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Assessing the Accuracy of Forward-Looking Information in Debt Contract Negotiations: Management Forecast Accuracy and Private Loans

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ABSTRACT: We examine a possible mechanism by which the lender can evaluate the borrower's ability to produce accurate forward-looking information. Forward-looking information is important to lenders to project the borrower's future performance and the loan's expected payoff. However, unlike historical financial statements, forward-looking information cannot be verified by lenders or external auditors. We contend that the borrower's past forecast accuracy provides a measure that allows the lender to assess the borrower's ability to produce accurate forward-looking information, allowing the lender to gain greater confidence in the borrower's projections of future value. Consistent with this argument, we find that the borrower's past forecast accuracy is negatively associated with the loan's initial interest spread. We also find that this relation is concentrated among non-relationship loans and borrowers with greater earnings volatility. Finally, we find that debt contracts to borrowers with more accurate managerial forecasts exhibit less interest rate mispricing.

JEL Classifications: G30; M40; M41.

Keywords: debt contracting; cost of debt; management forecasts; voluntary disclosure.

I. INTRODUCTION

In private debt contracting, the lender screens a prospective borrower prior to loan initiation to determine the borrower's creditworthiness and the loan's expected payoff. As part of the screening process, the borrower privately communicates forward-looking information (e.g., forecasts of expected future performance, investment opportunities) to the lender. The lender uses this forward-looking information, along with other information, to assess the distribution of the borrower's future value and determine the loan terms. Given the nature of forward-looking information, neither the lender nor third parties, such as independent auditors, can verify its accuracy *ex ante*. Yet, rather than disregarding the forward-looking information as not

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Supplemental material can be accessed by clicking the link in Appendix B.

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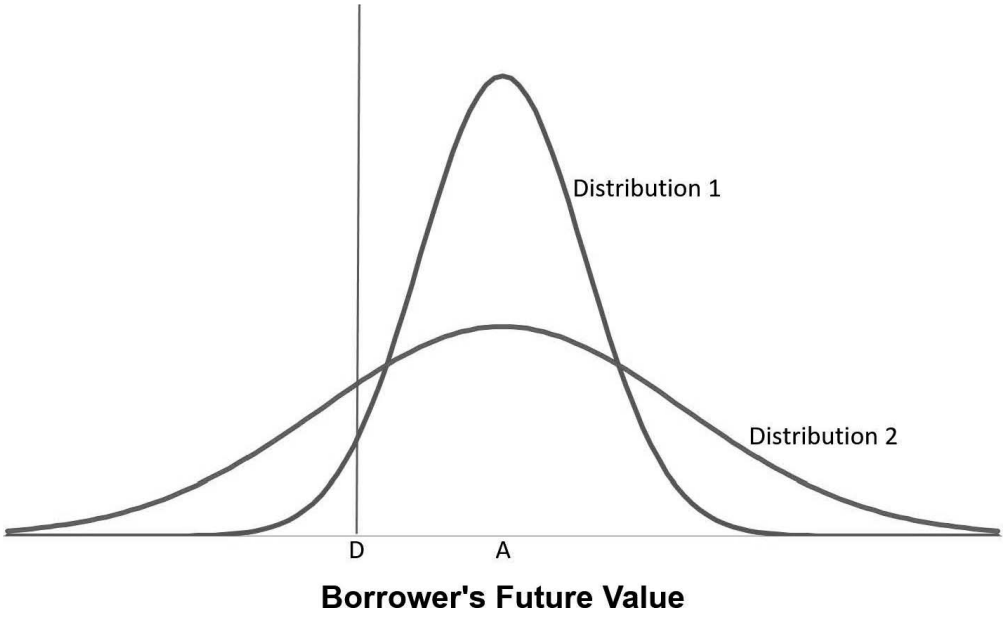
FIGURE 1
Borrower's Future Value and the Lender's Expected Payoff



Point *A* represents the borrower's expected future value for both Distributions 1 and 2. Point *D* represents the minimum borrower value required to make the interest and principal payments. Distribution 1 shows the distribution of the borrower's expected future value when the borrower has the ability to produce relatively accurate forward-looking information. Distribution 2 assumes the same underlying default risk but shows the distribution of the borrower's expected future value when the borrower has less of an ability to produce accurate forward-looking information. The inaccuracy of the information causes the lender to assess a wider range of outcomes, leading to the wider range in the realized distribution. Thus, the difference in distributions is not a function of differences in default risk, but rather differences in the borrower's ability to produce accurate forward-looking information.

useful, the lender can assess the borrower's ability to produce accurate forward-looking information and reduce uncertainty regarding the borrower's future performance. In this study, we explore a possible mechanism by which the lender can assess the expected accuracy of the forward-looking information disclosed by the borrower during contract negotiations, and how this assessment affects the lender's expected payoff.

Figure 1 provides intuition on how the lender's assessment of the accuracy of forward-looking information affects the lender's expected payoff from the loan. During contract negotiations, the borrower privately communicates forward-looking information that indicates an expected future value equal to *A* as well as a range of possible outcomes around *A* (i.e., the variance of the distribution). The expected value and variance of the distribution as assessed by the lender are both relevant when negotiating contract terms due to the lender's asymmetric payoff: the lender bears the cost of default when the borrower's future value declines but does not benefit when the borrower's future value increases (Watts 2003). In Figure 1, Point *D* represents the minimum future value of the borrower that is necessary to repay the loan (i.e., below Point *D* the borrower defaults).

The borrower's ability to produce accurate forward-looking information affects the distribution of the borrower's future value as assessed by the lender. In Figure 1, Distribution 1 shows the stochastic distribution of the borrower's expected future value when the borrower has the ability to produce relatively accurate forward-looking information. Distribution 2 represents the same borrower but with a lower ability to produce accurate forward-looking information. In this case, the inaccuracy of the information leads the lender to estimate a wider range of outcomes as the lender becomes less certain about the range of the borrower's future performance (Hirst, Koonce, and Miller 1999), while holding constant the expected value (Point *A* in Figure 1). It is important to note that both distributions in Figure 1 represent identical fundamental default risk and economic performance, and thus the *actual* likelihood of repayment is constant across both distributions. Figure 1 highlights the difference between Distributions 1 and 2 in how the lender *perceives* the accuracy of information and how differences in perception factor into the *assessment* of the expected payoff from the loan, which is the focus of this study. Furthermore, we are not suggesting that the borrower withholds information from or gives false information to the lender in either distribution. The increased variance of the borrower's future value in Distribution 2, as assessed by the lender, is driven only by the borrower's ability to produce accurate forward-looking information.

The wider variance, as assessed by the lender, increases the *expected* likelihood of default as indicated by the area under the distributions to the left of Point *D*. As Figure 1 illustrates, there is more area to the left of Point *D* under Distribution 2

relative to Distribution 1, which suggests a higher likelihood of default when the lender assesses the accuracy of the borrower's forward-looking information to be lower. Thus, the lender charges a higher interest rate to compensate for a higher expected likelihood of default (e.g., Merton 1974), *ceteris paribus,* as dictated by the borrower's ability to produce accurate forward-looking information. In total, this figure illustrates how the lender's perception of the accuracy of the information used to value the borrower affects the *expected* default risk and pricing of the debt, even after holding the underlying default risk constant.

Our objective in this study is to identify a mechanism by which the lender can assess the borrower's ability to produce accurate forward-looking information that is privately obtained during contract negotiations. Unlike historical information, which can be audited and verified, the lender cannot directly assess the accuracy of forward-looking information prior to its realization. The lender nonetheless must find a way to assess the accuracy of the forward-looking information in order to estimate the distribution of the borrower's future value. We contend that the accuracy of the borrower's past managerial earnings forecasts can provide a useful measure of the borrower's ability to produce accurate forward-looking information. In other words, the accuracy of managerial earnings forecasts is positively correlated with accuracy of the forward-looking information obtained by the lender. Therefore, the lender can use the borrower's past forecast accuracy to evaluate the expected accuracy of forward-looking information privately disclosed by the borrower during contract negotiations.[1] As a result, holding *actual* default risk constant, we predict that the accuracy of public management forecasts is associated with the lender's *assessment* of default risk.

Importantly, we are not suggesting that the lender relies on public management earnings forecasts to acquire information about the level of the borrower's future operations or profitability. Rather, we expect that the borrower privately furnishes forward-looking information to the lender during contract negotiations, and the lender estimates the expected accuracy of this forward-looking information to evaluate the distribution of the borrower's future value. We contend that the past managerial forecast accuracy (i.e., the time series of forecasted values relative to realizations) provides information about the borrower's ability to produce accurate forward-looking information and factors into the pricing of the loan.[2] We expect that management forecast accuracy could be particularly useful to the lender because it is observable, available at a low cost, and provides a quantifiable measure that the lender can use to estimate the borrower's ability to produce accurate forward-looking information. Thus, we predict that higher forecast accuracy implies a greater ability of the borrower to produce more accurate forward-looking information, which results in the lender estimating a lower variance in the borrower's expected future value. This, in turn, leads to a lower expected likelihood of default, which we predict results in a lower cost of debt (Fisher 1959; Jaffee 1975).[3]

We use a sample of Dealscan private debt contracts initiated between 2003 and 2012 to test this prediction. Consistent with our expectations, we find a negative association between the interest spread and the accuracy of the borrower's earnings forecasts issued prior to loan initiation.[4] In terms of economic significance, moving from the bottom to top decile of management forecast accuracy is associated with a lower rate in the borrower's cost of debt by approximately 11.5 percent after controlling for observable borrower characteristics, creditworthiness, economic uncertainty, future performance, and other loan-specific characteristics. This corresponds to a reduction of approximately 17 basis points for the median debt contract in our sample.

As an additional robustness test to improve our ability to draw inferences, we use a sample of firms with management turnover prior to contract initiation. We find a negative association between the forecast accuracy at the executive's prior firm (prior to the manager's turnover date) and the cost of debt at the new firm (following the manager's hire date). Using the borrower's forecast accuracy while employed by the prior firm allows us to capture our underlying construct of interest, the borrower's ability to provide accurate forward-looking information, while mitigating the possibility that unobservable borrower characteristics affect our results.

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[1] A traditional "signaling" theory would suggest that a high-ability borrower incurs costs to signal their type to the lender and separate from a low-ability type (e.g., Spence, 1973). While there are costs to providing accurate managerial forecasts, we do not believe that the borrower is primarily incurring these costs to obtain a lower cost of debt.

[2] In this sense, we focus on the second-order information (the accuracy of forecasts over time) rather the first-order effect (the directional information content of the manager's forecasts.)

[3] A number of studies link past forecast accuracy with the accuracy of future information (e.g., Williams 1996; Goodman, Neamtiu, Shroff, and White 2014). Additionally, Lee, Matsunaga, and Park (2012) interpret management forecast accuracy as a measure of the borrower's ability to produce accurate forward-looking information. Taken collectively, these studies support the idea that past forecast accuracy is useful to the lender in assessing the distribution of the borrower's future value.

[4] We measure average quarterly forecast accuracy over the three-year period prior to debt contract initiation. We note, however, that our results are qualitatively similar using annual management forecasts; the first or last management forecast issued during the period; and measuring forecast accuracy over the two-to-five-year window prior to debt contract initiation. Please refer to Section III for more discussion of these measurements. We also perform robustness tests using the standard deviation of management forecast errors as an alternative measure of the accuracy of forward-looking information; we discuss this analysis in Section V.

