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Private information and lender discretion across time and institutions

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Abstract

We assess the extent to which discretion, unexplained variations in the terms of a loan contract, has varied across time and lending institutions and show that part of this discretion is due to private information that lenders have on their borrowers. We find that discretion is lower for secured loans and loans granted by a larger group of lenders, and is larger when the lenders are larger and more profitable. Over time, discretion is also lower around recessions although the private information content is higher. The results suggest that bank discretionary and private information acquisition behaviour may be important features of the credit cycle.

Keywords: credit screening, private information, credit cycle, syndicated loans

JEL: D82, G14, G21, G28

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1. Introduction

A key ingredient to banking and financial crises is the systematic deterioration of bank loan portfolios that largely go unnoticed in the preceding credit boom. Perhaps one of the significant factors behind this deterioration is a fall in credit screening, the production of private information about borrower fundamentals which may also be costly to communicate (e.g. 'soft' information).[1] Several mechanisms have been put forth on why this may be the case. The benefits of screening may fall when borrower quality is 'too high' in a boom (Ruckes, 2004; Dell'Ariccia and Marquez, 2006; Gorton and Ordonez, 2014).[2] Increasing demand for securities (Keys et al., 2010, 2012) and pro-cyclical competition among banks (Hauswald and Marquez, 2006; Gorton and He, 2008) are other possible channels. These may further be exacerbated by the counter-cyclical quality of credit ratings (Bolton et al., 2012; Bar-Isaac and Shapiro, 2013). These conjectures raise the following empirical questions. How does the private information acquisition behavior of lenders vary across time and institutions? What are the institutional determinants to such activity? How has this evolved over time?

In this paper, we take the first step in answering these questions by constructing a measure of lender discretion using detailed syndicated loan data merged with other bank and borrower information from multiple sources. Discretion refers to factors that determine the terms of a loan contract that is orthogonal to public and 'hard' information. Consequently, discretion may embed lender private information acquisition or screening activity. Thus, studying and characterizing the evolution of

[1]On the other hand, lending standards or *rules* may refer to loan contract decisions based on publicly observable or costlessly verifiable 'hard' information.

[2]Institutions and systems which rely solely on hard information are not necessarily immune to these incentives as shown in Berg et al. (2015). Further, Berger and Udell (2004) argue that financial institutions' ability to screen borrowers may itself decline during booms. Beck et al. (2018) also point out that relationship lending, through the acquisition of information about borrowers, can help mitigate the effects of downturns on firms.

lender discretion across time and institutions is an important first step to answering these questions. We then document evidence that part of bank discretionary behavior reflects private and superior information on borrower fundamentals and evaluate the extent to which such private information acquisition behavior has evolved over time.

Our dataset allows us to provide a detailed characterization of discretion across lenders and time from which we can then tease out the extent to which lenders acquire private information about their borrowers. In particular, we use data on over eleven thousand syndicated term loans between 1987 and 2011 between U.S. borrowers and lenders from the *LPC Dealscan* dataset. We match this information to borrower balance sheet and stock market performance characteristics from the *Compustat* and *CRSP* datasets. We match lenders in the loan dataset to the Federal Reserve's Bank Consolidated Holdings database to obtain lender-specific information. These combined datasets provide us with an extensive set of variables that represent hard information relevant to a loan contract comprising the 'rules' component in the determination of its terms. Consequently, we decompose the variation in the terms of credit for these loans into that which can be explained by publicly available information, rules, and those that cannot, discretion.[3] We then decompose the variation due to non-public factors into several components relating to bank and borrower characteristics as well as across institutions and over time. Finally, we present novel evidence that lender discretion contains private information that lenders have acquired about their borrowers in the process of granting loans.

The main results are the following. First, we find that our measure of discretion varies across loan types, lender institutions, and time. Discretion is lower for secured loans, loans given by a large syndication of lenders, highly leveraged lenders, and for loans wherein the lender and borrower has had a previous lending relationship.

[3]As such we focus on a measure discretion on the intensive margin once a loan has been approved and conditional on a lender's decision to approve loans.

On the other hand, discretion is more pronounced for larger and more profitable lenders. We also find that discretion tends to be hump-shaped over expansions and lower around recessions. Our results of changing discretion over time are robust to explanations which relate to changes in borrower composition in that we employ a time-varying parameter approach and we find similar results using a sub-sample of more homogenous borrowers and loan contracts.

We then verify that discretion contains private and superior information that lenders have about their borrower fundamentals. We show that our measure can differentially explain abnormal borrower stock market returns around loan dates using an event study approach. Second, we find that our measure of discretion can help predict analyst forecast surprises with respect to future borrower profitability. Finally, using un-forecasted changes in borrower earnings two years into the future as a proxy variable for private information about borrower fundamentals, we show that the private information component to discretion is also changing over time and tends to rise around recessions.

