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The Impact of Analysts' Forecasts on Loan Terms: Past Behavior and Implications for the Pandemic

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Abstract
Building on prior research documenting an association between analyst forecasts and non-price loan characteristics, we predict and find that the precision of the private information in analysts' earnings forecasts is associated with price characteristics of private debt contracts and that this association varies in predictable ways. Specifically, we predict and find that the association between analysts' forecast prediction and interest rates is only statistically significant when formal loan terms do not require collateral, when information asymmetry may be at its strongest. Furthermore, we find statistical significance that indicates that during periods of heightened uncertainty, such as during the financial crisis, analysts' forecast precision is no longer associated with loan spreads, suggesting that lenders may include different inputs in their information set for decision-making during periods of high uncertainty, and may choose to be more selective in these periods. We conjecture that our findings may in turn be applicable during the current period of heightened uncertainty caused by the Coronavirus Pandemic of 2020. Overall, our empirical results build on our understanding of the impact of analysts' earnings forecasts on private lenders' loan contracts, and we provide further evidence that banks consider information provided by analysts when designing loan contracts for borrowers.

Keywords: Analysts; Collateral; Loan contracts

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1. Introduction

This paper responds to the call by Karabag (2020) to provide research and new knowledge to help us uncerstand the implications of the Coronavirus Pandemic in which we find ourselves. We build on Coyne and Stice (2018) by further examining whether and under which circumstances the precision of the private information contained in equity analysts' annual earnings forecasts is associated with more favorable private loan terms. The link between equity analysts' forecasts and bank loans is less intuitive than the links between sources of accounting information and the cost of debt explored in prior studies, and may even appear counterintuitive.[2] While Coyne and Stice (2018) document a previously unexplored association in the information environment among lenders and borrowers, this link was limited to non-price related loan terms such as collateral. We build on their work by demonstrating that the precision in analysts' forecasts is a predictor of price terms such as interest rate spread. Furthermore, we predict and find that the association between analysts' forecast precision and interest rates will be significant when information asymmetry is greatest, as is the case when loan terms do not require collateral. Finally, we predict and find that during periods of heightened uncertainty, such as during the financial crisis, lenders will rely less on external sources of information, such as analysts' forecasts, consistent with lenders being more selective in their information processing during these periods. We believe that these results are particularly relevant as a result of the Coronavirus Pandemic. While we continue to deal with heightened uncertainty, the inferences drawn from the observations from the financial crisis or Great Recession are unusually applicable.

In a sample of private loans, we expand the previously documented association between annual earnings forecasts and non-financial loan terms. We predict and find that higher analyst forecast precision, as defined by Barron et al. (1998) is associated with subsequent loans with lower interest spreads for the forecasted firm. We test for an association between analyst forecast precision and interest rate spread while considering a variety of variables intended to capture the strength of the borrower's information environment a credit quality. We regress interest spread on analysts' precision and control for a variety of relevant factors including deal size, date of maturity and the forecast itself and find a significant negative association. We further parse out our sample based on whether or not the borrower's loan terms include collateral. We find that the association between analysts' precision and loan spread is only significant in the absence of collateral. This is consistent with our expectation that lenders will rely more on analysts' forecasts in the presence of information asymmetry and higher expected losses in the event of default.

In our final tests, we investigate the effect of the recent financial crisis. Using all loans issued during 2007-2009, we find that the precision of analysts' private information is no longer associated with loan spread, though our documented relation holds in the periods prior to and following the financial crisis. This result is consistent with banks changing their loan pricing models, as well as the model inputs, during the financial crisis when analysts'

[2] See Armstrong et al. (2010) for a review of the recent literature investigating the role of financial reporting in debt contracting.

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information-processing abilities were affected by the overall increase in uncertainty (Arand and Kerl, 2012; Amiram et al., 2014).[3] We may observe that banks alter their loan pricing models again, as the Coronavirus Pandemic impacts the economy in a way seldom observed throughout history.

Our results further this line of research by investigating a salient component of analysts' reports in a private debt setting by documenting an association between analysts' forecast quality and pricing (i.e., spread) of private loans and the nuances of that association. The resulting information sets available to each group of debt holders may have very little overlap, and the conclusion that equity analyst reports are a useful component of the information set of bondholders does not necessarily extend to banks because of their access to privileged information as firms insiders.