We also examine variation in the relation between past managerial forecast accuracy and the cost of debt using two cross-sectional tests. First, we find that the negative association between past forecast accuracy and the cost of debt is concentrated among non-relationship lenders. Lenders that have an existing relationship with the borrower (e.g., relationship banking) have direct knowledge regarding the borrower's ability to produce accurate forward-looking information, and therefore are less likely to rely on the forecast accuracy of public managerial forecasts to assess the borrower's ability to produce accurate forward-looking information. Second, we find a stronger negative association between past forecast accuracy and the cost of debt when screening borrowers with greater variability in performance, consistent with the argument that assessing the borrower's ability to produce accurate forward-looking information is particularly important for borrowers with higher *ex ante* default risk.[5]

Finally, we consider how the expected accuracy of the borrower's forward-looking information is associated with the lender's ability to predict and price the future value of the borrower. The interest rate charged on the loan reflects the expected future performance of the borrower during contract negotiations (Plumlee, Xie, Yan, and Yu 2015). Therefore, if more accurate forward-looking information facilitates the lender's screening activities, we expect the loan to be priced more efficiently *ex ante*. Our evidence suggests that the negative association between the interest spread and the borrower's realized future performance is stronger among borrowers with greater forecast accuracy prior to debt contract inception.

We note that the cross-sectional tests, the management turnover test, the loan mispricing test, and other robustness tests do not completely rule out the possibility of a correlated omitted variable. However, when examined in aggregate, we contend these tests reduce the likelihood of a correlated omitted variable affecting our results. As such, we believe that we can draw reasonable inferences from our results, despite endogeneity concerns.

Our study makes three contributions to the literature. First, although the lender likely assesses the expected accuracy of the borrower's forward-looking information when screening the borrower, the literature is largely silent on how the lender can perform this assessment and how it affects contract terms. Prior research examines how historical information, such as the quality of a borrower's reported financial statements, affects debt contract terms. Measures of quality in the prior literature include accruals-based metrics (Bharath, J. Sunder, and S. Sunder 2008), internal control weaknesses (Costello and Wittenberg-Moerman 2011), and accounting conservatism (Zhang 2008). In contrast, we study how the lender can assess the borrower's ability to produce accurate forward-looking information obtained during contract negotiations. Furthermore, these results hold when controlling for the inherent uncertainty in the firm's business and default risk, which suggests an incremental pricing effect beyond a simple compensation for default risk. By examining an aspect of information quality that has received little attention in the literature, our evidence complements existing research on the determinants of debt contract terms.

Second, we provide evidence on a mechanism that users can use to validate the quality of information that falls outside the purview of the independent external audit. Research on debt contracting typically focuses on financial statement information, much of which is subject to a mandatory review by an external auditor. While audited information is certainly useful for debt contracting, privately communicated unverifiable information (e.g., forecasts, projections) represents a crucial source of information to screen borrowers. Our research identifies a plausible method by which lenders can estimate the accuracy and usefulness of unaudited forward-looking information. Third, we provide evidence that voluntary disclosure is not only useful for valuation but also for contracting purposes. The majority of the extant literature examines how voluntary disclosure is useful for equity valuation purposes (e.g., Beyer, Cohen, Lys, and Walther 2010; Lennox and Park 2006). We provide evidence consistent with the borrower's past forecast accuracy representing a measure that lenders can use as an input to contract negotiations, ultimately affecting the borrower's cost of debt.

We note that our paper adds to the literature examining the inputs to assessing borrower creditworthiness. Shivakumar, Urcan, Vasvari, and Zhang (2011) provide evidence that managerial forecast news impacts credit default swap (CDS) spreads. Mansi, Maxwell, and Miller (2011) provide evidence on how analyst forecast characteristics affect credit ratings. Call, Donovan, and Jennings (2019) provide evidence that private lenders use analyst forecasts to set debt covenants. While these papers provide evidence that forward-looking information affects assessments of creditworthiness, they do not focus on how forecast information can be used by lenders to assess the borrower's ability to predict future outcomes in private debt contracting. This aspect of pre-contracting screening is largely unstudied, making the inferences from our study distinct from prior work.

II. HYPOTHESIS DEVELOPMENT

Prior to initiating a loan, the lender screens potential borrowers by collecting information to determine the likelihood that the borrower will make the required interest and principal payments. The lender uses information collected during screening to set the initial contract terms, including the interest spread. Research suggests that the lender collects information about the

[5] We define high-risk borrowers as those with a standard deviation of seasonally-adjusted quarterly net income over the three-year period prior to debt contract initiation above the sample median.

borrower's historical and future performance to screen borrowers (Bharath et al. 2008; Plumlee et al. 2015). Historical information refers to past transactions and investments, including the borrower's financial statements. We refer to the information about the borrower's future performance (including expected future sales and expenses, budgets, and payoffs from investments) as "forward-looking information." One of the key advantages that banks have in providing capital (relative to investors in public capital markets) is their ability to gather and analyze private, forward-looking information obtained directly from borrowers (Fama 1985).

When evaluating a loan's payoff value, a higher expected future value of the borrower leads to a lower risk of default, and a higher expected payoff to the lender. Further, under the assumption of stochastic future values, the variance of the distribution of the borrower's future value is also relevant because the lender's payout is asymmetric with respect to the future value of the borrower. The lender does not receive additional compensation beyond the required interest and principal payments when the borrower's value increases but bears the cost if the borrower's value falls below the minimum threshold required to repay the loan in full (Watts 2003). As a result, a higher variance in the borrower's future value decreases the expected payoff to the lender, even when holding the borrower's expected future value constant.[6] The interest spread charged on the loan reflects the lender's expected payoff; therefore, a higher (lower) variance in the borrower's future value as assessed by the lender increases (decreases) the cost of debt for the borrower.

We assume that the borrower privately discloses forward-looking information to the lender during contract negotiations. If the lender perceives the borrower's forward-looking information to be inaccurate, then the assessed variance of the borrower's future value is higher. This is consistent with Hirst et al. (1999), who find that more accurate forecasts lead to greater confidence in the information provided. In our setting, we expect that more accurate borrower forecasts prior to contract inception increase the lender's confidence in the borrower's ability to provide accurate forward-looking information during contract negotiations, resulting in a narrower range of outcomes in the distribution of the borrower's future value.

Figure 1 illustrates how the lender's assessment of the borrower's ability to provide accurate forward-looking information affects the *ex ante* prediction of default. As discussed in the introduction, Distribution 1 (Distribution 2) depicts the stochastic distribution of the borrower's expected future value when the borrower has the ability to produce relatively accurate (inaccurate) forward-looking information. As the lender perceives the borrower's information to be less accurate, the lender estimates a wider range of possible outcomes for the borrower's future performance (Hirst et al. 1999). It is worth noting that we are holding the expected value (Point *A* in Figure 1), fundamental default risk, and actual future economic performance of the firm constant in Figure 1. In other words, the *actual* likelihood of repayment is held constant across both distributions. The difference between Distributions 1 and 2 is how the lender *perceives* the accuracy of information and how the perceived accuracy factors into the *assessment* of the expected payoff from the loan. It is also worth noting that we are not assuming the borrower withholds information from or discloses false information to the lender in either distribution. The increased variance of the borrower's future value in Distribution 2, as assessed by the lender, is driven only by the borrower's ability to produce accurate forward-looking information. As the lender increases confidence in the borrower's ability to produce accurate information, the perceived variance of the borrower's future value decreases.

As the variance of the borrower's future value widens (Distribution 2), the lender's expectation for default increases, as indicated by the relative area to the left of Point *D* in Distributions 1 and 2. As a result, the lender charges a higher interest rate to compensate for a higher expected likelihood of default (e.g., Merton 1974), *ceteris paribus,* as dictated by the borrower's ability to produce accurate forward-looking information.

Despite the importance of assessing the borrower's ability to provide accurate forward-looking information, the means by which the lender makes this assessment remains an open question. In this study, we examine *how* the lender can assess the expected accuracy of the borrower's forward-looking information. A number of studies in the debt contracting literature focus on how the borrower's historical information in reported financial statements affects debt contracting outcomes. These papers generally find evidence that borrowers with higher quality financial statement information (based on empirical measures such as accrual quality, conservatism, internal control weaknesses, and restatements) negotiate more favorable debt contract terms.[7] This literature suggests that lenders have a variety of means at their disposal to assess the borrower's historical information. We are unaware, however, of any prior literature that examines how a private lender can assess the expected accuracy of *forward-*

[6] The relation between the variance of assets and the lender's expected return from the loan drives the asset substitution problem described in Smith and Warner (1979). The problem arises when a borrower sells low variance assets and replaces them with higher variance assets after the loan is in effect. If the lender prices the loan based on the original (lower) variance asset base, she will be undercompensated for the true risk of the borrower. Our situation differs from that examined in Smith and Warner (1979) because we examine when the *assessed* variance of the borrower is high *ex ante,* not altered *ex post*.

[7] Bharath et al. (2008) find that higher accrual quality is associated with lower interest rates. Costello and Wittenberg-Moerman (2011) find that loans to borrowers with internal control weaknesses are less likely to use accounting-based debt covenants, have higher interest rates, and are more likely to have collateral requirements. Zhang (2008) finds that borrowers with more conservative accounting have lower interest rates and interprets this as evidence of the value of conservative financial reporting for debt contracting (e.g. Watts 2003).

looking information used to screen the borrower.[8] The lender cannot verify forward-looking information (such as forecasts and projections) *ex ante,* nor can these be validated by an independent audit.[9] Rather than disregarding the forward-looking information as unverifiable and not useful, we expect the lender to identify a method to assess the borrower's ability to produce accurate forward-looking information. This assessment allows the lender to appropriately determine the borrower's creditworthiness and set contract terms.

Following prior literature, we propose that the accuracy of managerial earnings forecasts issued prior to debt contract inception provides a useful measure to evaluate the borrower's ability to predict future outcomes (Williams 1996; Lee et al. 2012; Goodman et al. 2014). Although earnings forecasts generated in prior periods may be irrelevant relative to the current projections obtained during contract negotiations, we expect that a similar set of skills and knowledge are required to produce both.[10] Specifically, prior period earnings forecasts and current projections provided to lenders both require the manager to have good foresight of future events and investment opportunities and the impact of the firm's future operations on reported performance. Thus, the lender can use the borrower's past forecast accuracy to assess the borrower's ability to provide accurate forward-looking information that is privately disclosed during debt contract negotiations. Specifically, we anticipate the lender will estimate a higher (lower) variance for the borrower's future value when the borrower's managerial forecasts are less (more) accurate in prior periods. As we discuss previously, we expect this assessed variance to be negatively associated with the lender's expected payoff. Therefore, in H1, we predict that borrowers with more accurate earnings forecasts prior to debt contract inception receive a lower cost of debt:

H1: Borrowers with more accurate earnings forecasts prior to debt contract inception receive a lower cost of debt.

