general equilibrium.

2. Background and Hypothesis Development

Most accounting research examines the role of accounting information in equity markets, but findings in equity markets do not necessarily carry over to debt markets (Armstrong et al. 2010; Blankespoor, Linsmeier, Petroni, and Shakespeare 2013). Equity holders' claims can be viewed as a call option on the firm's assets with an exercise price equal to the face value of the firm's debt; in contrast, debt holders' claims are a concave function of the firm's assets and the face value of the firm's debt (Merton 1974). Given their different payoff functions, debt holders have different information needs than equity holders. Debt holders are especially concerned about downside risk. That is, they might be extending money to a borrower that lacks the ability and willingness to make future interest and principal payments.

The credit risk that debt holders face has two components (Duffie and Lando 2001; Bharath et al. 2008; Demerjian 2019). The default risk component is inherent in a borrower's operations and investments. The information risk component is due to the fact that lenders have imperfect information about the borrowing firm and have less information than the firm itself. When lenders perceive information risk to be high, they price-protect themselves by charging higher effective interest rates. Our study focuses on how forward looking *public* voluntary disclosure facilitates loan contracting by reducing information risk.[5]

[5] Several studies have examined the role of financial reporting quality in debt contracting. Bharath et al. (2008) find that firms with poor accruals quality are more likely to use loans than bonds and that in loan markets, lenders charge higher interest rates for borrowers with lower accruals quality. Beatty, Liao, and Weber (2010) report that firms with lower accruals quality are more likely to borrow in the form of leases because lenders can repossess, as a protection, the leased property in the case of default. Costello and Wittenberg-Moerman (2011) find that lenders increase loan

For a given fiscal period, forward looking information is more timely than realized financials in informing lenders about borrowers' ability to make future payments. Thus, lenders' acquisition of accounting information from borrowers includes forward looking information (Minnis and Sutherland 2017; Carrizosa and Ryan 2017). For example, interviews conducted by Danos, Holt, and Imhoff (1989) indicate that loan officers collect both historical and forward looking information during office visits, and especially use forward looking information to assess a borrower's plan of utilizing and repaying the proposed loan. Lenders' effort to collect forward looking information in the loan negotiation stage does not necessarily mean that *MEFs* per se should be useful. It is very likely that the cash flow news contained in MEFs is communicated to lenders through their private access to the borrower and, therefore, MEFs provide no additional information about the borrower's default risk.

MEFs may facilitate loan negotiations by reducing information risk. In debt contracting, borrowers' interests may not align with those of lenders', and borrowers may communicate opportunistically to obtain favorable contracting terms. This is even more true with privately supplied forward looking information because such confidential communication cannot be monitored and scrutinized by a third party. Public disclosure can mitigate the credibility concern of such private communication. One feature of public disclosure is that it is received by a multitude of audiences. In cheap-talk models that consider unverified disclosure, the sender's and receiver's preferences differ and the sender has incentive to make a biased disclosure (e.g., Crawford and Sobel 1982; Farrell and Gibbons 1989). In certain situations, the sender must simultaneously send one message to multiple receivers who have diverse concerns (e.g., shareholders, competitors, creditors, and labor unions).[6] The diverse audiences discipline the sender into providing signals that more truthfully reveal her private information (Farrell and Gibbons 1989; Gigler 1994). For this

spreads and decrease their use of accounting-based contract terms after a borrower reports material internal control weaknesses. Graham, Li, and Qiu (2008) report a substantial increase in loan spreads for new loans originated after a firm announces an accounting restatement.

[6] Managers may wish to report optimistically to capital markets but reveal pessimistic information to competitors and labor unions.

reason, public disclosures are considered more credible than private communication (Bushman, Chen, Engel, and Smith 2004).

From our conversations with loan officers, we learned that lenders do not blindly trust what they receive from borrowers, but instead use public information to verify privately collected information. In addition, loan officers often need to justify their judgment and defend their lending decisions to their team members or before a committee (Danos et al. 1989). As forward looking public disclosures, MEFs provide an appropriate frame of reference for lenders to corroborate their private information. In addition to being received by a multitude of audiences, MEFs are subject to media scrutiny, private enforcement (e.g., litigation), and public enforcement (e.g., SEC actions).

Indeed, managers may make other types of forward looking public disclosures in the loan negotiation stage that lenders could also use for corroboration purposes. We use MEFs as a proxy for a borrower's forward looking public disclosures in the negotiation stage because of their three advantages. First, projected earnings are the most common type of information requested by lenders in private communication (Rajan and Winton 1995). Second, all firms have private information about their future earnings and, therefore, non-disclosure is not due to a lack of information endowment. Last, MEFs are reliably available in commercial databases, whereas other types of forward looking public disclosures are not. We acknowledge that the forward looking information presented in MEFs may not be exactly the same as the private information communicated to lenders. While MEFs are projections of an aggregated performance number, private communication may include disaggregated earnings, budgets, strategies, and investment plans. Lenders nevertheless can use MEFs to assess the reasonableness and consistency of private communication.

In addition to enhancing the credibility of private information that lenders, as a group, receive from a borrower, MEFs may decrease lenders' information risk by reducing information asymmetry within a loan syndicate. The vast majority of corporate loans are syndicated loans (Standard & Poor's 2011; Sufi 2007). Syndicate participants depend on the lead arranger to assess the true credit quality of the borrower even though the lead arranger contributes only a portion of the loan amount. The lead arranger receives upfront fees for managing a syndication process, including collecting the borrower's private information, setting a range for the interest rate, and negotiating contract terms. This practice gives rise to information asymmetry and moral hazard problems between the lead arranger and other participants, hindering the latter from holding large proportions of the loan amount. When information asymmetry within a syndicate is higher, the final interest rate is likely at the higher end of the range or even outside the range if the loan is undersubscribed.[7] MEFs may reduce this information asymmetry by corroborating private information that the lead arranger shares with other participating lenders or simply by making relevant information available to all participants.

As information risk decreases, lenders are expected to require a lower rate of return and therefore charge a lower loan spread. Therefore, we predict:

Hypothesis: A borrower's MEF activity in the loan negotiation stage with a forecast horizon beyond the loan origination date is negatively associated with loan spreads.

3. Sample and Key Measurements

3.1. Sample Selection

We collect loan data from the DealScan database assembled by Thomson-Reuters Loan Pricing Corporation. We begin our sample with 107,239 loan facilities originated by U.S. firms from January 1, 1998 to March 31, 2017.[8] Each loan deal (also referred to as a "package") may comprise multiple facilities that are negotiated together. To avoid dependence among facilities in the same package, we follow Houston, Jiang, Lin, and Ma (2014) and keep the largest facility in the package. This procedure reduces the number of loan facilities to 76,307. We exclude loan facilities that belong to financial firms, utility firms, and firms not in Compustat (private firms and a few public firms with total assets missing). This procedure reduces

[7] Before 1998, the lead arranger generally set a target spread before syndicating a loan. If the loan was later undersubscribed, the lead arranger ended up taking a larger share of the loan than what he had desired, but the loan spread remained fixed except for extreme cases. After the 1998 Russian debt crisis, market flex was introduced to allow the lead arranger to first set a range of spreads (also referred to as "price talk") and then determine where in the range to price the loan based on the demand from participating lenders (Standard & Poor's 2011).

[8] Our sample period begins in 1998 because MEF coverage is less complete before 1998. We end the sample period in March 2017 because the "Compustat Linking Table" in DealScan is updated to March 2017 (Chava and Roberts 2008).

our sample to 23,059 loan facilities. We require a firm-loan observation to have non-missing firm characteristic variables used in our primary analyses; 14,386 observations satisfy these data requirements. Finally, we require loan features (spread, size, maturity, type, and purpose) to be available in DealScan. This requirement reduces our firm-loans to 12,493.

We obtain MEF data from the union of First Call's Company Issued Guidelines (CIG) and Thomson-Reuters' IBES Guidance. CIG coverage begins in 1991, but is incomplete before 1998 (Chuk, Matsumoto, and Miller 2013). Thomson Reuters acquired First Call, discontinued CIG in early 2011, and replaced it with IBES Guidance. In untabulated analyses, we observe that CIG has more coverage than IBES before 2001 and IBES has more coverage than CIG after 2003. We use the union of the two datasets to identify MEFs.

One serious concern in our study is selection bias. That is, firms that choose to provide MEFs as a corporate disclosure policy might differ substantially from firms that choose not to. Some differences might be related to both MEF disclosure policies and credit risk, inducing a relation between MEFs and loan spreads. To address this concern, we exclude firms that do not provide any MEFs in the 24 months preceding loan origination. In other words, we examine firms that appear to have a corporate policy of providing MEFs but differ in MEF activity in the loan negotiation stage. Our final sample comprises 5,991 firm-loan originations. Table 1 summarizes the sample selection process and Panel A of Table 2 presents the sample distribution by year.

3.2. Key Measurements and Descriptive Statistics

Our sample firm-loans have a mean (median) value of $432 ($250) million for loan amount (*LoanSize*). Figure 1 plots the distribution of loan amount scaled by total assets at the end of the most recent fiscal quarter preceding loan origination. A typical loan accounts for 16.2% of a firm's total assets (untabulated). We observe time-series variation in loan size with a downward trend during economic recessions (2000-2003 and 2008-2009). The mean (median) loan maturity (*Maturity*) is 47 (60) months. On average, a loan has roughly 1.6 financial covenants (*FinCovenant*). In our sample, 73.9% of the loans are revolvers (*Revolver*) typically issued by banks and 17.0% are term loans issued by institutions such as structured investment vehicles, hedge funds, mutual funds, and insurance companies (*InstLoan*).[9] Using DealScan codes for the purposes of loans, we observe that 65.5% of the loans in our sample are for general corporate purposes and working capital purposes, followed by the purposes of takeover and acquisition (13.3%), debt repayment (8.8%), commercial paper backup (7.0%), and other (5.4%).