Based on our results, we conclude the following. First, the precision of analysts' forecasts (as a result of their superior information-processing ability) is associated with lower price terms, specifically interest spread. Our study is more generalizable than prior research. Specifically, analysts provide information to sophisticated market participants that have access to private information (i.e., banks), and the precision of private information from analysts affects both the price and non-price terms of borrowers in the syndicated loan market.

Second, we document that higher precision of analysts' private information is most relevant to banks when setting loan terms when information asymmetry between lenders and borrowers is highest. Last, this association is interrupted during periods of uncertainty, such as during the financial crisis, when firms may be more restrictive in their use of external information. This finding is consistent with banks changing the information that they consider as inputs to the debt contract-design process when outside market participants are less likely to have relevant information compared with firm insiders. We conjecture that these results may extrapolate to the current conditions observed in the economy as a result of the Coronavirus Pandemic.

2. Literature Review and Hypotheses Development

Credit ratings are not the only source of information regarding a borrower's ability to repay loans. Using audited financial statements, lenders can calculate profitability ratios and estimate default risk. The ability of financial statements to reduce information asymmetry hinges, in part, on the quality of the information in the financial statements. For example, several studies have investigated the consequences of low accruals quality on market outcomes (Armstrong et al., 2010). In applying these findings in a debt setting, Bharath et al. (2008) hypothesize and find that higher accruals quality is associated with preferable price and non-price terms of public and private debt. Additionally, Wang (2014) and Hollander and Verriest (2016) document that borrowers with higher accruals quality can access less proximate lenders. They conclude that high quality accruals provide sufficient information to alleviate the need for lenders to access information through other channels (e.g., direct communication with management). Analysts'

[3] This inference is also supported by statements from banking executives that erroneous modeling assumptions masked the true level of risk in loan portfolios.

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forecasts represent one such potential information channel for lenders.

Prior research also provides evidence that private lenders use private information from borrowers in lending decisions (Ramakrishnan and Thakor, 1984). Bharath et al. (2008) conclude that the preference of firms with poorer accounting quality to access the private debt market is attributable, in part, to lenders' ability to impound private information into the lending contract. Furthermore, firms with low accounting quality have more proximate lenders because the ability to access the borrower's private information increases with the proximity of the lender (Hauswald and Marquez, 2006; Wang, 2014; Hollander and Verriest, 2016). Because of lenders' private access to management, as well as their ability to require special information and reports in order to consider a loan, loan officers can have knowledge from management including and beyond what analysts know, especially in the post-Reg FD era.

However, in addition to acquiring non-public information, analysts' forecasts contain internally generated private information acquired through superior information processing. Because of the proprietary nature of methods for calculating earnings forecasts, this information-generation process represents information unique to the analyst. As a result, even after excluding information from management, analysts' forecasts may continue to represent private information analysts have to offer that can reduce information asymmetry between borrowers and lenders, which can, in turn, reduce the cost of debt. We anticipate that when analysts' forecasts contain more precise private information, the resulting reduction in information uncertainty will result in more favorable price-related loan terms such as interest rate. This leads to our first hypothesis:

H1: Borrowers whose analysts issue earnings forecasts with higher private precision have lower interest rates.

Although we expect that private precision will be associated with lower interest rates, pricing is only one mechanism available to lenders to mitigate or compensate for default risk. Requiring collateral, a non-price loan term, serves an alternative. In the presence of collateral, the lender faces a reduced risk of unmitigated loss given their ability to claim and liquidate collateralized assets. By contrast, loans without collateral represent a greater risk to lenders if a default occurs. Therefore, we expect that the absence of collateral in loan terms, lenders will rely significantly on analysts' forecasts in setting price-related loan terms such as interest rates. Our second hypothesis is then:

H2: The effect of analyst forecast private precision on interest rates will be significant for borrowers whose contracts do not include collateral.

Additionally, we anticipate that lenders will reduce their reliance on information from external sources during periods of macroeconomic uncertainty. While the Pandemic that began in 2020 has caused massive economic problems, it will take time to study its effect with precision. Fortunately, we can rely on a recent period of strong uncertainty in a prior decade. One such recent example of strong macroeconomic uncertainty in our sample period is the financial crisis

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of 2008. Ivashina and Scharfstein (2010) document that lending decreased by 47% during the peak of the financial crisis compared with the prior quarter and by 79% compared with peak lending in the prior year. A survey by Campello, Harvey and Graham (2010) indicates that many firms bypassed investment opportunities because they were constrained by an inability to borrow. Given these radical reductions in lending in the face of uncertainty, we anticipate that lenders, in addition to restricting the capital they outlay, may also restrict the process they use to determine credit worthiness. Our third hypothesis is then:

H3. During periods of uncertainty, private precision will not affect interest rates.