We note several reasons why we may not find empirical evidence consistent with H1. First, while projections provided to lenders during contract negotiations likely include some earnings projections, lenders will also analyze non-earnings projections, such as changes to the customer base or the value of investment opportunities. In this case, past managerial forecast accuracy may not be the most useful measure to the lender in assessing the accuracy of this forward-looking information. Additionally, earnings forecasts disclosed by managers in prior periods on a quarterly basis may have different time horizons than the projections and forward-looking information that borrowers provide to lenders during contract negotiations.[11] Nevertheless, we predict that the borrower's past forecast accuracy is a useful input to the lender when assessing the borrower's ability to provide accurate forward-looking information.

We further expect that certain loan or borrower features may alter the usefulness of the borrower's prior forecast accuracy to the lender. We first consider lending relationships, when a borrower and lender repeatedly contract over some period. Petersen and Rajan (1994) note that lending relationships lower information asymmetry, while Bharath, Dahiya, Saunders, and Srinivasan (2007) suggest that lenders reap the benefits of this superior information environment. Bharath et al. (2007; 2011) show that relationship lending leads to more favorable loan terms, and Costello and Wittenberg-Moerman (2011) find evidence that the positive relation between internal control weaknesses and interest rates is weakened among relationship lenders. Following this literature, we expect that lenders in existing relationships do not need to assess the borrower's ability to produce accurate forward-looking information using public managerial earnings forecasts because they can determine this ability based on the information obtained during prior negotiations with the borrower. In other words, relationship lenders need not rely on a public signal of forecast accuracy because they are privy to the accuracy of the borrower's historical, internal, private information, which allows them to more precisely assess the accuracy of the forward-looking information provided to the

[8] We note that Shivakumar, Urcan, Vasvari, and Zhang (2011) examine the impact of managerial forecast news on the change in credit default swap (CDS) spreads. They find that CDS spreads decrease when positive news is released. Mansi, Maxwell, and Miller (2011) examine the impact of analyst revisions on credit ratings and find that the standard deviation of analyst forecasts and the volatility of analyst revisions are negatively associated with credit ratings. They do not provide evidence that analyst forecast accuracy is associated with credit ratings. While these papers provide some evidence that forward-looking information impacts assessments of creditworthiness, these papers do not examine whether private lenders use the borrower's forecast accuracy to assess the borrower's ability to predict future outcomes.

[9] Since a lending relationship can be a repeated game, we do expect the borrower to be untruthful in their private information disclosures. However, even in the presence of truthful disclosures, the borrower's ability to provide accurate forward-looking information is not known at the contract's negotiation. Therefore, we expect that the lender desires to assess the accuracy of the forward-looking information disclosed by the borrower at the time of contract negotiation.

[10] We contend that lenders assess the borrower's ability to produce accurate forward-looking information, which could be provided to lenders using public or private (unobservable) forecasts. Given that we cannot observe private forward-looking information exchanges between the borrower and the lender, we contend that the accuracy of the borrower's public forecasts is positively correlated with that of private forward-looking information (but not perfectly so).

[11] Untabulated analysis is consistent with this argument. Specifically, we find that our results are significantly stronger for debt contracts with maturity below the sample median, where the horizon of the forward-looking information obtained by the lender more closely matches the short-term horizon of managerial earnings forecasts in prior periods.

lender. As such, in H2, we predict that the negative relation between the borrower's past forecast accuracy and the cost of debt is attenuated when the borrower and lender have a prior lending relationship:

H2: The negative relation between the borrower's forecast accuracy and the cost of debt is attenuated when the borrower and the lender have a prior lending relationship.

Next, we consider how the borrower's riskiness assessed prior to considering forward-looking information affects the usefulness of the borrower's forecast accuracy. Risk, in this context, pertains to the variability of the borrower's performance. Following Smith and Warner's (1979) discussion of asset substitution, we expect that more variable borrower performance leads to a higher risk of default, holding the expected value of performance constant. When the likelihood of default is unconditionally low and the borrower's future value is sufficient to repay the debt, the lender's *ex ante* payoff is relatively inelastic to the assessed variance of the borrower's future value. In contrast, we anticipate that the lender's assessment of the borrower's ability to provide accurate forward-looking information is more relevant for borrowers that have a higher likelihood of default prior to considering forward-looking information, due to a more elastic relation between the lender's *ex ante* payoff and changes to the lender's assessment of the variance in the borrower's future value. Thus, we expect that the lender's use of past forecast accuracy to assess the borrower's ability to produce accurate forward-looking information is more relevant when screening borrowers that have a higher default risk prior to considering forward-looking information. Therefore, in H3, we predict the negative relation between forecast accuracy and the cost of debt to be amplified for high-risk borrowers:

H3: The negative relation between the borrower's forecast accuracy and the cost of debt is amplified for high-risk borrowers.

III. DATA

Data Sources

We use several databases to construct our sample of debt facilities. We collect loan data from Dealscan, which includes detailed information on private debt contracts, such as the borrower, lender, face value, maturity, loan pricing, and many other contract features (e.g., contract type and covenant use).[12] We collect financial information from Compustat using the most recent fiscal year available prior to debt contract inception. We measure the borrower's historical forecast accuracy using the Company Issued Guidance (CIG) and I/B/E/S databases. We measure all return-related control variables using CRSP stock returns. In order to be included in our sample, each observation must have complete loan data from Dealscan (including interest spread, maturity, loan size, and covenants), sufficient data from Compustat to calculate control variables, and sufficient data from CIG and I/B/E/S to calculate management forecast accuracy. Our selection procedure results in a sample of 2,487 private debt contracts issued between 2003 and 2012.[13]

Variable Definitions and Descriptive Statistics

We use management forecast accuracy as a proxy for the borrower's ability to produce accurate forward-looking information. We measure forecast accuracy over the three-year period prior to debt contract inception. In untabulated descriptive statistics, we find that the mean (median) borrower in our sample issues 5.5 (4.0) quarterly EPS forecasts over the three-year period prior to debt contract inception. We calculate forecast accuracy (*Forecast Accuracy*) as the absolute value of the difference between the final quarterly management EPS forecast and I/B/E/S actual quarterly EPS, divided by the absolute value of the forecast.[14,15] To facilitate the interpretation of our results, we multiply *Forecast Accuracy* by −1 so that higher values represent more accurate forecasters. In Table 1, we note that the median management forecast accuracy (*Forecast*

[12] We thank Michael Roberts for providing the dataset linking the Compustat and Dealscan databases. See Chava and Roberts (2008) for details.

[13] Our sample period starts in 2003 to include management forecasts issued prior to contract inception following the passage of Regulation Fair Disclosure (Reg FD), and due to limited forecast data availability prior to 2002 (Chuk et al. 2013).

[14] We eliminate all pre-announcement forecasts issued after the period-end date because we are interested in capturing the firm's ability to predict future economic outcomes. We also eliminate stale forecasts that have been outstanding for more than 365 days to ensure our results are not driven by these potential outliers. Additionally, if borrowers issue a range forecast, we use the midpoint of the range to calculate forecast accuracy.

[15] Our results are qualitatively similar if we measure forecast accuracy: (1) using either quarterly or annual earnings forecasts; (2) based on the first forecast, average forecast over the period, or final forecast issued for each period-end date; or (3) over the two, three, four, or five-year period prior to contract inception. Results are also qualitatively similar if we scale forecast accuracy by stock price. Finally, results are qualitatively similar if we measure forecast accuracy as the standard deviation of the difference between the management forecast and actual EPS. We more fully discuss this alternative specification in Section V.

TABLE 1

Descriptive Statistics

Variable	n	Mean	25th Pctl	Median	75th Pctl	Std. Dev.
Dependent Variable:						
Spread	2,487	164.850	75.000	150.000	225.000	114.720
Treatment Variables:						
Forecast Accuracy	2,487	−0.328	−0.300	−0.136	−0.065	0.600
Control Variables:						
Future ROA	2,487	0.029	0.015	0.043	0.073	0.107
Total Assets	2,487	8,658.730	616.503	1,767.200	4,477.700	47,459.240
Leverage	2,487	0.255	0.101	0.235	0.365	0.194
MTB	2,487	2.787	1.489	2.259	3.384	16.060
ROA	2,487	0.047	0.024	0.049	0.081	0.085
Sales Growth	2,487	0.130	0.017	0.093	0.186	0.257
Rating	2,487	11.615	10.000	12.000	13.000	2.346
Z-Score	2,487	50.461	2.242	3.903	8.057	280.999
Firm Age	2,487	24.471	10.000	16.000	36.000	19.306
Std(Earnings)	2,487	0.052	0.005	0.014	0.039	0.127
Std(Stock Returns)	2,487	0.116	0.077	0.103	0.142	0.058
ICW	2,487	0.056	0.000	0.000	0.000	0.231
Consecutive Loss	2,487	0.072	0.000	0.000	0.000	0.258
Relationship Lender	2,487	0.390	0.000	0.000	1.000	0.488
Analyst Following	2,487	9.624	5.000	8.000	14.000	6.558
Institutional Ownership	2,487	0.789	0.694	0.833	0.932	0.189
Disc Accruals	2,487	0.215	0.034	0.082	0.208	0.567
Revolver	2,487	0.693	0.000	1.000	1.000	0.461
Performance Pricing	2,487	0.778	1.000	1.000	1.000	0.416
BS Covenant	2,487	0.351	0.000	0.000	1.000	0.478
IS Covenant	2,487	0.858	1.000	1.000	1.000	0.349
Syndicate Size	2,487	10.382	4.000	9.000	14.000	8.244
Capex Restrict	2,487	0.199	0.000	0.000	0.000	0.399
Inst Tranche	2,487	0.130	0.000	0.000	0.000	0.337
Sweep Covenant	2,487	0.391	0.000	0.000	1.000	0.488
Dividend Restrict	2,487	0.733	0.000	1.000	1.000	0.442
Collateral	2,487	0.507	0.000	1.000	1.000	0.500
Debt Size	2,487	806.559	150.000	375.000	850.000	1,791.820
Maturity	2,487	50.469	36.000	60.000	60.000	18.515

This table reports descriptive statistics for all sample firms with available information in the intersection of the Dealscan, Compustat, and CIG or I/B/E/S databases. Financial and loan-specific variables are used to estimate the impact of management forecast accuracy on initial debt contract terms. Variables are defined in Appendix A.

Accuracy) over the three-year period prior to contract inception is −13.6 percent, indicating that the median earnings realization differs from the median earnings forecast by approximately 13.6 percent.