We follow the standard practice in the loan literature and use the "all-in-spread drawn" (AISD) in DealScan to measure loan pricing at origination. AISD, measured in bps, is the effective interest rate at which a borrower pays over LIBOR, including the coupon spread and annual fee. For this reason, loan pricing is also referred to as “loan spread.” The mean (median) loan spread (*LoanSpread*) of our sample loans is 183 (150) bps. Figure 1 plots the distribution of loan spreads for our sample. Like loan size, loan spreads exhibit time-series variation with increases during economic recessions. Due to the skewness of the variable, we follow Graham et al. (2008) and use the natural logarithm of loan spreads in regression analyses.

In constructing our MEF variables, we consider all MEFs regardless of periodicity (i.e., forecasts for either fiscal year or fiscal quarter earnings) and specificity (i.e., point, range, open-interval, or qualitative forecasts). We exclude MEFs that are issued after the forecasted fiscal period end because those MEFs are generally preannouncements of earnings. We measure the MEF variables in the negotiation stage and require the forecasted fiscal period to end after the loan origination date. We refer to such MEFs as “outstanding” at loan origination.[10]

Following Dhaliwal et al. (2011) and Lo (2014), we examine the occurrence, frequency, and precision of MEFs. The indicator variable, *MEFdum*, is 1 if a firm issues an outstanding MEF in the loan negotiation stage and 0 otherwise. Panel B of Table 2 reports that the mean of *MEFdum* is 0.621, indicating

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9 A *revolver loan* is an arrangement that allows the loan amount to be withdrawn, repaid, and redrawn repeatedly until the arrangement period expires and is also called “line of credit” (Sufi 2009). A *term loan* is a loan for a specific amount that has a specified repayment schedule and a fixed or floating interest rate.

10 For example, assume a firm issues an MEF on February 18 for Q1 with the forecasted period end on March 31. If a loan is originated on March 15, the MEF is outstanding. If a loan is issued on April 15, the MEF is not outstanding. Our requirement is more restrictive (e.g., we count fewer MEFs) than the requirement that MEFs be issued before the firm’s earnings announcement. After a fiscal period is over and before loan signing, lenders could ask for preliminary financial statements before their public release and this request may reduce the value of existing MEFs.

that 62.1% of our firm-loan observations have an outstanding MEF in the negotiation stage. Panel A of Table 2 shows the distribution of *MEFdum* by year and we observe an upward trend. The trend suggests that firms with a policy of issuing MEFs increasingly provide MEFs in the negotiation stage before loan origination over the years. We measure forecast frequency, *MEFfreq,* as the number of outstanding MEFs issued in the negotiation stage and set *MEFfreq* to 0 if no outstanding MEF is issued. The mean (median) value of *MEFfreq* for our sample is 1.533 (1).[11] *MEFfreq* also exhibits an upward trend in Panel A of Table 2.

Dhaliwal et al. (2011) use a categorical variable to measure forecast precision and set the variable to 3 for point estimates, 2 for range estimates, 1 for other estimates, and 0 for firms without an MEF. During our sample period, approximately 81% of MEFs are range estimates, so using one value for all range forecasts appears crude. We refine Dhaliwal et al.'s measure by using forecast width. We set forecast width to 0 for point estimates and compute the width of range estimates as the difference between the upper- and lower-bound estimates scaled by the absolute value of their midpoint. For ease of interpretation, we define precision as forecast width multiplied by -1 so that a higher value indicates greater precision. For a firm-loan observation, forecast precision, *MEFprecision,* is the mean precision value of all outstanding MEFs in point or range format issued in the negotiation stage. Untabulated results show that our sample mean (median) of *MEFprecision* for firm-loans with at least one point or range outstanding MEF in the negotiation stage is -0.091 (-0.050) and the maximum (minimum) value is 0 (-1.0). These statistics are consistent with Cheng, Luo, and Yue (2013).

We cannot calculate *MEFprecision* for 2,419 firm-loan observations (40.4% of the sample). In this group, 2,271 observations do not have an outstanding MEF in the negotiation stage and the remaining 148 observations have at least one outstanding MEF but not in point or range format. To avoid losing these observations, we set the value of *MEFprecision* for these observations to -1.1, just below the minimum value of *MEFprecision* for firm-loans that have a point or range forecast. This assignment is similar to the

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[11] If we calculate forecast frequency using only firms that provide at least one outstanding MEF in the negotiation stage, the mean (median) forecast frequency is 2.469 (2).

research design choices in Dhaliwal et al. (2011) and Baginski and Rakow (2012), who set the value of their catogorical precision measure to 0 for observations without any MEF. After this assignment, the mean (median) value of *MEFprecision* is -0.498 (-0.127).

4. MEF Properties and Loan Pricing

4.1. Research Design

We use Equation (1) to test the relation between MEF properties in the loan negotiation stage and loan spreads. The dependent variable is the natural logarithm of loan spread. The explanatory variables are the MEF variables: *MEFdum*, *MEFfreq*, and *MEFprecision.*

$$\begin{aligned}\text{Log}(\textit{LoanSpread}) = \alpha &+ \beta\,(\text{MEF variable}) + \gamma\,(\text{Firm characteristics}) \\ &+ \delta\,(\text{Loan features}) + \theta\,(\text{Macroeconomic factors}) \\ &+ \text{Industry fixed effects} + \text{Year fixed effects.} \qquad (1)\end{aligned}$$

Following Bharath et al. (2008) and Graham et al. (2008), we include three sets of control variables: firm characteristics, loan features, and macroeconomic factors (see Appendix 1 for variable definitions). We control for firm characteristics that are associated with default risk or expected loss recovery given default. The variables include firm size (*Size*), profitability (*ROA*), earnings volatility (*StdROA*), financial structure (*Leverage*), market-to-book ratio (*MTB*), asset tangibility (*Tangibility*), interest coverage (*IntCov*), financial distress (*Oscore*), and S&P credit rating for the issuer (*CreditRate*).[12] All the variables except *Oscore* are measured at the end of the most recent fiscal quarter before loan origination. We measure financial distress (*Oscore*) using the accounting information for the most recent fiscal year preceding loan origination and the formula provided by Ohlson (1980). A higher *Oscore* indicates greater financial distress risk and a lower ability to honor financial obligations.

The firm characteristics also include accruals quality (*AbsAccrual*) measured at the end of the most recent fiscal year preceding loan origination. *AbsAccrual* is the absolute value of the residual from the

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[12] We collect ratings data from Captial IQ S&P Credit Ratings. The original credit rating variable is coded as an ordinal value corresponding to ratings ranging from D (lowest credit rating) to AAA (highest credit rating). We recode this variable so that the value of *CreditRate* is 0 for the 2,793 firms without a rating and an integer value from 1 to 22 for firms with a rating, where 1 corresponds to the lowest credit rating and 22 the highest.

accruals model estimated in an industry panel dataset with firm fixed effects and year fixed effects (Kothari, Mizik, and Roychowdhury 2016). The firm fixed effects allow a firm's accruals to deviate from the industry norm because of its unique operations without being flagged. Higher *AbsAccrual* indicate lower accounting reporting quality. In addition, we control for analyst coverage because analysts can turn private information into public information, helping reduce loan spreads, and demand MEFs for their own earnings forecasting.

The loan-features variables include loan size (Log[*LoanSize*]), maturity (Log[*Maturity*]), number of financial covenants (*FinCovenant*), loan type (*Revolver* and *InstLoan*), and loan purpose. Revolver loans (*Revolver*) are often priced at lower interest rates, whereas institutional term loans (*InstLoan*) are riskier, have more severe agency problems, and are priced at higher interest rates (Costello and Wittenberg-Moerman 2011). Loan purpose may be a signal of loan risk. We follow Sufi (2007) and aggregate loan purposes into five categories: (1) general corporate purpose and working capital, (2) takeover and acquisition, (3) debt repayment, (4) commercial paper backup, and (5) all others. We control for loan purposes by including their fixed effects.

Macroeconomic conditions, especially market-wide default risk, may affect individual loan pricing (Graham et al. 2008) and firms' decisions to issue MEFs (Kim, Pandit, and Wasley 2016). We include credit spread (*CreditSpread*) and term spread (*TermSpread*). Credit spread is the difference between the yields of BAA- and AAA-rated corporate bonds. Because lenders require a higher premium for increased default risk in bad economic times, credit spreads tend to widen in recessions and shrink in expansions. Term spread is the difference between the 10-year and 2-year U.S. Treasury yields and reflects investors' expectations of future interest rates. We collect data from the Federal Reserve Board of Governors and construct the variables in the most recent month preceding loan origination.

Finally, we include industry fixed effects to account for industry factors in raising capital and include year fixed effects to account for credit supply variation. We use the Fama and French 48-industry classifications and cluster standard errors by firm in regression estimations.

4.2. Primary Results

Panel B of Table 2 presents descriptive statistics of the variables used in Equation (1). The average sample firm owns $4,379 million in total assets; reports a return on assets of 0.009; funds 29.1% of total assets using debt; and has a market-to-book ratio of 1.761, PPE intensity of 26.0%, interest coverage ratio of 19.658, Ohlson's (1980) O-score of -1.141, and absolute abnormal accrual of 0.071. The mean value of credit rating is 6.399, which falls between CCC+ and B-. If we exclude firms without S&P credit ratings, the mean value of credit rating is 12.47, a rating between BBB- and BB+ (untabulated). The average sample firm is followed by approximately eight analysts.[13] Compared with the average Compustat firm, our sample firms are much larger (4,379 vs. 1,050 million in *TA*) and less levered (0.291 vs. 0.452 in *Leverage*), and they perform better (0.009 vs. -0.152 in *ROA*).