3. Data and Methodology

3.1 Research Design

We examine the association between analysts'precision and interest rate spread by employing the following model:

$$Loan\ Spread_i = \alpha + \beta_1 Private\ Precision_i + \sum \beta_j Control_{i,j} + \varepsilon_i \tag{1}$$

where *Loan Spread* is equal to the natural log of all-in-spread drawn over LIBOR, in basis points.

Our calculation of *Private Precision* follows Coyne and Stice (2018) and Barron et. al (1998) as follows:

$$Private\ Precision = \log \frac{D}{\left[\left(1 - \frac{1}{N}\right) \text{x}\ D + SE\right]^2} \tag{2}$$

where *D* is forecast dispersion (i.e., forecast variance), *SE* is the squared forecast error and *N* is the number of forecasts. We utilize the log form of the calculation to address potential skewness (Botosan et al., 2004).

To test H1, we regress *Loan Spread* on *Private Precision*. Because higher values of *Loan Spread* indicate worse loan terms for the borrower, we anticipate a negative association between β_1 and each dependent variable. Following Coyne and Stice (2018), we report descriptive statistics unscaled, but scale the variable in regressions so that a one-unit change in *Loan Spread* can be interpreted as a one standard deviation change in analyst precision.

In each of our regression specifications we include controls for the known determinants of interest spreads. The loan controls we include are *Deal Size* (natural log of the loan facility amount), *Maturity* (natural log of the number of months until maturity), *Covenants* (number of loan covenants), and *Collateral* (a binary variable equal to 1 if collateral was a requirement as part of the loan and zero otherwise).

We also include the following borrower controls: *EA Speed* (the natural log of the number

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of days between fiscal period end and earnings announcement date scaled by -1), *Size* (natural log of total assets), *Leverage* (long-term debt / total assets), *BTM* (book-value of equity / (fiscal year-end price x common shares outstanding), *ROA* (income before extraordinary items / total assets), *Earnings Volatility (*standard deviation of the past five years of earnings divided by average total assets), *Interest Coverage* (a binary variable equal to 1 if income before interest expense and extraordinary items divided by interest expense is greater than 1.5 and zero otherwise), *Earnings Forecast* (median analyst earnings estimate in the month prior to fiscal period end), and *Investment Grade* (a binary variable equal to 1 if the borrower's most recent S&P rating prior to loan issuance is BBB- or higher and zero otherwise).[4] We also include year and four-digit SIC industry code to control for fixed effects. We anticipate that *EA Speed*, which is a measure of the quality of private information from management (Coyne and Stice, 2018), *Size* and *ROA* will be negatively correlated with *Loan Spread* and that *Leverage* and *BTM* will be positively correlated with *Spread*. We further predict that *Earnings Volatility* will be positively correlated with *Spread*.

3.2 Data Sources and Sample Selection

Table 1 depicts our sample. We begin with all sole lender and syndicated loans issued to public companies in U.S. currency from 1994-2012 in the Dealscan database. This sample range is key as it allows us to evaluate the periods of uncertainty before during and following the great recession. Although we are unable to observe the impact of the Coronavirus on lending practices in 2020, the behaviors observed during this prior period of uncertainty are likely to provide insight into behavior during the current crisis. As expected, our sample contains primarily syndicated loans. We exclude financial firms due to the regulatory-related constraints they face. We merge the remaining observations with Compustat and I/B/E/S[5]. After winsorizing at the 1% and 99% levels and excluding observations with missing variables, our sample contains 8,753 distinct loans issued to 2,243 borrowers.

3.3 Descriptive Statistics

Table 2 contains descriptive statistics and univariate correlation matrices. In Panel A, the descriptive statistics indicate that the median loan spread is 150 basis points. Median firm size is slightly greater than $1.5 billion, and median leverage is .25. The average deal size is 250 million, and less than half of these require collateral. In Panel B, we present correlations. Pearson correlations appear above the line while Spearman correlations appear below the diagonal. The most significant correlations occur between *Size* and *Deal Size*, indicating an intuitive link between the firm size and the capital it is able to obtain in the debt market. *Size* is also significantly correlated with *Investment grade*. Among variables of interest, *Loan Spread* is significantly negatively associated with *Investment grade* and positively significantly associated with *Collateral*.