We measure the borrower's cost of debt using the loan's stated interest rate above LIBOR from Dealscan (*AllInDrawn*), which we label *Spread*. As we report in Table 1, the average interest rate (*Spread*) in our sample is 165 basis points above LIBOR, consistent with prior literature (e.g., Graham, Li, and Qiu 2008). We also present descriptive statistics for several borrower characteristics in Table 1. Borrowers in our sample are large, with average (median) total assets (*Total Assets*) equal to approximately $8.7 billion ($1.8 billion) and average leverage (*Leverage*) equal to 26 percent of total assets prior to contract inception. The majority of the borrowers are profitable: The 25th percentile of return on assets for borrowers in our sample is equal to 0.024 and only 7.2 percent of the borrowers in our sample have reported two consecutive quarters of negative income before extraordinary items immediately prior to debt contract initiation. The average borrower in our sample has an S&P credit

TABLE 2

Correlation Matrix

	Forecast Accuracy	*Log (Spread)*	*Log (Debt Size)*	*Log (Maturity)*	*Collateral*	*Financial Covenant*	*IS Covenant*
Forecast Accuracy		−0.233	0.224	0.011	−0.231	0.043	−0.033
		< 0.0001	< 0.0001	0.59	< 0.0001	0.03	0.10
Log(*Spread*)	−0.217		−0.262	0.098	0.543	−0.044	0.252
	< 0.0001		< 0.0001	< 0.0001	< 0.0001	0.03	< 0.0001
Log(*Debt Size*)	0.221	−0.236		0.144	−0.263	−0.051	−0.163
	< 0.0001	< 0.0001		< 0.0001	< 0.0001	0.01	< 0.0001
Log(*Maturity*)	0.037	−0.017	0.234		0.157	0.073	0.167
	0.06	0.41	< 0.0001		< 0.0001	0.00	< 0.0001
Collateral	−0.231	0.549	−0.263	0.135		−0.078	0.166
	< 0.0001	< 0.0001	< 0.0001	< 0.0001		0.00	< 0.0001
Financial Covenant	0.043	−0.062	0.002	0.065	−0.078		0.514
	0.03	0.00	0.92	0.00	0.00		< 0.0001
IS Covenant	−0.033	0.202	−0.159	0.134	0.166	0.514	
	0.10	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	

This table reports correlation coefficients and p-values for all sample firms with available information in the intersection of the Dealscan, Compustat, and CIG or I/B/E/S databases. Spearman correlation coefficients are presented below the diagonal; Pearson correlations are presented above the diagonal. Variables are defined in Appendix A.

rating approximating BB+.[16] Only 5.6 percent of the borrowers in our sample report an internal control weakness (*ICW*) in the annual period prior to contract inception based on data available on Audit Analytics. Additionally, borrowers in our sample have relatively robust information environments, with 9.6 analysts following the borrower (*Analyst Following*) and 79 percent institutional ownership (*Institutional Ownership*) on average.

In Table 1, we also present descriptive statistics for several loan-level characteristics. The average contract size (*Debt Size*) is approximately $800 million with a maturity (*Maturity*) of 50 months. Consistent with prior literature, the majority of debt contracts in our sample include a contract provision written directly on public information (Demerjian 2011): 86 percent of contracts contain a financial covenant (*BS Covenant* and *IS Covenant*) and 78 percent of contracts include a performance pricing provision (*Performance Pricing*). We also find that approximately 51 percent of debt contracts require collateral (*Collateral*) and 39 percent of contracts are between borrowers and lenders with a prior lending relationship (*Relationship Lender*). We define all variables in Appendix A.

In Table 2, we provide the correlations between *Forecast Accuracy* and select loan characteristics, such as *Spread, Debt Size, Maturity, Collateral, Financial Covenant,* and *IS Covenant* variables.[17] We find a negative correlation (1 percent level) between *Forecast Accuracy* and *Log*(*Spread*), providing preliminary evidence that borrowers with more accurate earnings forecasts prior to contract inception receive a lower cost of debt. We also find significant correlations between forecast accuracy and other debt contract characteristics, including the principal value and maturity, collateral requirements, and the use of financial covenants. These correlations suggest that *Forecast Accuracy* is an important input to the lender's screening activities.

[16] In untabulated analysis we include actual long-term S&P credit ratings from Compustat as an additional control variable (*S&P Rating*), which restricts our sample to 1,471 observations. After including *S&P Rating* as an additional control variable, we continue to find a negative but insignificant (t-stat −0.73) relation between *Forecast Accuracy* and *Log*(*Spread*). We note two reasons why the coefficient on *Forecast Accuracy* is insignificant. First, the insignificant result could be due to a reduced sample size, resulting in a low-powered test. Second, credit ratings often have a direct contractual relationship with the cost of debt in private debt contracts through contract provisions, which could soak up much of the variation between interest spreads and firm fundamentals. Consistent with this explanation, we note that the coefficient on several firm fundamentals (e.g., *Size, Leverage,* and *MTB*) are no longer statistically significant when actual long-term S&P credit ratings are included in the model. In additional untabulated analysis, we find that our primary results presented in Table 3 are qualitatively similar if we (1) restrict the sample to only firms with long-term S&P credit ratings or (2) include S&P credit rating grade level fixed effects. We tabulate the above results in the Online Appendix (see Appendix B for the link to the downloadable document). Finally, we also note that we find no cross-sectional variation in the relation between *Forecast Accuracy* and *Log*(*Spread*) based on whether S&P issues a long-term credit rating for the borrower.

[17] We do not provide univariate correlations for other variables used in our empirical tests for brevity.

Main Empirical Model

We formally test whether the borrower's forecast accuracy prior to debt contract inception affects the cost of debt by estimating the following multivariate regression model at the Dealscan facility level.[18]

$$\begin{aligned} Log(Spread) = {} & \alpha_0 + \beta_1 Forecast\ Accuracy + \beta_2 Future\ ROA + \beta_3 Size + \beta_4 Leverage + \beta_5 MTB + \beta_6 ROA \\ & + \beta_7 Sales\ Growth + \beta_8 Rating + \beta_9 Z\text{-}Score + \beta_{10} Firm\ Age + \beta_{11} Std(Earnings) \\ & + \beta_{12} Std(Stock\ Returns) + \beta_{13} ICW + \beta_{14} Consecutive\ Loss + \beta_{15} Relationship\ Lender \\ & + \beta_{16} Analyst\ Following + \beta_{17} Institutional\ Ownership + \beta_{18} Disc\ Accruals + \beta_{19} Revolver \\ & + \beta_{20} Performance\ Pricing + \beta_{21} BS\ Covenant + \beta_{22} IS\ Covenant + \beta_{23} Syndicate\ Size \\ & + \beta_{24} Capex\ Restrict + \beta_{25} Inst\ Tranche + \beta_{26} Sweep\ Covenant + \beta_{27} Dividend\ Restrict + \beta_{28} Collateral \\ & + \beta_{29} Log(Debt\ Size) + \beta_{30} Log(Maturity) + \sum Industry + \sum Year + \varepsilon \end{aligned} \tag{1}$$

Our primary variable of interest is the borrower's forecast accuracy over the three-year period prior to contract inception (*Forecast Accuracy*). We decile rank the *Forecast Accuracy* variable and transform it to take values between 0 and 1, which facilitates the interpretation of the coefficient.[19] The identification assumption of our analysis is that, after controlling for firm and debt-contract characteristics discussed below, the relation between *Forecast Accuracy* and *Log*(*Spread*) reflects the lender's pricing of the borrower's ability to produce accurate forward-looking information. H1 predicts a negative coefficient on *Forecast Accuracy*.

Equation (1) includes numerous control variables to reduce the likelihood that borrower and/or contract-specific characteristics affect our inferences. We control for the borrower's realized future performance (*Future ROA*) after debt contract inception as a proxy for the expected future value of the borrower and the manager's overall ability to operate the firm independently of their ability to provide accurate forward-looking information.[20,21] We also include controls for total assets (*Size*), leverage (*Leverage*), growth opportunities (*MTB*), profitability (*ROA*), sales growth (*Sales Growth*), and the age of the firm (*Firm Age*). We expect that larger, better performing, higher growth, and mature firms receive a lower cost of debt. We include numerous proxies to capture the inherent riskiness of the borrower, including the firm's credit rating (*Rating*), Altman Z-Score (*Z-Score*), the historical standard deviation of the firm's stock returns and earnings (*Std*(*Stock Returns*) and *Std*(*Earnings*)), and whether the firm reported losses in consecutive quarters prior to debt contract inception (*Consecutive Loss*). Additionally, we control for discretionary accruals (*Disc Accruals*) and an indicator variable for whether the firm disclosed a material weakness (*ICW*), because prior literature suggests that firms with lower accounting quality receive a higher cost of debt (Bharath et al. 2008; Costello and Wittenberg-Moerman 2011). Furthermore, we control for the firm's information environment using analyst following (*Analyst Following*) and the percentage of institutional ownership (*Institutional Ownership*), as prior literature demonstrates that firms with more robust information environments receive a lower cost of debt (e.g., Cheng and Subramanyam 2008).

We also control for contract characteristics that could affect loan pricing. We expect the principal value (*Log*(*Debt Size*)) and maturity (*Log*(*Maturity*)) of the loan to be positively associated with the interest spreads. We also include controls for the existence of various covenants (*BS Covenant, IS Covenant, Capex Restrict, Sweep Covenant,* and *Dividend Restrict*), the number of lenders participating in the loan (*Syndicate Size*), and indicator variables for revolving credit facilities (*Revolver*),

[18] We perform tabulated analysis at the Dealscan facility level. Results are qualitatively similar for analysis at the package level, using weighted average interest rates and maturities for each loan package with multiple facilities.

[19] Results are qualitatively similar using the level of forecast accuracy (i.e., not decile ranked) or the natural log of forecast accuracy.

[20] We include *Future ROA* as a proxy for the lender's expectation of the borrower's future performance. *Future ROA* allows us to control for information obtained prior to contract inception about the borrower's future performance. In other words, to the degree that the manager provides private information about the borrower's future performance to the lender, we are able to control for that information using the borrower's future ROA. Including other proxies, such as analyst expectations, would also test whether banks incorporate analyst expectations, which is not the goal of our study.

[21] We examine the borrower's ability to provide accurate forward-looking information and not the borrower's general ability to run the firm (e.g., identifying profitable investment opportunities, operational acumen), which we do not believe is driving our results for three reasons. First, if the borrower's past managerial forecasts simply captured another aspect of the borrower's abilities, then we would expect a significant relation regardless of relationship lending (Table 4), borrower risk (Table 5), the debt market (i.e. public debt, Table 8). Second, we at least partially control for reputational capital of the manager using the existence of an internal control weakness, discretionary accruals, and realized past and future earnings performance. Third, the borrower's ability to operate the firm would likely affect the expected future value of the borrower (i.e., Point *A* in Figure 1), which we specifically control for in our empirical results (e.g., *Future ROA*). In contrast, the borrower's ability to produce accurate forward-looking information likely impacts the variance of the borrower's future value rather than the expected value. In an untabulated robustness test, we control for managerial ability following Demerjian, Lev, and McVay (2012) and find qualitatively similar results (*Forecast Accuracy* coefficient −0.118, t-stat −2.41). We do not include managerial ability as a control in our primary tests to maximize sample size.

institutional tranches (*Inst Tranche*), performance pricing provisions (*Performance Pricing*), and secured debt (*Collateral*). Finally, we control for whether the lender and the borrower have an existing lending relationship (*Relationship Lender*). In all of our analyses, we include year fixed effects, Fama-French 48 industry fixed effects, and cluster standard errors by borrower to correct standard errors for potential serial-correlation.[22,23]

IV. EMPIRICAL RESULTS

We present the results for H1 in Table 3. Consistent with H1, we find a significantly negative coefficient on *Forecast Accuracy,* suggesting that borrowers with more accurate earnings forecasts prior to debt contract inception receive a lower cost of debt. This result is also economically significant, as moving *Forecast Accuracy* from the bottom to top decile is associated with a reduction in the interest spread of approximately 11.5 percent. Additionally, and consistent with our expectations, we find evidence that borrower size, analyst following, and greater profitability are associated with a lower cost of debt. We also find that higher operating volatility is associated with a higher cost of debt. The evidence in Table 3 is consistent with the borrower's prior forecast accuracy facilitating the lender's assessment of the borrower's ability to produce accurate forward-looking information during contract negotiations.[24]

We provide results related to tests of H2 and H3 in Tables 4 and 5. We examine whether the negative relation between the borrower's past forecast accuracy and interest spread is weaker when the borrower and the lender have an ongoing lending relationship in Table 4. We separately estimate Equation (1) for relationship and non-relationship loans. Following Costello and Wittenberg-Moerman (2011), we define a relationship loan based on whether the borrower has a contract with the lender as a lead-arranger reported on Dealscan at any point in the five-year period prior to contract initiation (*Relationship Lender*). In Column 1, we estimate the impact of forecast accuracy (*Forecast Accuracy*) on interest rate spreads (*Log*(*Spread*)) for non-relationship loans. Consistent with expectations, we find a negative and significant (5 percent level) coefficient on *Forecast Accuracy,* and the coefficient magnitude (−0.118) is similar to the magnitude of the coefficient for the overall sample reported in Table 3.