Table 3 reports pairwise correlations of the variables in Equation (1). The three MEF variables are highly correlated with one another. All three MEF variables are negatively correlated with loan spreads. Except for the correlations of *Size* with *CreditRate*, *Analyst*, and Log(*LoanSize*) and the correlation between *Leverage* and *Oscore*, all correlations are well below 0.500, suggesting minimal concern about multicollinearity.

Panel A of Table 4 reports univariate analyses with graphical illustration in Figure 2. We partition the sample in three ways. First, we separate firm-loan observations with a value of 0 for *MEFdum* from those with a value of 1. The mean (median) loan spread is 207.251 (175.000) bps for firms without any outstanding MEF in the negotiation stage, but 167.817 (150.000) bps for firms with an outstanding MEF. The former group bears significantly higher costs of debt than the latter group. Second, we partition the sample into three subsamples based on *MEFfreq*. We classify firms with a value of 0 for *MEFfreq* as "low" and sort the remaining observations into "medium" (below or equal to the median) and "high" (above the median) groups based on these observations' median value of *MEFfreq* each year. The mean (median) loan

[13] There are 747 firm-loan observations with zero analyst coverage. For observations with positive analyst coverage, the average number of analysts is 9.46, consistent with other loan studies (e.g., Ali et al. 2018).

spread is 207.251 (175.000) bps, 176.986 (150.000) bps, 154.428 (125.000) bps for the three subsamples, respectively, and the differences between consecutive subsamples are statistically significant.

Finally, we partition the sample into three subsamples based on *MEFprecision*. We classify firms without any point or range outstanding MEF in the negotiation stage as "low" and the remaining observations as "medium" (below or equal to the median) or "high" (above the median) based on these observations' median value of *MEFprecision* each year. The mean (median) loan spreads is 205.358 (175.000) bps, 183.897 (150.000) bps, 150.886 (125.000) bps for the three subsamples and the differences between consecutive subsamples are statistically significant. These results indicate that the loan spreads of firms with differential MEF activity in the negotiation stage differ significantly and that the differences are economically significant.

The first three columns of Panel B of Table 4 reports the OLS estimations of Equation (1) using the original sample.[14] In Column 1, the coefficient on *MEFdum* is significantly negative (coef. = -0.054; t = -3.40). Because the dependent variable is log transformed, this coefficient means that the average loan interest rate paid by firms with an outstanding MEF in the negotiation stage is 94.7% (exp[-0.054] = 0.947) of the average loan interest rate paid by firms without an outstanding MEF. The difference means that the former firms pay interest rates 11.0 bps lower than the rates paid by the latter firms, translating into $0.475 million of annual savings in interest payments.[15] This benefit is economically significant and comparable to the magnitude of interest saving in prior research. For example, Saunders and Steffen (2011) find that public firms incur $0.64 million lower annual loan interest charges than private firms.

In Column 2, the coefficient on *MEFfreq* is -0.010 (t = -2.10). This coefficient means that if a firm provides one more MEF in the negotiation stage, on average its loan interest rate becomes 99.0% (exp[-

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14 The Variance Inflation Factor is under 10 for each covariate in the regression, indicating that multicollinearity is not a concern. We also use a robust-regression estimation method (e.g., Proc Robustreg in SAS) and the results for *MEFdum*, *MEFfreq*, and *MEFprecision* are largely unchanged.

15 Let Y_1(Y_0) be the loan spread for firms with the value of 1 (0) for *MEFdum*. The coefficient of -0.054 on *MEFdum* means that $\text{Log}(Y_1) – \text{Log}(Y_0) = -0.054$. Thus, $Y_1/Y_0 = \exp(-0.054) = 0.947$. So, $(Y_1-Y_0)/Y_0 = -0.053$. Note that Y_0 = 207.251 bps according to Panel A of Table 4. Therefore, $Y_1-Y_0 = 207.251 * (-0.053) = -11.0$ bps. In our sample, the mean loan size is $432 million. The annual interest savings by the average firm that provides an outstanding MEF in the negotiation stage is $0.475 million ($432 * 0.0011 = $0.475).

0.010] = 0.990) of the rate level before issuing the additional MEF. The difference means an interest rate 1.8 bps (full-sample mean 182.766 * [1- 0.990] = 1.8) lower, equivalent to $0.078 million ($432 * 0.00018 = $0.078) of annual interest savings.

In Column 3, the coefficient on *MEFprecision* is significantly negative at -0.075 (*t* = -4.83). Recall that *MEFprecision* is 0 for firms with outstanding MEFs in point estimates and -1.1 for firms without any point or range outstanding MEF in the negotiation stage. This coefficient means that, on average, the loan spread of the former firms is 92.1% (exp[-0.075 * 1.1] = 0.921) of that of the latter firms. The difference—16.2 bps (205.358 * (1 - 0.921) = 16.2) lower interest rate—translates into $0.700 million ($432 * 0.00162 = $0.700) of annual interest savings.[16]

The estimation results for the control variables are consistent with our expectations. We find that larger firms, firms with higher growth options, and less-levered firms have smaller loan spreads. Firms with more tangible assets that could serve as collateral enjoy lower spreads. Firms that generate more operating income and are therefore better able to service their debt obligations enjoy lower spreads. Firms with higher earnings volatility and therefore greater uncertainty incur higher loan costs. Higher financial distress risk is associated with higher loan spreads; firms with higher credit ratings enjoy lower spreads.

Regarding loan features, loan size is negatively associated with loan spread. The coefficient on loan maturity is significantly positive, indicating that lenders demand a risk premium for loans with longer maturities. The positive coefficient on the number of financial covenants is consistent with the idea that lenders tend to include such covenants for riskier loans. These results suggest that several loan features go hand in hand: riskier loans bear higher interest rates, have smaller loan amounts, and have more financial covenants.[17]

[16] If we exclude firms without any point or range outstanding MEF in the negotiation stage, we have 3,572 observations and the coefficient on *MEFprecision* is -0.207 with *t*-statistic of -3.39. If we follow Dhaliwal et al. (2011) and use forecast specificity to measure precision (3 for point, 2 for range, 1 for other formats of forecasts, and 0 for no forecasts), the coefficient is -0.020 (*t* = -3.84).

[17] We do not find evidence that MEF properties in the loan negotiation stage are associated with non-price contract terms: loan size, maturity, the number of financial covenants, and the inclusion of performance pricing provisions (untabulated).

Despite our effort in addressing selection bias, our sample firms with outstanding MEFs in the negotiation stage (treatment firms) still differ from those without any outstanding MEF (control firms) in most of our covariates. The imbalanced covariates may result in a biased estimate of the treatment effect. To further address selection bias, we use entropy balancing to achieve covariate balance (Hainmueller 2012). As suggested by Hainmueller and Xu (2013), we impose the constraint that after reweighting, the control firms' covariates have the same first moments as the treatment firms' covariates. The technique produces a weight for each control observation; 77.6% of the weights are in the interval of [0.5, 1.5], 7.2% are less than 0.5, 7.7% are in the interval of (1.5, 2.5], and 7.5% are greater than 2.5. Then we estimate weighted least squares regressions and report the results in the last three columns of Panel B. The coefficients on *MEFdum* and *MEFprecision* remain significantly negative and the coefficient on *MEFfreq* is now weakly significantly negative. Three control variables have different results from Columns 1-3: *AbsAccrual* now has a significantly positive coefficient, consistent with Bharath et al. (2008); *Analyst* no longer has significant explanatory power; and the statistical significance for *CreditSpread* has weakened. From now on, we report results based on the original sample; our results using the entropy balanced sample are similar.

In sum, we find that the occurrence, frequency, and precision of MEFs issued in the loan negotiation stage that are still outstanding at the time of loan origination are significantly negatively associated with loan spreads. The effect of MEFs on loan pricing is economically meaningful.

4.3. Changes Analyses

To mitigate the concern that our inferences from estimating Equation (1) might be affected by omitted correlated variables, we now estimate the changes version of Equation (1) to purge the effects of time-invariant variables, including those observable and those unobservable. For the changes version of each variable, we subtract from the value of the current firm-loan observation the value of the most recent loan origination observation for the same firm in the [-36, -6] month window. We require the previous loan to be at least six months before the current loan so that the firm characteristics variables are different between the two loans. We limit the previous loan to be within 36 months of the current loan to reduce the chance that omitted correlated variables have undergone substantial changes by the time of the current loan origination. We do not include industry fixed effects and year fixed effects.[18]

We report the estimations of the changes regression in Table 5. The coefficients of -0.052 on Δ*MEFdum* (*t* = -2.74), -0.013 on Δ*MEFfreq* (*t* = -2.49), and -0.068 on Δ*MEFprecision* (*t* = -3.80) are all significantly negative, suggesting that lenders react favorably to a firm's improved MEF activity. Overall, the changes analyses alleviate the concern that our primary finding might be driven by time-invariant omitted correlated variables.

4.4. Cross-sectional Analyses

We explore three scenarios in which lenders' need for corroborating private information is greater and thus the effects of MEFs on loan spreads are expected to be more pronounced. The first scenario relates to borrowers' financial distress risk. When firms have high distress risk based on reported GAAP-compliant accounting numbers, managers may resort to private communication with current and future lenders. Such private communication could put a firm's current poor financial position or performance in context and guide lenders in projecting the firm's future performance. The credibility of private communication is arguably more important than ever because managers likely have strong incentives to provide a narrative that suits their goals. MEFs may enhance the credibility of lenders' private communication with high-distress-risk firms more than with low-distress-risk firms.

To facilitate interpreting the interaction terms, we create a dummy, *DistressRisk*, from *Oscore*. *DistressRisk* is 1 for a firm-loan observation if the firm's *Oscore* is above the median value of all sample observations in the same fiscal year and 0 otherwise. We estimate four variants of Equation (1): the first one has *DistressRisk* as the variable of interest without the MEF variables and the other three include

[18] A changes analysis might not be able to detect a relation between the changes in MEF properties and the changes in loan spreads if there is little variation in the MEF variables over time. In our sample, 393 (405) firms increase (decrease) *MEFdum* from the previous loan to the current loan; 935 (925) firms increase (decrease) forecast frequency; and 1,111 (1,031) firms increase (decrease) forecast precision. Thus, there is sufficient time-series variation in the MEF variables for the changes analyses.