[4] We calculate independent variables using annual data as of the most recent fiscal year end prior to loan issuance.

[5] We merge Compustat and I/B/E/S utilizing a linking table provided by Michael Roberts that runs through 2012.

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Table 1. Sample Selection Procedure*

Filters	Number of observations		
	Facilities	Packages	Borrowers
Sample of loans issued in the United States in United States Dollars	105,067	72,432	28,268
Sample after requiring Deal scan variables	75,869	51,197	20,611
Sample of loans matched with Compustat	40,691	28,725	8,248
Sample after excluding financial firms	35,515	24,520	7,027
Sample after requiring Compustat variables	18,310	12,888	4,014
Sample after requiring IBES variables	10,715	7,848	2,568
Sample after removing outliers of continuous variables	8,753	**6,479**	2,243

*Table 1 presents the sample selection procedure for sample years 1994-2012. All sample restrictions apply to borrowing firms.

Table 2a. Panel A: Descriptive Statistics

Variables	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**25%**	**Median**	**75%**	**Max.**
Loan spread (in basis points)	8,753	161.23	110.01	17.50	75.00	150.00	225.00	600.00
Loan spread (nlog)	8,753	4.81	0.80	2.86	4.32	5.01	5.42	6.40
Private precision	8,753	4.12	3.22	-6.93	2.10	4.59	6.52	9.57
EA speed	8,753	-3.64	0.35	-4.52	-3.91	-3.66	-3.37	-2.71
Size (assets in millions)	8,753	4752.07	8124.08	58.90	549.67	1533.27	4787.60	58176.00
Size (nlog)	8,753	7.41	1.50	4.08	6.32	7.34	8.49	10.97
Leverage	8,753	0.26	0.19	0.00	0.12	0.25	0.37	0.93
BTM	8,753	0.50	0.33	-0.38	0.29	0.44	0.65	2.05
ROA	8,753	0.04	0.06	-0.33	0.02	0.04	0.07	0.23
Earnings volatility	8,753	0.04	0.04	0.00	0.02	0.03	0.05	0.31
Interest coverage	8,753	0.74	0.44	0	0	1	1	1
Earnings forecast	8,753	1.69	4.62	-52.00	0.68	1.30	2.11	220.00
Miss	8,753	0.39	0.49	0	0	0	1	1
Investment grade	8,753	0.34	0.47	0	0	0	1	1
Deal size (in millions)	8,753	382.98	467.45	5.50	100.00	250.00	500.00	3000.00
Deal size (nlog)	8,753	19.13	1.21	15.52	18.42	19.21	20.03	21.82
Collateral	8,753	0.44	0.50	0	0	0	1	1
Maturity (in months)	8,753	47.41	22.01	6	35	60	60	98
Maturity (nlog)	8,753	3.69	0.65	1.79	3.56	4.09	4.09	4.58
Covenants	8,753	6.10	4.80	0	0	6	10	18

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Table 2b. Panel B: Pearson Correlation Coefficients*

	Loan spread	Private precision	EA spread	Size	Leverage	BTM	ROA	Earnings volatility	Interest coverage	Earnings forecast	Miss	Investment grade	Deal size	Collateral	Maturity	Covenants
Loan spread		-0.16	-0.37	-0.34	0.22	0.19	-0.28	0.22	-0.26	-0.10	0.10	-0.49	-0.29	0.52	0.26	-0.14
Private precision			0.10	-0.01	-0.12	-0.15	0.20	-0.10	0.17	-0.07	-0.23	0.06	0.02	-0.08	0.01	-0.01
EA spread				0.33	-0.10	-0.11	0.16	-0.09	0.15	0.07	-0.09	0.28	0.20	-0.29	-0.19	-0.2
Size					0.16	-0.02	-0.03	-0.26	0.05	0.09	-0.04	0.56	0.71	-0.36	-0.10	-0.33
Leverage						-0.08	-0.31	-0.09	-0.22	-0.06	0.08	-0.05	0.14	0.11	0.14	0.12
BTM							-0.24	-0.10	-0.10	-0.04	0.14	-0.04	-0.07	0.04	-0.08	-0.01
ROA								-0.14	0.58	0.16	-0.20	0.11	0.02	-0.17	0.01	-0.06
Earnings volatility									-0.20	-0.07	0.01	-0.23	-0.22	0.24	0.06	0.14
Interest coverage										0.15	-0.19	0.18	0.10	-0.18	-0.02	-0.08
Earnings forecast											-0.07	0.07	0.34	-0.26	-0.02	-0.05
Miss												-0.07	-0.06	0.07	-0.02	0.02
Investment grade													0.40	-0.43	-0.19	-0.31
Deal size														-0.22	0.03	0.32
Collateral															0.27	0.56
Maturity																0.24
Covenants																