In Column 2 we estimate the impact of forecast accuracy on the cost of debt for borrowers who have a previous relationship with the lender (*Relationship Lender* equal to 1). We find an insignificant coefficient on *Forecast Accuracy,* suggesting no association between the borrower's past forecast accuracy and interest spread. However, we cannot reject the null hypothesis that the difference between the coefficients on *Forecast Accuracy* in Columns 1 and 2 is statistically significant. Nevertheless, our evidence suggests that the negative relation between the borrower's forecast accuracy and the cost of debt is concentrated among non-relationship lenders. These findings suggest that borrowers in lending relationships are less reliant on forecast accuracy as a means to assess the accuracy of the borrower's forward-looking information because they can make this assessment based on their past interactions with the borrower.[25] We note that relationship lenders still price protect against forward-looking information that is expected to be less accurate, but they likely make this assessment based on their own prior experience with the borrower, and not based on the accuracy of prior managerial forecasts.

In Table 5, we examine whether the negative relation between the borrower's past forecast accuracy and interest spreads becomes stronger for higher-risk borrowers with greater volatility. We measure the borrower's riskiness using the standard deviation of seasonally-adjusted quarterly income over the three-year period prior to contract initiation, which matches the measurement window of *Forecast Accuracy*.[26]

We assume that as the borrower's future cash flows become riskier so does the borrower's ability to make future interest payments. We create an indicator variable equal to 1 if this standard deviation is above sample median (high-risk borrowers),

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[22] In untabulated analysis we find qualitatively similar results if we include deal purpose and loan type fixed effects in the regression model.

[23] In an untabulated robustness test, we include analyst forecast dispersion, analyst forecast accuracy, analyst revision volatility, and managerial forecast news as additional control variables. Analyst forecast dispersion, analyst forecast accuracy, and analyst revision volatility are included in Mansi et al. (2011) and managerial forecast news is included in Shivakumar et al. (2011). After including these additional control variables, we find that the results are qualitatively similar to those found in Table 3 (our primary result). We do not include these variables as additional control variables in our main tests because we believe that many of our existing control variables capture aspects of these additional control variables. For example, analyst following and the standard deviation of stock returns are highly correlated with analyst forecast accuracy, analyst revision volatility, and analyst forecast dispersion, and therefore likely capture the same underlying construct. In addition, managerial forecast news is at least partially captured by current and future ROA.

[24] In untabulated analysis we find that *Forecast Accuracy* has no effect on the inclusion of financial covenants in private debt contracts, or on the level of covenant slack in financial covenants. This evidence further supports our contention that lenders use past managerial forecast accuracy to assess the accuracy of the borrower's forward-looking information while screening borrowers prior to contract initiation and not to monitor borrowers after contract initiation. Debt covenants are primarily used to monitor the borrower after contract initiation.

[25] An alternative interpretation of these results is that, due to multi-stage nature of relationship lending, borrowers with more accurate forecasts do not enjoy lower loan spreads from relationship lenders because these banks care about the long-term borrower performance of the borrower, rather than the ability to repay them in the short-term, lessening the importance of this assessment.

[26] Prior literature supports the link between earnings volatility and risk (Graham et al. 2005; Dichev and Tang 2009). We seasonally-adjust quarterly income prior to measuring the standard deviation to ensure we do not identify firms operating in industries with greater seasonality (e.g. retail) as high risk.

TABLE 3

Management Forecast Accuracy and Interest Spreads

		Log(*Spread*)	
	Prediction	**Coefficient**	**t-stat**
Forecast Accuracy	−	−0.115**	(−2.45)
Future ROA		−0.596***	(−5.32)
Size		−0.071***	(−2.81)
Leverage		0.420***	(4.96)
MTB		−0.001**	(−2.29)
ROA		−0.337	(−1.34)
Sales Growth		0.021	(0.39)
Rating		0.020	(1.51)
Z-Score		−0.000	(−1.50)
Firm Age		−0.000	(−0.92)
Std(*Earnings*)		0.269	(1.29)
Std(*Stock Returns*)		1.173***	(3.68)
ICW		0.140**	(2.33)
Consecutive Loss		−0.019	(−0.35)
Relationship Lender		−0.006	(−0.27)
Analyst Following		−0.010***	(−3.95)
Institutional Ownership		0.261***	(3.51)
Disc Accruals		0.007	(0.35)
Revolver		−0.061**	(−2.10)
Performance Pricing		−0.103***	(−3.54)
BS Covenant		−0.031	(−1.10)
IS Covenant		0.196***	(3.91)
Syndicate Size		−0.072***	(−2.68)
Capex Restrict		0.098***	(2.95)
Inst Tranche		0.170***	(4.38)
Sweep Covenant		0.175***	(6.00)
Dividend Restrict		0.019	(0.62)
Collateral		0.287***	(9.26)
Log(*Debt Size*)		0.012	(0.49)
Log(*Maturity*)		0.049*	(1.90)
Year Fixed Effects		Yes	
Industry Fixed Effects		Yes	
Number Obs.		2,487	
R^2		0.694	

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table reports the results of a regression model testing the impact of management forecast accuracy on interest spreads of private debt contracts initiated over the period from 2003 to 2012. The dependent variable in this model is the natural log of interest spreads available on Dealscan. Standard errors are clustered by firm.
Variables are defined in Appendix A.

and 0 otherwise. In Column 1, we estimate the impact of forecast accuracy (*Forecast Accuracy*) on interest rate spreads (*Log*(*Spread*)) for high-risk borrowers. Consistent with expectations, we find a negative and significant coefficient on *Forecast Accuracy* for high-risk borrowers (Column 1). In Column 2, however, we find an insignificant coefficient on *Forecast Accuracy* for low-risk borrowers. We test the difference between the coefficient on *Forecast Accuracy* in Column 1 and Column 2 and find that it is statistically significant at the 5 percent level. These test results show a stronger association between past forecast accuracy and the interest spread for higher-risk borrowers, suggesting that assessing the borrower's ability to produce accurate forward-looking information is more important for high-risk borrowers.[27]

[27] An alternative interpretation of these findings is that management forecast accuracy is especially useful for lenders when future performance is inherently more difficult to predict.

TABLE 4

Cross-Sectional Test Based on Relationship Banking

	[1] *Log*(*Spread*)		[2] *Log*(*Spread*)			
	Coefficient	**t-stat**	**Coefficient**	**t-stat**	**Difference**	**p-value**
Forecast Accuracy	−0.118**	(−2.17)	−0.066	(−0.99)	0.052	0.26
Future ROA	−0.502***	(−3.39)	−0.788***	(−5.85)		
Size	−0.034	(−1.13)	−0.115***	(−3.24)		
Leverage	0.481***	(4.75)	0.195	(1.42)		
MTB	−0.004**	(−2.48)	−0.000**	(−2.16)		
ROA	0.058	(0.25)	−1.589***	(−4.49)		
Sales Growth	0.009	(0.14)	0.029	(0.35)		
Rating	0.035**	(2.36)	−0.009	(−0.47)		
Z-Score	−0.000	(−0.97)	−0.0001*	(−1.95)		
Firm Age	−0.001	(−0.90)	−0.001	(−0.70)		
Std(*Earnings*)	0.277	(1.00)	0.308	(1.56)		
Std(*Stock Returns*)	1.223***	(3.56)	0.739	(1.51)		
ICW	0.110	(1.59)	0.192**	(2.14)		
Consecutive Loss	0.016	(0.27)	−0.084	(−0.82)		
Analyst Following	−0.010***	(−3.68)	−0.009**	(−2.30)		
Institutional Ownership	0.176**	(2.07)	0.433***	(3.77)		
Disc Accruals	−0.004	(−0.19)	0.073**	(2.09)		
Revolver	−0.080**	(−2.07)	−0.048	(−1.14)		
Performance Pricing	−0.108***	(−2.64)	−0.076*	(−1.82)		
BS Covenant	−0.008	(−0.24)	−0.053	(−1.18)		
IS Covenant	0.197***	(3.45)	0.244***	(3.24)		
Syndicate Size	−0.058	(−1.65)	−0.088**	(−2.41)		
Capex Restrict	0.083**	(2.09)	0.171***	(3.16)		
Inst Tranche	0.205***	(3.91)	0.126**	(2.41)		
Sweep Covenant	0.212***	(5.92)	0.103**	(2.30)		
Dividend Restrict	0.049	(1.32)	−0.032	(−0.71)		
Collateral	0.290***	(7.69)	0.303***	(6.59)		
Log(*Debt Size*)	−0.001	(−0.04)	−0.0001	(−0.01)		
Log(*Maturity*)	0.048	(1.43)	0.042	(1.02)		
Constant	4.282***	(11.84)	5.413***	(11.04)		
Industry Fixed Effects	Yes		Yes			
Year Fixed Effects	Yes		Yes			
Number Obs.	1,518		969			
R^2	0.679		0.754			

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table reports the results of a regression model testing the impact of management forecast accuracy on interest spreads of private debt contracts initiated over the period from 2003 to 2012. The dependent variable in this model is the natural log of interest spreads available on Dealscan. Column 1 estimates the model for loans from non-relationship private lenders. Column 2 estimates the model for loans from relationship lenders. Standard errors are clustered by firm. Variables are defined in Appendix A.