DistressRisk and its interaction term with the three MEF variables one at a time. Panel A of Table 6 reports the estimation results.

In Column 1, *DistressRisk* alone has a positive coefficient, suggesting that loan spreads are higher for firms at high distress risk than for firms at low distress risk. In the remaining columns, the main effects of the MEF variables are not significantly different from zero, suggesting that MEFs do not affect the loan spreads of firms at low financial distress risk. In contrast, the sum of coefficients of the main effect and interaction effect is significantly negative across the three MEF variables (untabulated), suggesting that MEFs affect the loan spreads of firms at high financial distress risk. In other words, the negative associations between MEFs and loan spreads exist only for borrowers at high financial distress risk. Moreover, the interaction terms between *DistressRisk* and the MEF variables are all significantly negative, suggesting that the effects of MEFs on loan spreads are significantly stronger for borrowers at high financial distress risk than for other firms.

Second, we examine whether the associations between MEFs and loan spreads are stronger for non-relationship lending than for relationship lending. Although all lead arrangers bidding for a loan have access to a borrower's private information upon signing the confidentiality agreement, those who already have a lending relationship with the borrower have extensive, customer-specific soft information (Bharath, Dahiya, Saunders, and Srinivasan 2009). Borrowers may also be more inclined to reveal sensitive information to relationship lenders. Thus, relationship lenders may have less need to confirm their private information than non-relationship lenders.

Following Bharath et al. (2009), we define a loan as a non-relationship loan (*NonRelation* is 1) if the lead arranger did not serve as lead arranger of any loan to the firm in the five years preceding current loan origination and as a relationship loan (*NonRelation* is 0) otherwise. Our *NonRelation* variable is available for 5,267 firm-loans and 1,937 of them are non-relationship loans. When we use the full sample and add *NonRelation* and its interaction terms with the MEF variables to Equation (1), none of the interaction terms are statistically significant (untabulated).

Prior research finds that the benefits of relationship lending are greater for small firms than for large firms (Bharath et al. 2009; Chen and Martin 2011). To sharpen our tests, we focus on the 2,519 loans issued to small firms that have total assets below the median value each year. In this group, 1,142 are non-relationship loans. Panel B of Table 6 reports that the MEF variables are negatively associated with loan spreads for both relationship loans and non-relationship loans (sum-of-coefficient tests untabulated). The negative associations between *MEFdum* and loan spreads and between *MEFprecision* and loan spreads are weakly more significant for non-relationship loans than for relationship loans; the negative association between *MEFfreq* and loan spreads is not significantly different between relationship and non-relationship loans. Thus, we find some evidence that MEFs have a stronger effect on non-relationship loans than relationship loans among small firms.

The last scenario relates to business restructuring. Restructuring often involves reorganizing the corporate structure and downsizing various divisions. The changing corporate structure and business arrangements make it difficult for lenders to assess a firm's prospects. Moreover, accounting for restructuring uses many estimates, such as the costs of laying off employees and goodwill impairment. We expect increased private communication between borrowers and lenders when borrowers undergo restructuring and therefore expect a greater need for lenders to corroborate their private information.

Restructure is 1 if the sum of restructuring charges in the most recent fiscal year before loan origination and in the year of loan origination is more than 1% of the total assets at the end of the most recent year before loan origination and 0 otherwise. In our sample, 1,453 (24.3%) have a value of 1 for *Restructure*. We conduct four tests and report them in Panel C. *MEFdum* and *MEFprecision* are significantly negatively associated with loan spreads for firms without restructuring. All three MEF variables are significantly negatively associated with loan spreads for restructuring firms (sum-of-coefficient tests untabulated). More importantly, the effects of *MEFdum* and *MEFprecision* on loan spreads are significantly stronger and the effect of *MEFfreq* is weakly significantly stronger for restructuring firms than for other firms.

The consistent evidence in the above three scenarios indicates that MEF activity in the negotiation stage has a stronger effect on loan spreads when lenders have a greater need to corroborate their private communication. The results better our understanding of the mechanism through which MEFs affect loan spreads and help address the omitted variables concern because these variables are unlikely to induce predicted variation in the association across different subsamples.

5. Alternative Explanations

5.1. Is the Association between MEFs and Loan Spreads Due to a Firm's General Information Environment?

An alternative explanation for the negative association between MEFs and loan spreads is that firms with richer information environments enjoy lower loan spreads because of lower information asymmetry *and* these firms are more likely to issue MEFs and provide more precise MEFs in the negotiation stage. If a firm's information environment is largely stable, it should not contribute to the negative associations between the changes in MEF properties and the changes in loan spreads in Table 5. Now we directly control for information environment.

Following Carrizosa and Ryan (2017), we use *InfAsymmetry* to proxy for the overall information asymmetry between a firm's insiders and outsiders. The variable is the common factor from the principal component analysis of inverse firm age, bid-ask spread, and stock return volatility. We add *InfAsymmetry* to Equation (1) and report the estimated results in Panel A of Table 7. As expected, higher information asymmetry is associated with higher loan spreads. More importantly, after we control for *InfAsymmetry*, the coefficients on *MEFdum* and *MEFprecision* remain significantly negative and the coefficient on *MEFfreq* is weakly significantly negative. These findings suggest that our primary finding is not driven by a borrower's general information environment.

5.2. Is the Association between MEFs and Loan Spreads Due to Managerial Ability Signaling?

Given the finding of Demerjian et al. (2019), an alternative explanation for the association between MEFs and loan spreads is that managerial ability signaling through MEF forecast accuracy is an omitted correlated factor that drives our primary finding. We measure the accuracy of MEFs (in point or range format) that are realized in the 24 months preceding loan origination. The accuracy of each individual forecast is calculated as -1 times the absolute difference between the actual EPS and forecasted EPS (the upper bound is used for range forecasts), scaled by the absolute value of actual EPS. For a firm-loan observation with multiple realized MEFs in this window, we use the mean value of accuracy of all MEFs and call the variable *MEFaccuracy*. The variable is available for 5,237 firm-loan observations. We add *MEFaccuracy* to Equation (1) and report the estimation results in Panel B of Table 7. The coefficient on *MEFaccuracy* is significantly negative in Column 1, consistent with Demerjian et al. (2019). More importantly, after controlling for *MEFaccuracy*, the coefficients on *MEFdum* and *MEFprecision* are still significantly negative and the coefficient on *MEFfreq* is weakly significantly negative. Thus, our primary finding is robust to controlling for managerial ability signaling.

5.3. Is the Association between MEFs and Loan Spreads Due to Borrowers' Opportunism?

Hsieh et al. (2019) find weak evidence (e.g., significant at the 10% level) that firms tend to provide good-news MEFs before the quarter of new loan origination and that good-news MEFs are associated with lower loan spreads. Their findings suggest that borrowers' opportunistic disclosure can be a plausible explanation for our documented negative associations between MEFs and loan spreads. We conduct two tests to examine whether this is the case.

First, we additionally control for the news of MEFs issued in the negotiation stage in Equation (1). Forecast news for each MEF is calculated as the difference between the point estimate or the upper bound of range estimate and the most recent analyst consensus before MEF issuance, scaled by the absolute value of the consensus. For 246 firm-loans without analyst coverage, we use realized EPS for the previous year as the benchmark for annual MEFs and use realized EPS in the same fiscal quarter in the previous year as the benchmark for quarterly MEFs. If a firm provides more than one outstanding MEF in the negotiation stage, we aggregate forecast news. In an untabulated analysis, we find that MEF news does not have any explanatory power for loan spreads, suggesting that MEFs do not provide *cash flow* news to lenders, consistent with lenders having private access to borrowers.[19]

Second, we count firm-loans that are preceded by positive or negative MEF news in the negotiation stage. In our sample, 1,659 (27.7%) have positive MEF news, 1,784 (29.8%) have negative news, 96 have neutral news, 148 have MEFs that are not in point or range format, 33 have point or range MEFs but no proxy for expected earnings, and 2,271 have no outstanding MEFs (see Panel C of Table 7). Thus, the percentage of firm-loans with positive MEF news is very similar to that of firm-loans with negative MEF news, inconsistent with disclosure opportunism.

6. MEF Properties and Information Asymmetry within a Loan Syndicate

We proxy for information asymmetry within a loan syndicate by the lead arranger's share of the loan amount (*LeadShare*) and the concentration ratio of the loan amounts allocated to all participating lenders (*SynConcentration*) (Sufi 2007). We have 1,770 syndicated loans with available data to calculate *LeadShare* and *SynConcentration*.[20] More than half of these loans (53.3%) have one lead arranger, 28.3% have two lead arrangers, and the remaining 18.4% have more than two lead arrangers. For loans with more than one lead arranger, we sum the loan shares retained by all lead arrangers to calculate *LeadSahre*. The mean values of *LeadShare* and *SynConcentration* are 0.363 and 0.201, respectively.

We estimate a variant of Equation (1) with *LeadShare* and alternatively *SynConcentration* as the dependent variable. When *LeadShare* is the dependent variable, the coefficients on *MEFdum* and *MEFfreq* are significantly negative and the coefficient on *MEFprecision* is weakly significantly negative (see Panel A of Table 8). When *SynConcentration* is the dependent variable, the coefficients on *MEFdum* and *MEFfreq* are significantly negative and the coefficient on *MEFprecision* is not significantly different from

[19] Alternatively, we measure forecast news using the sum of market-adjusted stock returns from the day before to the day after MEF issuance and find similar results.