*All correlation coefficients greater than .02 are statistically significant at the .05% two-tailed level.

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Table 2c. Panel C: Spearman Correlation Coefficients*

	Loan spread	*Private precision*	*EA spread*	*Size*	*Leverage*	*BTM*	*ROA*	*Earnings volatility*	*Interest coverage*	*Earnings forecast*	*Miss*	*Investment grade*	*Deal size*	*Collateral*	*Maturity*	*Covenants*
Loan spread																
Private precision	-0.15															
EA spread	-0.36	0.08														
Size	-0.32	-0.03	0.34													
Leverage	0.20	-0.12	-0.08	0.19												
BTM	0.16	-0.13	-0.10	0.01	-0.02											
ROA	-0.30	0.20	0.16	-0.10	-0.38	-0.34										
Earnings volatility	0.24	-0.08	-0.12	-0.34	-0.16	-0.19	0.08									
Interest coverage	-0.28	0.16	0.14	0.04	-0.17	-0.06	0.61	-0.21								
Earnings forecast	-0.30	-0.05	0.21	0.37	-0.08	-0.07	0.40	-0.22	0.41							
Miss	0.10	-0.22	-0.08	-0.04	0.07	0.13	-0.22	0.00	-0.19	-0.20						
Investment grade	-0.47	0.05	0.28	0.56	-0.01	-0.02	0.10	-0.30	0.18	0.31	-0.07					
Deal size	-0.28	0.00	0.20	0.70	0.12	-0.09	0.06	-0.19	0.10	0.10	-0.07	0.39				
Collateral	0.53	-0.09	-0.29	-0.36	0.14	0.06	-0.18	0.22	-0.18	-0.08	0.07	-0.43	-0.22			
Maturity	0.22	0.01	-0.16	-0.16	0.13	-0.05	0.01	0.06	-0.02	0.00	-0.02	-0.24	0.08	0.26		
Covenants	-0.16	0.00	-0.20	-0.35	0.09	-0.03	-0.06	0.19	-0.09	-0.20	0.02	-0.32	0.32	0.57	0.23	

*All correlation coefficients greater than .02 are statistically significant at the .05% two-tailed level.

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4. Empirical Results and Discussion

4.1 The Effect of Private Precision on Loan Spreads and the Likelihood of Requiring Collateral

Table 3 presents the results of the test of H1 using Equation 1. For our dependent variable, the coefficient over *Private Precision* is negative and significant at higher than the 1% two-tailed level. A one standard deviation increase in precision corresponds to a 3-basis point decrease in loan spread. These results indicate that analyst forecast quality is associated with preferential loan terms with respect to price (i.e., spread). This finding is consistent with Mansi et al. (2011), who conclude that analyst forecast quality is negatively associated with the price of bonds. In addition, we find that *EA Speed* is negative and carries a significant association with our dependent variable, *Loan Spread*. In addition, *Size* is statistically significant and negative, as anticipated. These negative associations indicate factors that improve *Loan Spread*. *Leverage* is positively and significantly associated with *Loan Spread* as is *Book to Market*. This is expected as both debt and book-to-market are likely to be proxies at some level for risk, or at least volatility in a firm. It is intuitive to observe that an increase in these factors is associated with an increase in loan spread. In addition, *ROA* is negative and significantly associated with *Loan Spread* at the .01% level of statistical significance. As with *Leverage* and *Book to Market*, improvements in performance, as proxied by *ROA* would seem to be associated with corresponding improvements in information asymmetry and thus loan spreads. *Earnings Volatility* is another measure capturing risk of firms in our sample, as their reported earnings vary over time. As predicted, we observe an association which is statistically significant at the .05 level indicating that increases in the volatility of the earnings that a firm reports are associated with increases in *Loan Spread. Interest Coverage* is another variable which is associated with *Loan Spread.* As a firms' ability to service its debt as proxied by *Interest Coverage* increases, the riskiness of the firm decreases ceteris paribus. As a result, we observe a significant and negative association.