V. ROBUSTNESS TESTS AND ADDITIONAL ANALYSES

Alternative Measurement of Management Forecast Accuracy

In our primary analyses, we measure forecast accuracy using the percentage by which the borrower misses his forecast. As an alternative measure, we calculate *Forecast Accuracy* by scaling the absolute value of the borrower's forecast error by the firm's stock price (*Forecast Accuracy*/*Price*) to reduce the likelihood that the denominator is driving our results. We present these results in Column 1 of Table 6. Consistent with our hypothesis and previous results, we find that the coefficient on *Forecast Accuracy*/*Price* is significant (1 percent level) and equal to −0.131, suggesting a 13.1 percent decrease in the interest

TABLE 5

Cross-Sectional Test Based on Borrower Risk

	[1] *Log*(*Spread*)		[2] *Log*(*Spread*)			
	Coefficient	**t-stat**	**Coefficient**	**t-stat**	**Difference**	**p-value**
Forecast Accuracy	−0.188***	(−2.82)	−0.038	(−0.69)	−0.150**	0.03
Future ROA	−0.673***	(−4.23)	−0.345**	(−2.41)		
Size	−0.019	(−0.54)	−0.143***	(−4.55)		
Leverage	0.375***	(2.94)	0.453***	(4.29)		
MTB	−0.001	(−1.65)	−0.000	(−0.71)		
ROA	−0.011	(−0.04)	−1.140***	(−3.39)		
Sales Growth	−0.027	(−0.40)	0.061	(1.08)		
Rating	−0.0001**	(−2.24)	−0.000	(−0.72)		
Z-Score	0.023	(1.35)	0.020	(1.24)		
Firm Age	−0.001	(−0.63)	−0.001	(−1.63)		
Std(*Earnings*)	0.044	(0.20)	−1.448	(−0.58)		
Std(*Stock Returns*)	0.637	(1.33)	1.038***	(2.66)		
ICW	0.194*	(1.70)	0.092	(1.65)		
Consecutive Loss	0.088	(1.20)	−0.098	(−1.42)		
Relationship Lender	−0.039	(−1.11)	0.031	(1.03)		
Analyst Following	−0.007**	(−2.22)	−0.010***	(−2.75)		
Institutional Ownership	0.261**	(2.15)	0.257***	(3.37)		
Disc Accruals	−0.000	(−0.02)	0.015	(0.58)		
Revolver	−0.087*	(−1.96)	−0.031	(−0.90)		
Performance Pricing	−0.134***	(−2.95)	−0.086***	(−2.51)		
BS Covenant	−0.077*	(−1.76)	0.001	(0.03)		
IS Covenant	0.229***	(3.92)	0.077	(1.11)		
Syndicate Size	−0.070*	(−1.97)	−0.064*	(−1.90)		
Capex Restrict	0.110*	(1.94)	0.087**	(2.38)		
Inst Tranche	0.166***	(2.76)	0.164***	(3.39)		
Sweep Covenant	0.142***	(3.09)	0.194***	(5.49)		
Dividend Restrict	0.003	(0.10)	0.073*	(1.84)		
Collateral	0.288***	(6.41)	0.269***	(7.00)		
Log(*Debt Size*)	−0.029	(−1.01)	0.049	(1.59)		
Log(*Maturity*)	0.091***	(2.57)	0.013	(0.36)		
Industry Fixed Effects	Yes		Yes			
Year Fixed Effects	Yes		Yes			
Number Obs.	1,244		1,243			
R^2	0.755		0.656			

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

This table reports the results of a regression model testing the impact of management forecast accuracy on interest spreads of private debt contracts initiated over the period from 2003 to 2012. The dependent variable in this model is the natural log of interest spreads available on Dealscan. Column 1 estimates the model for high-risk borrowers with the standard deviation of seasonally-adjusted quarterly net income above the sample median. Column 2 estimates the model for low-risk borrowers with the standard deviation of seasonally-adjusted quarterly net income below the sample median. Standard errors are clustered by firm.

Variables are defined in Appendix A.

rate as *Forecast Accuracy*/*Price* moves from the bottom to the top decile. The economic magnitude of this result is similar to that reported in Table 3.

Intentional bias in public managerial forecasts is an additional concern of using forecast accuracy to measure the manager's ability to make accurate future predictions. Managers could intentionally induce directional bias into their earnings forecasts for reasons unrelated to private debt contracting. For example, managers may issue downward-biased forecasts to reduce the likelihood that an unexpected shock causes the manager to miss an expected performance target. If some managers systematically bias earnings forecasts downward to protect against negative shocks, our measure of forecast accuracy would

TABLE 6

Alternative Measurement of Management Forecast Accuracy

	[1] *Log*(*Spread*)		[2] *Log*(*Spread*)	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**
Forecast Accuracy/Price	−0.131***	(−2.80)		
Std(*Forecast Error*)			−0.099*	(−1.85)
Future ROA	−0.592***	(−5.32)	−0.604***	(−4.85)
Size	−0.070***	(−2.78)	−0.102***	(−3.44)
Leverage	0.388***	(4.63)	0.394***	(3.94)
MTB	−0.001**	(−2.32)	−0.001	(−0.71)
ROA	−0.343	(−1.37)	−0.403	(−1.42)
Sales Growth	0.023	(0.43)	0.055	(0.76)
Rating	0.021	(1.62)	0.016	(1.05)
Z-Score	−0.000	(−1.50)	−0.0001**	(−2.33)
Firm Age	−0.001	(−0.89)	−0.001	(−0.74)
Std(*Earnings*)	0.278	(1.33)	0.553***	(2.98)
Std(*Stock Returns*)	1.124***	(3.49)	0.768*	(1.93)
ICW	0.136**	(2.26)	0.129*	(1.88)
Consecutive Loss	−0.021	(−0.38)	−0.012	(−0.20)
Relationship Lender	−0.007	(−0.30)	−0.017	(−0.64)
Analyst Following	−0.009***	(−3.65)	−0.010***	(−3.44)
Institutional Ownership	0.269***	(3.62)	0.362***	(4.04)
Disc Accruals	0.008	(0.41)	0.013	(0.57)
Revolver	−0.057*	(−1.99)	−0.065*	(−1.98)
Performance Pricing	−0.102***	(−3.47)	−0.110***	(−3.25)
BS Covenant	−0.032	(−1.13)	−0.039	(−1.17)
IS Covenant	0.198***	(3.94)	0.180***	(3.24)
Syndicate Size	−0.075***	(−2.79)	−0.052	(−1.64)
Capex Restrict	0.107***	(3.18)	0.115***	(2.85)
Inst Tranche	0.173***	(4.45)	0.158***	(3.36)
Sweep Covenant	0.173***	(5.90)	0.155***	(4.27)
Dividend Restrict	0.020	(0.68)	0.023	(0.64)
Collateral	0.292***	(9.37)	0.284***	(7.83)
Log(*Debt Size*)	0.014	(0.58)	0.021	(0.74)
Log(*Maturity*)	0.043*	(1.67)	0.025	(0.81)
Industry Fixed Effects	Yes		Yes	
Year Fixed Effects	Yes		Yes	
Number Obs.	2,477		1,857	
R^2	0.695		0.698	

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table reports the results of a regression model testing the impact of management forecast accuracy on interest spreads of private debt contracts initiated over the period from 2003 to 2012. The dependent variable in this model is the natural log of interest spreads available on Dealscan. Standard errors are clustered by firm.
Variables are defined in Appendix A.

identify these managers as producing relatively inaccurate forecasts. However, sophisticated users of financial information, including lenders, can unravel any intentional and systematic bias, which will allow the borrower to demonstrate a higher ability to produce accurate forward-looking information under these circumstances. This argument is consistent with Hilary, Hsu, and Wang (2014), who provide evidence that biased but precise forecasts provide more information than unbiased but noisy forecasts.

As an alternative measure of forecast accuracy to reduce the possible effects of systematic and intentional bias on our previous measure of *Forecast Accuracy,* we calculate the standard deviation of signed managerial forecast errors over the three-

year period prior to contract inception (*Std*(*Forecast Error*)).[28,29] If managers produce systematically biased forecasts, the standard deviation of the forecast errors (as opposed to *Forecast Accuracy*) should reduce the influence of the systematic biases (whether forecasts are systematically optimistic or pessimistic).[30] We present the results in Column 2 of Table 6. Consistent with our primary results, we find that the coefficient on *Std*(*Forecast Error*) is negative and statistically significant at the 10 percent level. Overall, the evidence in Table 6 suggests a negative association between the borrower's cost of debt and the borrower's ability to produce accurate forward-looking information to be higher.

Management Turnover Sample

In our primary analyses (Table 3), we control for factors that could potentially affect both the borrower's forecast accuracy and the cost of debt. However, because we cannot randomly assign the treatment effect to observations in our sample, we cannot completely rule out the possibility that both the borrower's forecast accuracy and the cost of debt are correlated with unobservable variables.

As a robustness test, we select a sample of 104 borrowers experiencing management turnover in the year prior to debt contract initiation in our sample period. We identify management turnover based on executives joining the borrowing firm on ExecuComp over the one-year period prior to contract initiation.[31] We measure the manager's historical forecast accuracy at the prior firm (i.e., where the manager worked prior to joining the borrowing firm) over the three-year period prior to the manager's turnover date and examine its effect on the cost of debt at the new firm (i.e., the borrowing firm) after the turnover date.[32] Using the borrower's forecast accuracy at the prior firm allows us to better capture our underlying construct of interest, the manager's ability to produce accurate forward-looking information, while mitigating the possibility that unobservable characteristics of the borrowing *firm* affect our empirical results. Nevertheless, we cannot fully rule out endogeneity concerns due to the endogenous matching of employer to employee.

We estimate a regression of the borrower's cost of debt (*Log*(*Spread*)) on the manager's three-year average historical forecast accuracy at the prior firm before his/her appointment at the borrowing firm (*Prior Forecast Accuracy*). We include control variables for the total assets and profitability of both the new firm (*Size* and *ROA*) and the prior firm in the annual period prior to management turnover (*Prior Size* and *Prior ROA*). We also include the new firm's leverage (*Leverage*) and future profitability (*Future ROA*) to control for the borrower's riskiness and expected future performance at contract initiation. Including *Future ROA* also helps control for the manager's overall ability to run the firm, which allows us to isolate the borrower's ability to provide accurate forward-looking information. Finally, we include the size of the debt contract (*Log*(*Debt Size*)), the contract's stated maturity (*Log*(*Maturity*)), Fama-French 48 industry fixed effects, and year fixed effects.[33]

We present the results for the management turnover sample in Table 7. Consistent with H1 and the results presented in Table 3, we find a negative and significant (5 percent level) coefficient on *Prior Forecast Accuracy*. Overall, these results reduce the likelihood that unobservable features of the borrower that are correlated with both the borrower's historical forecast accuracy and the cost of debt are driving the results presented in Table 3.

Falsification Test: The Initial Cost of Debt in Public Debt Contracts

As discussed in Section II, bank lenders obtain access to a significant amount of private, forward-looking information to evaluate the borrower's creditworthiness. In contrast, public lenders (bondholders) have access to substantially less private, forward-looking information, because the borrower is more likely to provide private information to a small group of lenders

[28] We acknowledge that this variable captures the *precision* of the borrower's forecasts, which differs from our construct of interest, forecast *accuracy*. These two measures both capture how the forecast deviates from the realized earnings results, albeit in somewhat different ways. Empirically our measures of *Forecast Accuracy* and *Std*(*Forecast Error*) are highly correlated (correlation coefficient = 0.904).

[29] Similar to our calculation of the *Forecast Accuracy* variable, we use the prior three years of managerial forecasts prior to the debt contract initiation to calculate the standard deviation of forecast errors.