[20] We have loan amount allocations data for 30.4% of syndicated loans. This rate is between 28.4% in Chen and Martin (2011) and 40.5% in Sufi (2007). The loans with missing data tend to be institutional loans and have lower loan amounts and higher loan spreads than our test sample.

zero (see Panel B). Taken together, these findings suggest that MEF activity in the loan negotiation stage reduces information asymmetry within a syndicate.

7. Conclusion

Even though loans are the principal source of external funds to U.S. firms, we know very little about whether MEFs—the most common type of forward looking voluntary disclosure—matter in loan markets. The paucity of evidence is probably due to the long-held view that private lenders have substantial access to borrowers' private information and therefore have no need for MEFs. While they may not provide cash flow news to private lenders, MEFs can enhance the credibility of lenders' private information and therefore reduce information risk and loan spreads.

We find strong evidence that the occurrence, frequency, and precision of MEFs issued in the negotiation stage that remain outstanding at loan origination are negatively associated with loan spreads. The relations are stronger in situations where lenders' need for corroboration of private information is expected to be greater. Our findings are not due to a firm's general information environment, signaling of managerial ability, or disclosure opportunism. Moreover, we find evidence of lower information asymmetry within a loan syndicate for firms with more MEF activity in the loan negotiation stage. Our study provides new insights into the role of publicly disseminated MEFs in private loan markets.

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Appendix 1
Variable Definitions

Management Earnings Forecasts (MEF) variables. Source: CIG and IBES Guidance.

MEFdum	=	1 if the sample firm issues an MEF in the six months preceding the loan origination date and the forecasted period ends after the loan origination date (referred to as an "outstanding MEF") and 0 otherwise. The six months preceding the loan origination date is referred to as the "loan negotiation stage."
MEFfreq	=	the number of outstanding MEFs.
MEFprecision	=	the average precision score of outstanding MEFs. A precision score is forecast width multiplied by -1. Forecast width is set to 0 for point forecasts. For range forecasts, forecast width is the difference between the upper- and lower-bound estimates scaled by the absolute value of the midpoint. The minimum value of *MEFprecision* for our firm-loan observations that have an outstanding MEF in a point or range format is -1. For the firm-loan observations that do not have an outstanding MEF in a point or range format, we set the value of *MEFprecision* at -1.1 to preserve these observations.

Firm characteristics measured at the end of the most recent fiscal quarter preceding loan origination unless otherwise stated. Sources: Compustat unless otherwise stated. Variables in parentheses are the variable names in Compustat.

TA	=	total assets (ATQ) in millions of dollars.
Size	=	the natural logarithm of *TA*.
ROA	=	operating income after depreciation (OIADPQ) divided by *TA*.
StdROA	=	the mean of the absolute seasonal difference in *ROA* (i.e., *ROA* in a quarter minus *ROA* in the same quarter in the previous year) for the most recent 12 quarters before loan origination. We require a minimum of four seasonal differences to construct *StdROA*.
Leverage	=	long-term debt (DLTTQ) plus short-term debt (DLCQ) divided by *TA*.
MTB	=	*TA* minus book value of equity (CEQQ) plus market value of equity (PRCCQ*CSHOQ) divided by *TA* (see Graham et al. 2008).
Tangibility	=	property, plant, and equipment (PPENTQ), scaled by *TA*.
IntCov	=	operating income after depreciation (OIADPQ) divided by interest expense (XINTQ).
Oscore	=	Ohlson's (1980) O-score, calculated using the following formula: *Oscore* = -1.32 - 0.407 × log(AT / PPI) + 6.03 × (LT/AT) - 1.43 × ((ACT - LCT) / AT) + 0.0757 × (LCT / ACT) -1.72 × X - 2.37 × (NI / AT) - 1.83 × (OANCF / LT) + 0.285 × Y - 0.0521 × ((NI_t - NI_{t-1}) / (abs(NI_t) + abs(NI_{t-1})), where all variables are from the most recent fiscal **year** (*t*) preceding loan origination; PPI is price index; X = 1 if LT > AT and 0 otherwise; and Y=1 if the total of NI for years *t* and *t*-1 is negative and 0 otherwise. A higher value of *Oscore* indicates greater financial distress risk.
CreditRate	=	an ordinal coding of Standard & Poor's issuer-level credit ratings that ranges from 0 to 22. We set *CreditRate* to 0 for firms without a rating, 1 for firms with the lowest rating, and 22 for firms with the highest rating. The ratings data are from Capital IQ S&P Credit Ratings.
AbsAccrual	=	absolute value of the residual of the following regression estimated using the industry (2-digit SIC) panel dataset for all Compustat firms over the period of

1995 to 2016: $TotAccruals_t = d_0 + d_1(1/AT_{t-1}) + d_2(\triangle REV_t - \triangle AR_t) + d_3 PPE_t + d_4 Earn_{t-1}$ + firm fixed effects + year fixed effects + ε_t, where *TotAccruals* is the difference between earnings and operating cash flow (IBC - (OANCF - XIDOC)) scaled by lagged total assets; $\triangle REV_t - \triangle AR_t$ is the change in revenue (SALE) minus the change in accounts receivable (RECCH) scaled by lagged total assets; *PPE* is property, plant and equipment (PPNET) scaled by lagged total assets; and *Earn* is earnings before extraordinary items (IB) divided by lagged total assets. We use three more years before the beginning of our sample period to have a longer panel for estimation. *AbsAccrual* is measured for the most recent fiscal **year** preceding loan origination.

Analyst = the monthly mean number of analysts who provide annual earnings forecasts for the firm in the loan negotiation period according to IBES's summary data file.

Loan-specific variables. Source: DealScan.

LoanSpread = the interest rate that a borrower pays over LIBOR in basis points (bps).

LoanSize = loan amount in millions of dollars.

Maturity = loan maturity measured in months.

FinCovenant = the number of financial covenants. We follow Costello and Wittenberg-Moerman (2011) and set the variable to 0 when a loan is not subject to any financial covenants.

Revolver = 1 if the loan's type is a revolver loan (line of credit) and 0 otherwise.

InstLoan = 1 for institutional loans if the loan's type is Term Loan B or below (C, D, E, and F) and 0 otherwise.

Macroeconomic factors measured in the most recent month preceding loan origination. Source: Federal Reserve Board of Governors.

CreditSpread = the difference between the yields of BAA- and AAA-rated corporate bonds.

TermSpread = the difference between the yields of 10- and 2-year U.S. treasury bills.

Other variables

DistressRisk = 1 if a firm's *Oscore* for the most recent fiscal year preceding loan origination is above the median value of all sample observations in that fiscal year and 0 otherwise.

NonRelation = 1 if the lead arranger did not serve as lead arranger of any loan to the firm in the five-year period preceding loan origination and 0 otherwise. Source: DealScan.

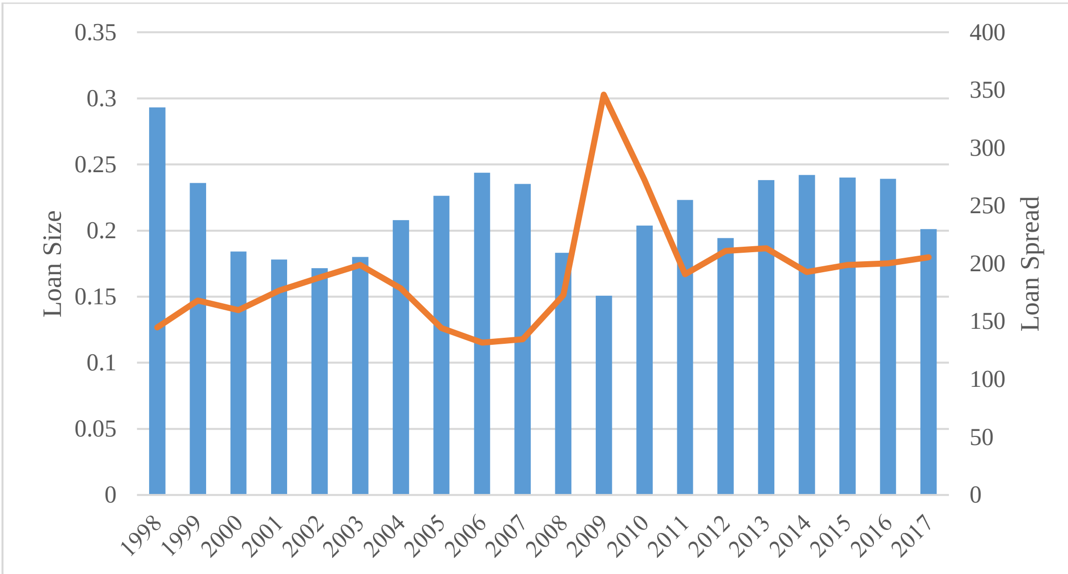
Restructure = 1 if the sum of restructure charges (RCP) in the most recent fiscal year before loan origination and the year of loan origination divided by total assets at the end of the most recent year before loan origination is greater than 1% and 0 otherwise. Source: Compustat.

InfAsymmetry = a composite measure of information asymmetry. It is the common factor extracted from the principal component analysis of inverse firm age (1/age), bid and ask spread, and stock return volatility. Bid-ask spread is the average monthly closing spread over the 1-year period before loan origination. Stock return volatility is the standard deviation of monthly abnormal return (raw stock return minus the return of the value-weighted market index) in the 1-year period before loan origination. Source: CRSP.

MEFaccuracy = the average accuracy of all MEFs realized in the 24-month window preceding loan origination. The accuracy of each forecast is calculated as -1 times the

		absolute difference between actual EPS and forecasted EPS scaled by the absolute value of actual EPS (obtained from IBES Actuals data file). The upper bound is used for range forecasts (Ciconte, Kirk, and Tucker 2014). Source: the union of CIG and IBES Guidance datasets.
LeadShare	=	the percentage of loan amount held by the lead arranger. The lead arranger's share is identified if the *LeadArrangerCredit* variable in DealScan is coded as "Yes" or the *LenderRole* variable is coded as "lead bank," "lead manager," "lead arranger," "agent," "bookrunner," "arranger," or "mandated lead arranger." These two variables are from the LenderShares data file in DealScan. If a loan has more than one lead arranger, we sum the loan shares retained by all lead arrangers.
SynConcentration	=	the sum of the squared loan share of each lender in a syndicated loan. We use the variable *BankAllocation* in the LenderShares data file in DealScan to identify the share of the loan allocated to each participating bank.