Table 4 presents the results of our test of H2. We present our results here by subsample: in Column (1), we restrict our sample to firms whose lending contracts require collateral, and in Column (2), we restrict our sample to firms whose lending contracts do not. In the presence of collateral, cases, *Private Precision* has a negative association with interest rate spread that is insignificant at standard levels. Column (2), in loans that do not require collateral, the association is significant at the .01 level. These results indicate that the association between private precision and interest rates is significant only when collateral is not a part of the loan contract, as predicted in H2.

Table 3: The Effect of Analysts' Information Precision on Loan Spread*

	Predicted Sign	Loan Spread
Private Precision	-	- 0.03***
		(-3.7)
EA Speed	-	-0.15***
		(-5.0)
Size	-	-0.07***
		(-6.1)
Leverage	+	0.57***
		(10.6)
BTM	+	0.22***
		(8.5)
ROA	-	-0.70***
		(-4.3)
Earnings Volatility	+	0.43**
		(2.4)
Interest Coverage	-	-0.05**
		(-2.5)
Earnings Forecast	-	-0.00
		(-1.2)
Miss	+	0.02*
		(1.7)
Investment	-	-0.27***
		(-10.0)
Deal Size	-	-0.07***
		(-6.7)
Collateral	+	0.33***
		(17.7)
Maturity	+	-0.05**
		(-2.5)
Covenants	+	0.00**
		(2.2)
Intercept		5.29***
		(21.9)
Observations		8,753
Adjusted R-square		0.70

*Table 3 presents the results of regressing all-in-spread drawn over LIBOR on the precision of analysts' private information (Private Precision following Barron et al., 1998) for the years 1994 through 2012. We include loan- and borrower-specific controls. All variables are calculated as of the fiscal-year end prior to loan issuance. Standard errors are clustered at the borrowing firm level. t-statistics are reported in parentheses.

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Table 4: Cross-sectional Tests of the Effect of Analysts' Information Precision on Loan Spread*

		With Collateral	Without Collateral
	Predicted Sign	(1)	(2)
Private Precision	-	-0.02*	-0.03***
		(-1.7)	(-2.9)
EA Speed	-	-0.06	-0.17***
		(-1.6)	(-4.0)
Size	+	-0.01	-0.10***
		(-1.1)	(-6.5)
Leverage	+	0.17***	0.93***
		(3.1)	(10.8)
BTM	-	0.12***	0.31***
		(4.3)	(6.8)
ROA	+	-0.59***	-0.72***
		(-3.4)	(-2.6)
Earnings Volatility	-	0.45**	0.79**
		(2.3)	(2.4)
Interest Coverage	-	-0.07***	-0.06**
		(-2.9)	(-2.0)
Earnings Forecast	+	-0.00	-0.00
		(-1.1)	(-0.9)
Miss	-	0.03	0.01
		(1.4)	(0.7)
Investment	-	-0.16***	- 0.26***
		(-3.9)	(-8.1)
Deal Size	-	-0.06***	-0.07***
		(-5.9)	(-5.1)
Maturity	-	0.02	-0.11***
		(0.9)	(-3.9)
Covenants	+	0.01***	-0.00
		(4.3)	(-0.0)
Intercept	+	5.34***	5.50***
		(14.2)	(17.2)
Observations		3,845	4,908
Adjusted R-square		0.49	0.70

*Table 4 displays the results of regressing all-in-spread drawn over LIBOR on the precision of analysts' private information (Barron et al. 1998) and loan- and borrower-specific controls for the years 1994 through 2012 after splitting the sample on whether the loan was collateralized. All variables are calculated as of the fiscal-year end prior to loan issuance. Standard errors are clustered at the borrowing firm level. t-statistics are reported in parentheses.

Table 5 provides our test of H3, that there will be no association between private precision and interest rates during the financial crisis. In this table, our data is restricted by time period.