[30] For both alternative measures in Table 6, we multiply by −1 so that higher values represent more accurate forecasters. We also decile rank and transform each variable to take values between 0 and 1, following the measurement of *Forecast Accuracy* in Equation (1).

[31] We eliminate firm employees who are unlikely to have a material effect on management earnings forecasts at the prior firm such as divisional managers, marketing executives, general counsel, and human resources. Our final sample includes individuals holding Chief Executive Officer, Chairman, Chief Financial Officer, Chief Operating Officer, and Chief Accounting Officer positions at the prior firm.

[32] The empirical estimation of *Prior Forecast Accuracy* follows the same method specified in Section III, except that we measure forecast accuracy of the three-year period prior to management turnover, as opposed to over the three-year period prior to debt contract inception. Results are qualitatively similar using the alternative measures of forecast accuracy discussed in Section V.

[33] Results are qualitatively similar if we include only limited control variables for the borrower (*Future ROA, Size, ROA*) and the face value of the debt contract (*Log*(*Debt Size*)). Results are also qualitatively similar if we include additional financial control variables for both the borrower and the manager's prior firm (*MTB, Sales Growth*), managerial ability (*MA SCORE*), and additional debt contract characteristics (*Revolver, PP, BS Covenant, IS Covenant, Syndicate Size, Capex Restrict, Inst Tranche, Sweep Covenant, Dividend Restrict,* and *Collateral*). We do not include other control variables in Table 3 to maximize the management turnover sample of 104 observations.

TABLE 7

Management Forecast Accuracy and Interest Spreads—Turnover Sample

		Log(*Spread*)	
	Prediction	**Coefficient**	**t-stat**
Prior Forecast Accuracy	−	−0.579**	(−2.01)
Future ROA		−0.484	(−0.92)
Size		−0.506***	(−3.93)
ROA		−3.251*	(−1.69)
Leverage		0.542	(0.65)
Prior Size		0.149**	(2.15)
Prior ROA		2.246	(1.31)
Log(*Debt Size*)		0.295*	(2.00)
Log(*Maturity*)		0.119	(0.67)
Industry Fixed Effects		Yes	
Year Fixed Effects		Yes	
Number Obs.		104	
R^2		0.846	

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table reports the results of a regression model testing the impact of management forecast accuracy on interest spreads of private debt contracts initiated over the period from 2003 to 2012. The dependent variable in this model is the natural log of interest spreads available on Dealscan. Standard errors are clustered by firm.
Variables are defined in Appendix A.

rather than a dispersed group of bondholders (Bhattacharya and Chiesa 1995; Bharath et al. 2008). Thus, public lenders (i.e., bondholders), relative to bank lenders, have less of a need to assess the borrower's ability to produce accurate forward-looking information, since they have limited access to such forward-looking information. If our interpretation of management forecast accuracy (as a signal for private information accuracy) holds, we do not expect historical forecast accuracy to significantly affect the borrower's cost of debt for public issuances.[34] Conversely, if our measure of forecast accuracy is correlated with an unobservable borrower characteristic that also effects the borrower's cost of debt, we should observe a significantly negative association between *Forecast Accuracy* and the initial interest spread in public bonds.

We examine the association between the historical accuracy of forward-looking information and initial interest rate spreads for public borrowers. We identify a sample of 2,120 public bond issuances on Mergent FISD with available financial information on Compustat and management forecast accuracy data available on CIG or I/B/E/S between 2003 and 2012. We estimate a regression model similar to Equation (1) for this sample, where the dependent variable (*Log*(*Bond Spread*)) is equal to the natural log of the initial bond interest rate on Mergent FISD less the one-year LIBOR rate available from the St. Louis Federal Reserve Bank website. The results we present in Table 8 are consistent with our expectations. Specifically, after controlling for firm and bond characteristics, we do not find a significant relation between *Forecast Accuracy* and the initial cost of debt in public bonds, providing no evidence that the historical accuracy of management earnings forecasts facilitates bondholder's activities.[35]

While the result that management forecast accuracy is not associated with interest spreads for borrowers with public debt may seem counterintuitive, the evidence is consistent with the argument that bondholders do not use historical managerial forecasts to assess the borrower's ability to provide accurate forward-looking information, which may be because borrowers provide less private information to bondholders (relative to private lenders). Borrowers are less likely to provide private

[34] As discussed in Section I, we do not expect that lagged managerial forecasts provide a direct source of information about the borrower's performance to either bondholders or banks. We note that bondholders still desire to obtain private, forward-looking information from the borrower; however, their access to forward-looking information is limited. We therefore do not expect that bond investors need to assess the accuracy of private information, so we do not expect a negative relation between past forecast accuracy and the cost of debt for bonds.

[35] Denis and Mihov (2003) provide evidence that the borrower's credit risk is the primary determinant of the choice between public and private debt. To reduce the likelihood that our results are driven by differences in risk and uncertainty between these two markets, we re-estimate the relation between the borrower's historical forecast accuracy and interest spreads in private debt contracts using a sample of Dealscan loan facilities for which the borrowers also have public bond data available on either TRACE or Mergent FISD over the sample period. Results are qualitatively similar. We also verify that our results hold for a sub-sample of borrowers with an S&P credit rating available on Compustat.

TABLE 8

Management Forecast Accuracy and Interest Spreads of Public Bonds

		Log(*Bond Spread*)	
	Prediction	**Coefficient**	**t-stat**
Forecast Accuracy	?	0.151	(1.32)
Future ROA		−0.937*	(−1.71)
Size		0.031	(0.92)
Leverage		0.352	(1.18)
MTB		−0.000	(−1.46)
ROA		−0.274	(−0.87)
Sales Growth		0.126	(0.86)
Rating		0.029	(1.19)
Z-Score		−0.005	(−0.64)
Firm Age		−0.002*	(−1.74)
Std(*Earnings*)		2.035*	(1.69)
Std(*Stock Returns*)		0.820	(0.86)
ICW		−0.066	(−0.46)
Consecutive Loss		0.138	(1.32)
Analyst Following		−0.017***	(−3.65)
Institutional Ownership		0.008	(0.07)
Disc Accruals		−0.019	(−0.65)
Financial Covenant		−0.077	(−1.00)
Negative Pledge Covenant		0.012	(0.23)
Debt Restriction		0.354***	(3.90)
Merger/Acquisition Restriction		0.066	(0.99)
Redeemable		−0.018	(−0.29)
Convertible		−1.044***	(−8.42)
Rule 144a		0.192***	(2.84)
Cross Default Provision		−0.216**	(−2.27)
Collateral		0.050	(0.58)
Log(*Debt Size*)		−0.018	(−1.12)
Log(*Maturity*)		0.347***	(4.81)
Industry Fixed Effects		Yes	
Year Fixed Effects		Yes	
Number Obs.		2,120	
R^2		0.560	

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table reports the results of a regression model testing the impact of management forecast accuracy on interest spreads of public debt contracts initiated over the period from 2003 to 2012. The dependent variable in this model is the natural log of the initial interest rate on FISD above LIBOR available from the St. Louis Federal Reserve. Standard errors are clustered by firm.
Variables are defined in Appendix A.

information to a small group of lenders rather than a dispersed group of bondholders (Bhattacharya and Chiesa 1995; Bharath et al. 2008). The lack of a significant result for public bonds is consistent with our assertion that forecast accuracy provides information about the expected accuracy of the borrower's private, forward-looking information. When the accuracy of prior managerial forecasts is not useful for assessing the expected accuracy of forward-looking information, it does not affect debt pricing.

Management Forecast Accuracy, Future Performance, and the Cost of Debt

In our final analysis, we consider whether the lender's assessment of the borrower's ability to produce accurate forward-looking information is associated with the lender's ability to accurately price the future value of the borrower at contract initiation. The interest rate charged on the loan reflects the lender's expectation of repayment, which is based on the estimated distribution of the borrower's future value. *Ceteris paribus,* more accurate forward-looking information improves the lender's screening activities by increasing the precision of the estimate for the borrower's

future value. As a result, the lender's *ex ante* assessment of the borrower's future value better predicts the borrower's realized future performance. Therefore, we expect the loan to be priced more efficiently *ex ante* when the lender assesses the borrower's ability to produce accurate forward-looking information to be higher. We test this prediction using the following model:

$$Log(Spread) = \alpha_0 + \beta_1 Forecast\ Accuracy + \beta_2 Future\ ROA + \beta_3 Forecast\ Accuracy * Future\ ROA + Control\ Variables + \sum Industry + \sum Year + \varepsilon \quad (2)$$

Similar to Equation (1), the dependent variable is *Log*(*Spread*). Following Gallimberti (2016), we select the interaction between the borrower's forecast accuracy (*Forecast Accuracy*) and the borrower's realized future profitability (*Future ROA*) as an indication of the lender's ability to price future performance. *Ceteris paribus,* borrowers with higher expected future performance have a lower cost of debt, as indicated in Table 3 by a negative and significant coefficient on *Future ROA*. If the borrower's past forecast accuracy facilitates the lender's estimation of the borrower's future value, then we expect the coefficient on the *Forecast Accuracy* ∗ *Future ROA* interaction to be negative, indicating that the pricing of the loan is more sensitive to the borrower's future performance. In contrast, a positive coefficient on this interaction suggests a higher degree of interest rate mispricing. We include the same control variables in Equation (2) that were included in Equation (1).

We present the results in Table 9. Consistent with our expectations, we find a negative and significant (1 percent level) coefficient on the *Forecast Accuracy* ∗ *Future ROA* interaction, which suggests that more accurate forward-looking information is associated with lower interest-rate mispricing by strengthening the relation between the borrower's realized future performance and the cost of debt. In other words, these results suggest that lenders are able to provide a more accurate estimate of the borrower's future performance at contract inception when past managerial forecast accuracy is higher. Consistent with the prior results, this evidence suggests that the borrower's past forecast accuracy is useful in assessing the borrower's ability to produce accurate forward-looking information obtained during contract negotiations and improves the lender's screening activities.

VI. SUMMARY AND CONCLUSION

We examine whether the borrower's past earnings forecast accuracy represents an observable measure that can be used by the lender to assess the borrower's ability to provide accurate forward-looking information obtained during contract negotiations. We find that borrowers with more accurate forecasts prior to debt contract inception have a lower cost of debt. This result is robust to alternative specifications and measurement choices. We also find these results to be concentrated among higher-risk borrowers and borrowers that have not had a previous relationship with the lender. Additionally, we find that debt contracts to borrowers with higher forecast accuracy exhibit lower interest rate mispricing, suggesting that using managerial forecasts as an input to estimate the distribution of the borrower's future value improves the lender's screening activities.

These results contribute to the accounting literature by illustrating a channel by which the lender can assess the borrower's ability to produce accurate forward-looking information obtained during contract negotiations. Despite the importance of forward-looking information when determining the loan's contract terms, the literature is largely silent on identifying a mechanism that the lender can use to assess the accuracy of this information. Prior research focuses on the association between the quality of the financial statements, which are historical and can be examined by an external auditor, and the loan's contract terms. Since the forward-looking information obtained by the lender during contract negotiations falls outside the purview of the external audit, lenders must find another way to assess the borrower's ability to produce accurate forward-looking information. Our results suggest that using the borrower's past forecast accuracy to assess the borrower's ability to provide accurate forward-looking information is an important input to debt contracting and has an economically meaningful effect on loan pricing.