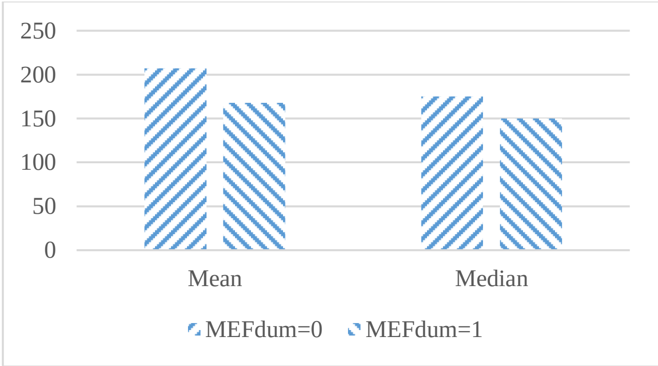
Figure 1
Loan Size and Loan Spread by Year



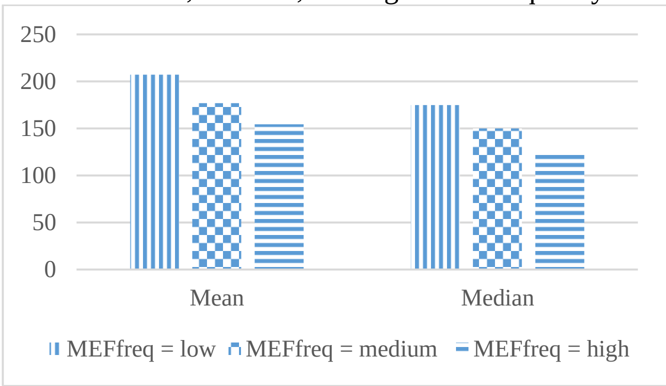
Note: The graph is based on our sample of 5,991 firm-loans originated by U.S. firms during January 1, 1998–March 31, 2017. Loan size is the loan amount scaled by total assets at the end of the most recent fiscal quarter preceding loan origination. Loan spread is the interest rate in basis points that a borrower pays over LIBOR. The bars represent the mean loan size; the line represents the mean loan spread for each year during our sample period.

Figure 2
MEFs and Loan Pricing—Subsample Comparisons

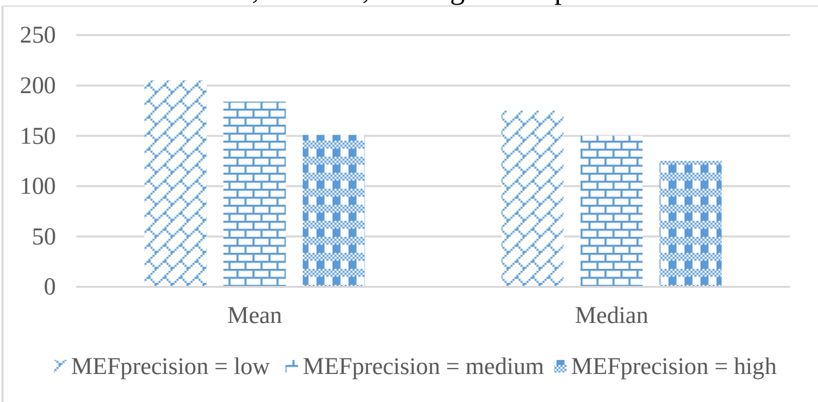
Panel A: Loan spreads of firms with vs. without MEFs



Panel B: Loan spreads of firms with low, medium, and high MEF frequency



Panel C: Loan spread of firms with low, medium, and high MEF precision



Note: The graphs are based on our sample of 5,991 firm-loans. We plot the mean and median of loan spreads in basis points. In Panel A, we separate firms with outstanding MEFs (*MEFdum*=1) from firms without outstanding MEFs (*MEFdum*=0). In Panel B, we classify firms with a value of 0 for *MEFfreq* as "low" and sort the remaining observations into "medium" (below or at the median) and "high" (above the median) groups based on these observations' median value each year. In Panel C, we classify firms with neither point nor range outstanding MEFs (i.e., *MEFprecision* = -1.1) as "low" and sort the remaining observations into "medium" (below or at the median) and "high" (above the median) groups based on these observations' median value of *MEFprecision* each year. See variable definitions in Appendix 1.

Table 1
Sample Selection

	Attrition	Remaining observations
Loan facilities issued to U.S. firms during 01/01/1998–03/31/2017 (DealScan)		107,239
Retain the largest loan facility in a package (deal)	(30,932)	76,307
Exclude loan facilities whose borrowers are financial or utility firms or not in Compustat (e.g., private firms)	(53,248)	23,059
Exclude loan facilities whose borrowers lack data for the firm characteristic control variables	(8,673)	14,386
Exclude loan facilities without information for loan characteristics	(1,893)	12,493
Exclude firms that do not issue any management earnings forecast in the 24 months before loan origination	(6,502)	5,991
Final sample of firm-loan originations		5,991

Note: An MEF is a firm's earnings forecast for a fiscal year or a fiscal quarter issued before the end of the forecasted fiscal period. In other words, we count both annual and quarterly earnings forecasts but exclude preannouncements. We refer to an MEF as "outstanding" if it is issued by a sample firm in the six months preceding the loan origination date and the forecasted period ends after the loan origination date. The total number of outstanding MEFs issued by our sample firms is 12,770, including 8,125 (63.6%) forecasts for fiscal earnings and 4,645 (36.4) for quarterly earnings. The mean (median) value of forecast horizon (i.e., forecasted period end date minus forecast date) is 176.5 (153) days.

Table 2
Descriptive Statistics

Panel A: Distribution by year

Year	N	*MEFdum*	*MEFfreq*	*MEFprecision*
1998	206	0.306	0.597	-0.843
1999	284	0.349	0.486	-0.869
2000	360	0.283	0.508	-0.864
2001	429	0.457	0.991	-0.675
2002	486	0.519	1.329	-0.595
2003	449	0.597	1.463	-0.532
2004	495	0.715	1.921	-0.441
2005	402	0.674	1.801	-0.444
2006	360	0.697	1.825	-0.409
2007	348	0.710	1.756	-0.386
2008	189	0.693	1.841	-0.400
2009	134	0.522	1.164	-0.624
2010	174	0.690	1.885	-0.430
2011	304	0.813	2.158	-0.266
2012	218	0.807	2.138	-0.294
2013	285	0.779	1.968	-0.314
2014	272	0.787	2.114	-0.288
2015	260	0.785	1.935	-0.306
2016	258	0.736	1.581	-0.356
2017	78	0.551	0.897	-0.508
Total	5,991			

Panel B: Summary statistics

Variables	Mean	Std. Dev.	25^{th}	Median	75^{th}
MEF variables:					
MEFdum	0.621	0.485	0	1	1
MEFfreq	1.533	1.745	0	1	2
MEFprecision	-0.498	0.508	-1.100	-0.127	-0.042
Firm-specific characteristics:					
TA	4,379	10,749	567	1,577	4,032
ROA	0.009	0.029	0.004	0.012	0.021
StdROA	0.015	0.021	0.005	0.009	0.017
Leverage	0.291	0.186	0.167	0.272	0.388
MTB	1.761	0.868	1.176	1.523	2.067
Tangibility	0.260	0.199	0.108	0.205	0.360

IntCov	19.658	59.606	2.307	5.722	13.068
Oscore	-1.141	1.574	-2.100	-1.172	-0.253
AbsAccrual	0.071	0.069	0.028	0.054	0.092
CreditRate	6.399	6.602	0.000	7.000	13.000
Analyst	8.277	6.825	3.000	6.833	12.167
Loan-specific characteristics:					
LoanSpread	182.766	131.148	92.500	150.000	250.000
LoanSize	431.811	535.430	100.000	250.000	505.000
Maturity	46.740	21.246	36.000	60.000	60.000
FinCovenant	1.603	1.454	0	2	3
Revolver	0.739	0.439	0	1	1
InstLoan	0.170	0.376	0	0	0
Macroeconomic factors:					
CreditSpread	0.982	0.309	0.790	0.900	1.130
TermSpread	1.280	0.932	0.261	1.462	2.096

Note: Panel A presents the distribution of our sample observations by year as well as the mean values of MEF variables by year. Panel B presents the summary statistics of the variables used in our primary analyses. See variable definitions in Appendix 1. We winsorize continuous variables at the 1^{st} and 99^{th} percentiles.