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Column (1) presents data prior to the financial crisis, column (2) presents data during the financial crisis and column (3) presents data following the financial crisis. Our variable of interest continues to be *Private Precision*. While the signs and estimated coefficients suggest monotonicity in the relationship during the crisis, the t-values do not. Specifically, a negative and statistically significant relationship exists before and after the financial crisis, but the relationship is not statistically significant during the crisis. These results are consistent with our prediction that during periods of uncertainty, lenders may be more restrictive about the use of external information in their evaluation process. This is consistent with Sidhu and Tan (2011) who report that equity analysts were less accurate during the financial crisis. A slightly more nuanced interpretation might be that during this period of uncertainty, the primary change was that the volatility in lenders' use of analysts' forecasts increased, i.e., some lenders may have decreased their reliance on outside information while others may have increased it). Note that this result is unlikely to be driven by a decline in analyst accuracy because our measure of precision remains unchanged[6].

5. Conclusion and Summary

We investigate the relevance to bankers of information provided by financial analysts. Specifically, we examine the effect of analysts' private information precision on interest rates in loan contracts. Using Barron at al.'s (1998) measure of private precision in analysts' forecasts, we find that higher private precision is negatively associated with interest rate spreads. This finding further generalizes prior work that has found that analysts' private information precision increases the favorability of borrowers' non-price loan terms.

Further, we predict and find that the relation between analysts' private information precision and interest spreads is affected by the presence of collateral in a loan agreement. Specifically, we find that the association between private precision in analysts' forecasts and interest spreads is only significant among firms whose loan contracts do not require collateral. Finally, we find that during periods of uncertainty, such as during the financial crisis, the relationship between private precision and analysts' forecast is not statistically significant. This finding is consistent with lenders being more selective in their information processing during periods of uncertainty. This finding is particularly relevant as the Pandemic unfolds and financial institutions adjust to the economic realities and uncertainty we currently face. Overall, this study adds to the growing body of new research that demonstrates that lenders utilize information obtained from external sources, such as financial analysts.

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[6] All of our results are robust to clustering by firm and year.

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Table 5: The Effect of Analysts' Information Precision on Collateral Before, During, and After the Financial Crisis*

	Before	**During**	**After**
	(1)	**(2)**	**(3)**
Private Precision	-0.02**	-0.03	-0.04***
	(-2.4)	(-1.2)	(-2.7)
EA Speed	-0.16***	-0.19*	-0.07
	(-4.2)	(-1.8)	(-1.4)
Size	-0.09***	-0.02	-0.03**
	(-6.7)	(-0.4)	(-2.0)
Leverage	0.59***	0.76***	0.41***
	(8.9)	(5.1)	(4.2)
BTM	0.21***	0.34***	0.15***
	(6.5)	(4.3)	(3.4)
ROA	-0.78***	-0.27	-0.58**
	(-4.3)	(-0.6)	(-2.2)
Earnings Volatility	0.66***	-0.04	0.40*
	(2.7)	(-0.1)	(1.8)
Interest Coverage	-0.09***	0.05	-0.01
	(-3.3)	(0.7)	(-0.3)
Earnings Forecast	-0.00	-0.00	-0.01
	(-1.5)	(-0.9)	(-1.6)
Miss	0.03*	0.04	0.02
	(1.8)	(0.7)	(0.9)
Investment	-0.29***	-0.43***	-0.15***
	(-9.2)	(-4.7)	(-4.4)
Deal Size	-0.08***	-0.08***	-0.04**
	(-6.1)	(-2.6)	(-2.6)
Collateral	0.37***	0.30***	0.15***
	(16.5)	(4.4)	(5.0)
Maturity	-0.05*	-0.10	0.02
	(-1.9)	(-1.5)	(0.6)
Covenants	0.00*	-0.00	-0.00
	(1.9)	(-0.0)	(-1.5)
Intercept	5.46***	5.41***	5.75***
	(19.8)	(7.4)	(14.7)
Observations	6,327	1,113	1,313
Adjusted R-square	0.72	0.73	0.71

* Table 5 displays the results of regressing collateralization on the precision of analysts' private information (Barron et al. 1998) and loan- and borrower-specific controls for the years 1994 through 2012. All variables are calculated as of the fiscal-year end prior to loan issuance. Standard errors are clustered at the borrowing firm level. Z-statistics are reported in parentheses. Column 1 reports results for loans issued prior to the Financial Crisis. Column 2 reports results for loans issued during the Financial Crisis. Column 3 reports results for loan issued after the Financial Crisis.

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