We note certain issues that may limit the inferences from our study. First, we use the historical accuracy of the borrower's earnings forecasts as a measure that the lender could use to assess the borrower's ability to provide accurate forward-looking information. Not all borrowers with loans covered by Dealscan provide earnings forecasts; therefore, our results do not yield inferences for non-forecasters.[36] Second, many factors affect the cost of debt, including such prominent items as borrower size

[36] An extensive literature examines the decision to issue voluntary disclosure such as management forecasts (see Healy and Palepu [2001] and Beyer et al. [2010] for literature reviews). An alternative approach to focusing only on forecasters is to compare forecasters (where the lender receives information about forward-looking accuracy) and non-forecasters (where no information is provided). Based on the literature, we expect that forecasters and non-forecasters are fundamentally different. Moreover, we believe the decision to issue a forecast is likely unrelated to debt contracting concerns (i.e., it is likely due to other capital market demands.) As such, we believe that including non-forecasters would damage the inferences that we could draw due to the nature of the forecast decision, so we focus solely on forecasters in our empirical tests.

TABLE 9

Management Forecast Accuracy and Mispricing in Private Debt Contracts

		Log(*Spread*)	
	Prediction	**Coefficient**	**t-stat**
Forecast Accuracy		−0.095**	(−2.03)
Future ROA		−0.279	(−1.66)
Forecast Accuracy * *Future ROA*	−	−0.842***	(−2.56)
Size		−0.068***	(−2.73)
Leverage		0.422***	(5.04)
MTB		−0.001**	(−2.27)
ROA		−0.305	(−1.25)
Sales Growth		0.014	(0.27)
Rating		0.022	(1.67)
Z-Score		−0.000	(−1.49)
Firm Age		−0.001	(−0.81)
Std(*Earnings*)		0.264	(1.27)
Std(*Stock Returns*)		1.123***	(3.52)
ICW		0.139**	(2.32)
Consecutive Loss		−0.012	(−0.21)
Relationship Lender		−0.008	(−0.33)
Analyst Following		−0.009***	(−3.76)
Institutional Ownership		0.260***	(3.50)
Disc Accruals		0.008	(0.40)
Revolver		−0.062**	(−2.17)
Performance Pricing		−0.101***	(−3.47)
BS Covenant		−0.035	(−1.23)
IS Covenant		0.194***	(3.87)
Syndicate Size		−0.073***	(−2.72)
Capex Restrict		0.103***	(3.11)
Inst Tranche		0.169***	(4.40)
Sweep Covenant		0.172***	(5.90)
Dividend Restrict		0.019	(0.62)
Collateral		0.286***	(9.26)
Log(*Debt Size*)		0.009	(0.41)
Log(*Maturity*)		0.051*	(1.95)
Industry Fixed Effects		Yes	
Year Fixed Effects		Yes	
Number Obs.		2,487	
R^2		0.695	

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table reports the results of a regression model testing the impact of management forecast accuracy on interest spreads of private debt contracts initiated over the period from 2003 to 2012. The dependent variable in this model is the natural log of interest spreads available on Dealscan. Standard errors are clustered by firm.
Variables are defined in Appendix A.

and performance, leverage, default risk, and operating volatility. Although we expect that the lender's assessment of the accuracy of the borrower's forward-looking information to be decision-useful, we acknowledge that the effect we document is likely of second-order importance relative to borrower fundamentals. Third, we note that our study provides descriptive evidence suggesting a method through which lenders can use public managerial forecast accuracy to assess the borrower's ability to produce accurate forward-looking information. We provide several additional tests, including an analysis of borrowers experiencing management turnover, to provide comfort regarding the robustness of our results. However, we acknowledge that in the absence of an exogenous shock to management forecast accuracy we are unable to draw causal inferences. Despite these limitations, we believe this study contributes to the debt contracting literature by providing

meaningful evidence on the role of information in debt pricing. Lastly, the results in this paper do not directly document the actions taken by lenders to assess the borrower's ability to produce accurate forward-looking information. Our results suggest that lenders could use the borrower's past managerial forecasts to assess his/her ability to produce accurate forward-looking information. In addition, we believe that the theoretical underpinnings of this paper help to understand why lenders would charge a lower interest spread when past managerial forecasts are more accurate. We hope that the evidence in this paper spurs additional research to examine the actions lenders take to assess the borrower's ability to provide accurate forward-looking information.

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APPENDIX A

Variable Definitions

Variable	Definition
Analyst Following	I/B/E/S analyst following in the period prior to contract inception.
Bond Spread	The initial interest rate on FISD above LIBOR available from the St. Louis Federal Reserve.
BS Covenant	Indicator variable equal to 1 if the debt contract available on Dealscan includes a leverage ratio, debt-to-equity ratio, net worth, current ratio, or quick ratio covenant, and 0 otherwise.
Capex Restrict	Indicator variable equal to 1 if the debt contract available on Dealscan includes a covenant restricting the level of capital expenditures, and 0 otherwise.
Collateral	Indicator variable equal to 1 for secured debt contracts available on Dealscan, and 0 otherwise.
Consecutive Loss	Indicator variable equal to 1 if the firm reported two consecutive quarters of negative income before extraordinary items (IBQ) in the two quarters immediately prior to debt contract inception.
Convertible	Indicator variable equal to 1 if the contract on FISD is convertible debt, and 0 otherwise.
Cross Default Provision	Indicator variable equal to 1 if the debt contract on FISD contains a cross-default provision, and 0 otherwise.
Debt Restriction	Indicator variable equal to 1 if the debt contract on FISD contains a negative covenant restricting the borrower from taking on additional debt, and 0 otherwise.
Debt Size	Face value (in millions) of the debt facility on Dealscan.
Disc Accruals	Absolute value of the difference between total accruals (income before extraordinary items less operating cash flows from the statement of cash flows scaled by average total assets) and expected accruals based on the fitted value of total accruals regressed on lagged, current, and future operating cash flows following Dechow and Dichev (2002), estimated annually by Fama-French 48 industry affiliation.
Dividend Restrict	Indicator variable equal to 1 if the debt contract available on Dealscan includes a dividend restriction, and 0 otherwise.
Financial Covenant	Indicator variable equal to 1 if the debt contract on FISD includes a financial covenant, and 0 otherwise.
Firm Age	Firm age (in years) based on the first date the firm appears in Compustat or CRSP.
Forecast Accuracy	Average management forecast accuracy over the three-year period prior to contract inception, measured as −1 multiplied by the absolute value of the difference between the management forecasted and I/B/E/S actual EPS, scaled by the absolute value of forecasted EPS.
Forecast Accuracy/Price	Average management forecast accuracy over the three-year period prior to contract inception, measured as the decile rank (divided by 9) of −1 multiplied by the absolute value of the difference between the management forecasted and I/B/E/S actual EPS, scaled by price.
Future ROA	Income before extraordinary items (IB) scaled by total assets (AT), measured in the first annual period following debt contract inception.
ICW	Indicator variable equal to 1 if the firm reported an internal control weakness in the annual period prior to contract inception based on data available on Audit Analytics, and 0 otherwise.
Inst Tranche	Indicator variable equal to 1 if the debt contract available on Dealscan has a Term Loan B or higher, and 0 otherwise.
Institutional Ownership	Thomson-Reuters institutional ownership in the period prior to contract inception.
IS Covenant	Indicator variable equal to 1 if the debt contract available on Dealscan includes an interest coverage ratio, fixed charge, debt service, minimum EBITDA, or debt-to-earnings covenant, and 0 otherwise.
Leverage	Total debt (DLTT + DLC) scaled by total assets (AT).
Maturity	Maturity (in months) of the debt facility on Dealscan.
Merger/Acquisition Restriction	Indicator variable equal to 1 if the contract on FISD contains a negative covenant restricting the borrower's M&A activity, and 0 otherwise.
MTB	Market value of equity (CSHO * PRCC_F) scaled by book value of equity (CEQ).
Negative Pledge Covenant	Indicator variable equal to 1 if the debt contract on FISD contains a negative pledge restriction, and 0 otherwise.
Performance Pricing	Indicator variable equal to 1 if the debt contract available on Dealscan includes a performance pricing provision, and 0 otherwise.
Prior Forecast Accuracy	Average management forecast accuracy over the three-year period prior to management turnover, measured as the decile rank (divided by 9) of −1 multiplied by the absolute value of the difference between the management forecasted and I/B/E/S actual EPS, scaled by the absolute value of forecasted EPS.

(continued on next page)

APPENDIX A (continued)

Variable	Definition
Prior ROA	Income before extraordinary items (IB) scaled by total assets (AT) for the manager's prior firm, measured in the final annual period prior to manager turnover.
Rating	Estimated creditworthiness based on the predicted value of a regression of credit ratings on firm size, ROA, leverage, and indicator variables for loss-making firms, firms paying dividends, and firms with subordinated debt following Barth, Hodder, and Stubben (2008) and Beatty, Weber, and Yu (2008).
Redeemable	Indicator variable equal to 1 if the contract on FISD is redeemable, and 0 otherwise.
Relationship Lender	Indicator variable equal to 1 if the borrower has a debt contract with the same lender available on Dealscan in the five-year period prior to loan inception, and 0 otherwise.
Revolver	Indicator variable equal to 1 if the debt contract available on Dealscan is a revolving credit facility, and 0 otherwise.
ROA	Income before extraordinary items (IB) scaled by total assets (AT).
Sales Growth	Percentage change in annual revenue (Compustat REVT) from the prior year.
Rule 144a	Indicator variable equal to 1 if the contract on FISD is issued under SEC Rule 144a, and 0 otherwise.
Size	Natural log of 1 plus total assets (AT) on Compustat.
Spread	Interest rate (*AllInDrawn*) of the debt facility on Dealscan.
Std(*Forecast Error*)	Standard deviation of the forecast error over the three-year period prior to contract inception, measured as the decile rank (divided by 9) of −1 multiplied by the difference between the management forecasted and I/B/E/S actual EPS.
Std(*Earnings*)	Standard deviation of quarterly earnings (IBQ) measured over the previous three-year period.
Std(*Stock Returns*)	Standard deviation of monthly stock returns available on CRSP measured over the previous three-year period.
Sweep Covenant	Indicator variable equal to 1 if the debt contract available on Dealscan includes an excess cash flow sweep, asset sales sweep, debt issuance sweep, equity issuance sweep, or insurance proceeds sweep, and 0 otherwise.
Syndicate Size	The number of syndicate lenders in the syndicated debt contract available on Dealscan.
Total Assets	Total assets (AT) on Compustat.
Z-Score	Estimated measure of bankruptcy risk, equal to $1.2 * X_1 + 1.4 * X_2 + 3.3 * X_3 + 0.6 * X_4 + 0.99 * X_5$, where X_1 = current assets (ACT) minus current liabilities (LCT) scaled by total assets (AT); X_2 = retained earnings (RE) scaled by total assets; X_3 = earnings before interest and taxes (NI − XINT − TXT) scaled by total assets; X_4 = market value of equity scaled by total debt ((PRCC_F * CSHO)/(DLTT + DLC)); and X_5 = sales (REVT) scaled by total assets.

APPENDIX B

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