Table 3
Pairwise correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1.Log(*LoanSpread*)	1																				
2.*MEFdum*	**-0.137**	1																			
3.*MEFfreq*	**-0.134**	**0.687**	1																		
4.MEFprecision	**-0.159**	**0.903**	**0.674**	1																	
5.*Size*	**-0.343**	**0.217**	**0.227**	**0.236**	1																
6.*ROA*	**-0.273**	**0.194**	**0.167**	**0.224**	**0.116**	1															
7.*StdROA*	**0.240**	**-0.131**	**-0.135**	**-0.166**	**-0.280**	**-0.184**	1														
8.*Leverage*	**0.215**	**-0.056**	**-0.044**	**-0.059**	**0.161**	**-0.128**	0.022	1													
9.*MTB*	**-0.281**	**0.174**	**0.165**	**0.200**	**0.034**	**0.339**	**0.070**	**-0.103**	1												
10.*Tangibility*	**-0.063**	**-0.128**	**-0.105**	**-0.148**	**0.049**	-0.023	**-0.061**	**0.176**	**-0.093**	1											
11.*IntCov*	**-0.087**	**0.032**	**0.034**	**0.051**	**-0.110**	**0.250**	-0.018	**-0.343**	**0.294**	**-0.066**	1										
12. *Oscore*	**0.341**	**-0.156**	**-0.135**	**-0.183**	**-0.138**	**-0.333**	**0.226**	**0.647**	**-0.193**	**0.097**	**-0.373**	1									
13.*AbsAccrual*	**0.089**	**-0.062**	**-0.058**	**-0.073**	**-0.144**	**-0.059**	**0.218**	**0.044**	**0.077**	**0.276**	0.019	**0.085**	1								
14.*CreditRate*	**-0.306**	**0.114**	**0.131**	**0.123**	**0.535**	**0.102**	**-0.156**	**0.175**	**0.039**	**0.088**	**-0.135**	-0.013	**-0.066**	1							
15.*Analyst*	**-0.280**	**0.224**	**0.235**	**0.244**	**0.572**	**0.189**	**-0.155**	**-0.031**	**0.305**	**0.033**	**0.079**	**-0.288**	**-0.040**	**0.305**	1						
16.Log(*LoanSize*)	**-0.305**	**0.217**	**0.198**	**0.248**	**0.750**	**0.176**	**-0.271**	**0.136**	**0.106**	-0.009	**-0.056**	**-0.147**	**-0.091**	**0.381**	**0.478**	1					
17.Log(*Maturity*)	**0.211**	**0.112**	**0.096**	**0.124**	-0.018	**0.090**	**-0.069**	0.025	-0.018	**-0.041**	**0.037**	**-0.038**	**-0.059**	**-0.109**	0.024	**0.167**	1				
18.*FinCov*	**0.173**	**-0.088**	**-0.075**	**-0.093**	**-0.344**	-0.020	**0.043**	**-0.028**	**-0.085**	0.002	**0.028**	**0.047**	**0.031**	**-0.203**	**-0.222**	**-0.183**	**0.109**	1			
19.*Revolver*	**-0.363**	**-0.031**	-0.016	**-0.033**	**-0.076**	**0.032**	-0.017	**-0.230**	-0.002	0.011	0.024	**-0.142**	**-0.062**	**-0.049**	**-0.040**	**-0.031**	**-0.148**	**0.043**	1		
20.*InstLoan*	**0.356**	0.002	-0.010	-0.004	-0.010	**-0.059**	**0.051**	**0.245**	**-0.031**	0.021	-0.021	**0.172**	**0.057**	0.007	**-0.049**	**-0.030**	**0.236**	0.020	**-0.762**	1	
21.*CreditSpread*	**0.121**	**0.038**	**0.040**	**0.045**	0.016	**-0.052**	-0.008	**-0.047**	**-0.065**	**-0.029**	**0.033**	**-0.028**	**0.028**	-0.008	-0.001	**-0.044**	**-0.086**	0.003	-0.009	0.001	1
22.*TermSpread*	**0.236**	**0.142**	**0.130**	**0.155**	**0.075**	-0.013	**0.038**	-0.016	**-0.032**	**-0.043**	0.009	0.002	**-0.037**	0.010	**0.074**	**0.040**	**0.035**	-0.011	-0.023	0.009	**0.322**

Note: The table presents Pearson correlations of the variables used in our primary analyses. The correlations that are statistically significant at the 5% level are in boldface. See variable definitions in Appendix 1. We winsorize continuous variables at the 1st and 99th percentiles.

Table 4
MEFs and Loan Pricing—Levels Analyses

Panel A: Subsample comparisons

	N	*LoanSpread* Mean	*LoanSpread* Median
Group with *MEFdum*=0	2,271	207.251	175.000
Group with *MEFdum*=1	3,720	167.817	150.000
Between-group test statistics		10.91***	11.50***
Group with low *MEFfreq*	2,271	207.251	175.000
Group with medium *MEFfreq*	2,208	176.986	150.000
Group with high *MEFfreq*	1,512	154.428	125.000
Between-group test statistics for low vs. medium		7.51***	7.77***
Between-group test statistics for medium vs. high		5.79***	5.80***
Group with low *MEFprecision*	2,419	205.358	175.000
Group with medium *MEFprecision*	1,794	183.897	150.000
Group with high *MEFprecision*	1,778	150.886	125.000
Between-group test statistics for low vs. medium		5.13***	4.77***
Between-group test statistics for medium vs. high		8.42***	9.01***

Panel B: Multivariate analyses

	Dependent variable =Log(*LoanSpread*)					
	Original Sample			Entropy Balanced Sample		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
MEFdum	-0.054***			-0.044***		
	(-3.40)			(-2.80)		
MEFfreq		-0.010**			-0.008*	
		(-2.10)			(-1.83)	
MEFprecision			-0.075***			-0.062***
			(-4.83)			(-3.93)
Size	-0.067***	-0.067***	-0.067***	-0.081***	-0.080***	-0.080***
	(-4.97)	(-4.93)	(-4.95)	(-5.51)	(-5.43)	(-5.48)
ROA	-2.090***	-2.132***	-2.040***	-2.636***	-2.617***	-2.593***
	(-6.79)	(-6.94)	(-6.66)	(-6.70)	(-6.62)	(-6.61)
StdROA	3.102***	3.130***	3.022***	4.482***	4.451***	4.414***
	(7.74)	(7.81)	(7.62)	(7.82)	(7.71)	(7.77)
Leverage	0.451***	0.451***	0.454***	0.469***	0.469***	0.471***
	(7.13)	(7.16)	(7.21)	(6.37)	(6.37)	(6.37)
MTB	-0.145***	-0.146***	-0.143***	-0.144***	-0.143***	-0.144***
	(-10.88)	(-10.92)	(-10.78)	(-10.10)	(-10.03)	(-10.14)
Tangibility	-0.330***	-0.325***	-0.337***	-0.343***	-0.347***	-0.346***
	(-5.00)	(-4.91)	(-5.11)	(-4.74)	(-4.79)	(-4.78)
IntCov	0.000	0.000	0.000	0.000	0.000	0.000

	(0.77)	(0.88)	(0.73)	(1.08)	(1.09)	(1.07)
Oscore	0.059***	0.060***	0.059***	0.054***	0.054***	0.054***
	(7.24)	(7.31)	(7.15)	(5.72)	(5.72)	(5.68)
AbsAccrual	0.137	0.132	0.144	0.328**	0.329**	0.338**
	(1.03)	(0.99)	(1.09)	(1.96)	(1.95)	(2.03)
CreditRate	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.008***
	(-4.56)	(-4.57)	(-4.52)	(-4.19)	(-4.19)	(-4.18)
Analyst	-0.005**	-0.005**	-0.005**	-0.002	-0.002	-0.002
	(-2.50)	(-2.48)	(-2.51)	(-1.04)	(-1.00)	(-1.06)
Log(*LoanSize*)	-0.097***	-0.098***	-0.096***	-0.098***	-0.098***	-0.098***
	(-7.35)	(-7.38)	(-7.30)	(-6.84)	(-6.84)	(-6.83)
Log(*Maturity*)	0.081***	0.081***	0.082***	0.096***	0.098***	0.096***
	(4.77)	(4.76)	(4.79)	(5.12)	(5.19)	(5.11)
FinCovenant	0.031***	0.032***	0.032***	0.030***	0.030***	0.030***
	(5.30)	(5.30)	(5.33)	(4.63)	(4.62)	(4.66)
Revolver	-0.251***	-0.250***	-0.252***	-0.267***	-0.267***	-0.266***
	(-8.82)	(-8.75)	(-8.85)	(-8.51)	(-8.51)	(-8.50)
InstLoan	0.206***	0.206***	0.206***	0.200***	0.199***	0.201***
	(6.78)	(6.73)	(6.76)	(5.93)	(5.90)	(5.96)
CreditSpread	0.112***	0.113***	0.111***	0.083*	0.084*	0.082*
	(3.06)	(3.08)	(3.05)	(1.69)	(1.71)	(1.69)
TermSpread	0.083***	0.082***	0.084***	0.067***	0.068***	0.068***
	(4.04)	(3.98)	(4.12)	(2.88)	(2.92)	(2.90)
Intercept	6.191***	6.182***	6.110***	6.557***	6.522***	6.485***
	(44.53)	(44.43)	(43.58)	(37.14)	(43.94)	(43.51)
Loan purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,991	5,991	5,991	5,991	5,991	5,991
R^2	63.3%	63.3%	63.4%	64.7%	64.6%	64.8%

Note: Panel A presents the subsample statistics of *LoanSpread*. First, we separate firms with outstanding MEFs (i.e., MEFs issued in the six months preceding loan origination and whose forecasted period ends after the loan origination date; *MEFdum*=1) from firms without outstanding MEFs (*MEFdum*=0). Second, we classify firms with a value of 0 for *MEFfreq* as "low" and sort the remaining observations into "medium" (below or at the median) and "high" (above the median) groups based on these observations' median value of *MEFfreq* each year. Last, we classify firms with neither point nor range outstanding MEFs (i.e., *MEFprecision* = -1.1) as "low" and sort the remaining observations into "medium" (below or at the median) and "high" (above the median) groups based on these observations' median value of *MEFprecision* each year. We report between-group test *t*-statistic in the "mean" column and Wilcoxon *z*-statistic in the "median" column. Panel B presents the OLS estimations of our primary models using both our original sample and entropy balanced sample of 5,991 firm-loan originations. See variable definitions in Appendix 1. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels based on two-tailed tests, respectively.

Table 5
MEFs and Loan Pricing—Changes Analyses

	Dependent variable = Δlog(*LoanSpread*)		
Variables	Model 1	Model 2	Model 3
Δ*MEFdum*	-0.052*** (-2.74)		
Δ*MEFfreq*		-0.013** (-2.49)	
Δ*MEFprecision*			-0.068*** (-3.80)
Intercept	0.049*** (5.34)	0.050*** (5.39)	0.050*** (5.41)
ΔControl variables	Yes	Yes	Yes
N	2,753	2,753	2,753
R^2	35.8%	35.7%	35.9%

Note: This table presents the OLS estimations of the changes analyses. The changes model is the changes version of Equation (1). A changes variable is calculated by subtracting from the value of the current loan observation the value of the most recent loan observation originated in the [-36, -6] month window before the current loan origination date. We lose 54.0% of the original sample observations because these firms do not have a recent loan. ΔControl variables include the changes in the five loan purpose indicator variables. See the definitions of the levels variables in Appendix 1. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels based on two-tailed tests, respectively.

Table 6
MEFs and Loan Pricing—Cross-Sectional Analyses

Panel A: Financial distress risk

	Dependent variable = Log(*LoanSpread*)			
Variables	Model 1	Model 2	Model 3	Model 4
DistressRisk	0.139*** (6.65)	0.203*** (7.31)	0.175*** (7.31)	0.088*** (3.45)
MEFdum		-0.006 (-0.27)		
*MEFdum*DistressRisk*		-0.101*** (-3.31)		
MEFfreq			0.000 (0.01)	
*MEFfreq*DistressRisk*			-0.022** (-2.46)	
MEFprecision				-0.029 (-1.32)
*MEFprecision*DistressRisk*				-0.102*** (-3.47)
Intercept	6.082*** (43.47)	6.046*** (43.08)	6.050*** (43.10)	6.021*** (42.81)
Control Variables	Yes	Yes	Yes	Yes
N	5,991	5,991	5,991	5,991
R^2	63.2%	63.4%	63.3%	63.5%

Panel B: Non-relationship lending to small firms

	Dependent variable = Log(*LoanSpread*)			
Variable	Model 1	Model 2	Model 3	Model 4
NonRelation	-0.001 (-0.04)	0.034 (1.26)	0.014 (0.64)	-0.040 (-1.54)
MEFdum		-0.047** (-2.00)		
*MEFdum*NonRelation*		-0.067* (-1.91)		
MEFfreq			-0.018** (-2.47)	
*MEFfreq*NonRelation*			-0.013 (-1.23)	
MEFprecision				-0.055** (-2.35)
*MEFprecision*NonRelation*				-0.064* (-1.85)
Intercept	6.579*** (36.82)	6.558*** (36.83)	6.556*** (36.69)	6.498*** (36.07)

Control Variables	Yes	Yes	Yes	Yes
N	2,519	2,519	2,519	2,519
R^2	54.0%	54.4%	54.3%	54.5%

Panel C: Business restructuring

	Dependent variable = Log(*LoanSpread*)			
Variable	Model 1	Model 2	Model 3	Model 4
Restructure	-0.011 (-0.50)	0.031 (1.05)	0.022 (0.86)	-0.061** (-2.21)
MEFdum		-0.037** (-2.05)		
*MEFdum*Restructure*		-0.069** (-2.00)		
MEFfreq			-0.004 (-0.83)	
*MEFfreq*Restructure*			-0.021* (-1.89)	
MEFprecision				-0.053*** (-2.95)
*MEFprecision*Restructure*				-0.096*** (-2.75)
Intercept	6.192*** (44.75)	6.189*** (44.61)	6.180*** (44.54)	6.135*** (43.87)
Control Variables	Yes	Yes	Yes	Yes
N	5,991	5,991	5,991	5,991
R^2	63.3%	63.4%	63.3%	63.5%

Note: This table presents the OLS estimations of cross-sectional variation in the associations between MEF properties and loan spreads. We examine three situations in which lenders' need for corroborating their private information is expected to vary. Panel A examines firms with different levels of financial distress risk. Panel B examines only small firms that differ in relationship vs. non-relationship lending. Small firms are those with total assets at the end of the most recent fiscal quarter preceding loan origination below the median value of sample firms in the same sample year. Panel C examines firms that are restructuring (i.e., the sum of restructuring charges in the most recent fiscal year before loan origination and the year of loan origination is greater than 1% of the total assets at the end of the most recent fiscal year before loan origination) vs. firms that are not restructuring. We include loan purpose fixed effects, industry fixed effects, and year fixed effects in all regressions. See variable definitions in Appendix 1. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels based on two-tailed tests, respectively.

Table 7
Addressing Alternative Explanations

Panel A: Is the association between MEFs and loan spreads due to a firm's general information environment?

	Dependent variable = Log(*LoanSpread*)			
Variables	Model 1	Model 2	Model 3	Model 4
MEFdum		-0.047***		
		(-2.93)		
MEFfreq			-0.008*	
			(-1.72)	
MEFprecision				-0.064***
				(-4.12)
InfAsymmetry	0.172***	0.169***	0.171***	0.168***
	(9.63)	(9.48)	(9.59)	(9.45)
Intercept	5.955***	5.960***	5.948***	5.892***
	(40.90)	(40.77)	(40.68)	(40.00)
Control Variables	Yes	Yes	Yes	Yes
N	5,795	5,795	5,795	5,795
R^2	64.59%	64.7%	64.6%	64.7%

Panel B: Is the association between MEFs and loan spreads due to managerial ability signaling?

	Dependent variable = log(*LoanSpread*)			
Variables	Model 1	Model 2	Model 3	Model 4
MEFdum		-0.048***		
		(-2.78)		
MEFfreq			-0.008*	
			(-1.69)	
MEFprecision				-0.072***
				(-4.34)
MEFaccuracy	-0.031***	-0.030***	-0.031***	-0.029***
	(-5.65)	(-5.48)	(-5.60)	(-5.30)
Intercept	6.238***	6.241***	6.229***	6.166***
	(40.23)	(40.01)	(39.97)	(39.22)
Control variables	Yes	Yes	Yes	Yes
N	5,237	5,237	5,237	5,237
R^2	63.9%	64.0%	63.9%	64.1%

Panel C: Is the association between MEFs and loan spreads due to disclosure opportunism?

Firm-loans	Having Positive MEF News	Having Negative MEF News	Other
5,991	1,659	1,784	2,548
100%	27.7%	29.8%	42.5%

Note: Panel A examines whether our MEF variables have significant explanatory power for loan spreads after controlling for a borrower's general information environment. We lose 196 observations because data are unavailable for calculating *InfAsymmetry*. The variable is the common factor extracted from the principal component analysis of inverse firm age (1/age), bid and ask spread, and stock return volatility, where bid-ask spread is the average monthly closing spreads (CRSP) over the 1-year period before loan origination and stock return volatility is the standard deviation of monthly abnormal return (raw stock return minus the return of the value-weighted market index) in the 1-year period before loan origination (Carrizosa and Ryan 2017). Panel B examines whether our MEF variables have significant explanatory power for loan spreads after controlling for managerial ability signaling (Demerjian et al. 2019). *MEFaccuracy* is the average accuracy of all MEFs *realized* in the 24-month window preceding loan origination, where the accuracy of each forecast is calculated as -1 times the absolute difference between actual EPS and forecasted EPS scaled by the absolute value of actual EPS (obtained from IBES Actuals data file). The upper bound is used for range forecasts. We lose 754 observations because these firms do not have a point or range MEF realized in the 24 months preceding loan origination for us to calculate the variable. Panel C presents firm-loans with positive or negative MEF news in the negotiation stage. Forecast news for each MEF is calculated as the difference between the point estimate or the upper bound of range forecast and the most recent analyst consensus (based on the IBES summary data file) before MEF issuance, scaled by the absolute value of the consensus. If there is no analyst coverage, we proxy for expected earnings by the firm's previous year EPS for annual MEFs and the firm's EPS in the same quarter in the previous year for quarterly MEFs. If a firm provides multiple MEFs in the negotiation stage, we aggregate the forecast news of all these MEFs. The "Other" category includes 96 firm-loans with neutral MEF news, 148 with MEFs that are not in point or range format, 33 with point or range MEFs but no proxy for expected earnings, and 2,271 with no outstanding MEFs. In all regression estimations, we include loan purpose fixed effects, industry fixed effects, and year fixed effects. See variable definitions in Appendix 1. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels based on two-tailed tests, respectively.

Table 8
MEFs and Information Asymmetry within a Loan Syndicate

Panel A: MEFs and the lead arranger share of loan amount

	Dependent variable = *LeadShare*		
Variables	Model 1	Model 2	Model 3
MEFdum	-2.612**		
	(-2.31)		
MEFfreq		-0.817***	
		(-2.80)	
MEFprecision			-2.069*
			(-1.89)
Intercept	116.857***	115.838***	114.447***
	(11.52)	(11.51)	(11.17)
Control variables	Yes	Yes	Yes
N	1,770	1,770	1,770
R^2	35.5%	35.5%	35.4%

Panel B: MEFs and syndicate concentration ratio of loan amount allocations

	Dependent variable = *SynConcentration*		
Variables	Model 1	Model 2	Model 3
MEFdum	-0.020**		
	(-2.15)		
MEFfreq		-0.006***	
		(-2.62)	
MEFprecision			-0.013
			(-1.50)
Intercept	1.070***	1.063***	1.055***
	(12.88)	(12.87)	(12.60)
Control variables	Yes	Yes	Yes
N	1,770	1,770	1,770
R^2	46.0%	46.0%	45.9%

Note: This table presents OLS estimations that examine the associations between MEF properties and proxies for information asymmetry within a loan syndicate. We have 1,770 observations for *LeadShare* and *SynConcentration* because of missing information in DealScan. The missing rate is similar to that in prior research. The control variables are those in Equation (1). In all regression estimations, we include loan purpose fixed effects, industry fixed effects, and year fixed effects. See variable definitions in Appendix 1. Standard errors are clustered by firm and *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels based on two-tailed tests, respectively.