Our paper complements several theoretical contributions in the literature on credit screening activity which, along several strands, indicates that screening activity should vary over time and may have cyclical properties. Hauswald and Marquez (2003) link improvements in information and communication technology to the cost of information production.[4] Ruckes (2004) provide a theory in which, due to shifts in average borrower quality, screening is pro-cyclical. Cyclical fluctuations in banking competition (Marquez, 2002) or the degree of adverse selection in credit markets (Dell'Ariccia and Marquez, 2006) may also induce cyclicality in screening. Further, in the context of relationship banking, we also follow Bolton et al. (2016) who link relationship banking with better information, and Degryse and Ongena (2007) who document evidence which associates more intense competition to relationship-based

[4]See as well Qian et al. (2015) for recent evidence. See also Nakamura and Roszbach (2016) for evidence of monitoring by banks.

lending. Finally, bank risk-taking and consequently screening activity may also inherit the cyclical properties of monetary policy.[5]

Our empirical approach is shared with a related literature which examines the relative importance and determinants of soft or qualitative information for small business loans (Cerqueiro et al., 2011) or within the loan portfolio of a large bank such as in Degryse and Ongena (2005); Agarwal and Hauswald (2010); Cerqueiro et al. (2016) and Becker et al. (2015).[6] These papers focus on the cross-sectional and spatial determinants to soft information production using the loan portfolio of a single bank over a short period of time. On the other hand, we use two decades of term loan data from a representative sample of the largest and most economically significant (non-financial) borrowers in the United States.[7] This allows us to evaluate how market-wide discretion has evolved across both time and institutions. Further, we provide novel evidence that lender discretion includes private information that lenders have about borrower fundamentals.

Our paper also extends the literature evaluating the role of information asymmetries in the syndicated loan market. One might expect that private information and screening play a small role in this market where both banks and borrowers are mostly publicly listed and among the most transparent (Stein, 2002).[8] For instance, Gropp and Guettler (2018) show that borrowers self-select to relationship- and transaction-type banks where transaction-type banks invest less in soft information. However, there is evidence that suggests that private information (and

[5]See for instance Dell'Ariccia et al. (2014); Ioannidou et al. (2015); Maddaloni and Peydro (2011); Jimenez et al. (2012, 2014) for theory and evidence.

[6]A similar strategy has also been employed in the evaluation of qualitative or private information in credit ratings. See Griffin and Tang (2012) and Norden and Roscovan (2014). See also Fisman et al. (2017) who show that social and cultural proximity may alleviate information asymmetry problems.

[7]Our dataset also allows us to control for a rich set of factors, including other non-price terms of the loan contract (e.g. the presence and tightness of covenants) and stock market prices which may reflect public information about borrower quality that would otherwise not be reflected in standard accounting information, which may determine the loan rate

[8]See Strahan (1999); Dennis and Mullineaux (2000); Lee and Mullineaux (2004) and Ivashina and Scharfstein (2010) for characterizations of the syndicated loan market.

asymmetries) is still non-negligible in the syndicated loans segment of credit markets. Sufi (2007) argues that the lead arranger play an important role as *informed capital* (a la Holmstrom and Tirole, 1997) in the syndication. Sufi (2009) provide evidence on the information content of credit ratings for syndicated loans which implies that indeed there is scope for private information. Ivashina (2009) estimates a non-trivial cost to asymmetric information between the lead arranger and other members of the syndication. Prior relationships, and hence private information, between the lead arranger and the borrower is also an important determinant of the terms of the syndicated loan contract as documented in Santos and Winton (2008) and Ivashina and Kovner (2011).[9] Our results also indicate that a wide range of publicly observable borrower, lender, and market-wide features cannot account for a sizable fraction of the variation in the terms of credit for syndicated loans. This implies that such loans cannot be sufficiently characterized as arms-length lending based purely on public and hard information.

The rest of the paper is organized as follows. The next section briefly describes the empirical framework for measuring screening activity and describes the data used in the analyses. In Section 3, we report the results pertaining to the measurement and decomposition of discretion. In section 4, we provide evidence linking discretionary behaviour to private information. Finally, Section 5 concludes.

[9]See also Botsch and Vanasco (2018) for evidence on the importance of relationship time in the syndicated loan market and Gustafson et al. (2017) for evidence of monitoring. See also Khan and Ozel (2016) on how bank loan portfolios can help predict local economic activity.

2. Data and Empirical Framework

2.1 Framework

We employ the multiplicative heteroscedasticity regression model by Harvey (1976) which jointly specifies explanatory variables for the mean of a dependent variable and the heteroscedastic residual variance. Cerqueiro et al. (2011) (and Cerquiero et al. 2013) have previously used a similar application of the methodology on loan data to distinguish between *rules*, concrete and observable determinants, and *discretion*, unobserved (to the outsider) and potentially qualitative factors, in the setting of the terms of a loan contract.

In the framework, the loan rate (log spread) on a loan by borrower i from lender j at time t ($logSpread_{i,j,t}$) is determined by a linear combination of aggregate credit market conditions at time t, observable borrower's credit quality and other characteristics, and the lender's ability to supply credit,

$$logSpread_{i,j,t} = \alpha_t + \theta_j + \gamma_q + \xi_{fs} + \phi_{lp} + \sum_{k=1}^{K} \beta_t^k X_{i,j,t}^k + \epsilon_{i,j,t} \quad (1)$$

$$log\hat{\epsilon}_{i,j,t}^2 = \delta_t + \rho_j + \sum_{c=1}^{C} \gamma^c Z_{i,j,t}^c + \eta_{i,j,t} \quad (2)$$

where $X_{i,j,t}^k \beta_t^k$ reflect the impact on loan spreads of the other loan characteristics, borrower-specific variables, lender-specific variables, and a host of fixed effect dummy variables such as θ_j for lender fixed effects, γ_q for two-digit SIC industry fixed effects, ξ_{fs} are dummy variables controlling for the auditor's report on the quality of the financial statements in *Compustat*, ϕ_{lp} are dummy variables on the stated purpose for the loan.[10] The fraction of β_t^k corresponding to borrower-specific variables

[10] We have also run regressions with the spread in levels with similar results. However, the model specification with the spread in logs seems to fit the data better. Consequently, we report only the results with spreads in logs. Regression results with the spread in levels are available upon

may be interpreted as a (time-varying) credit score based on public information. We allow for the coefficients to vary over time to take into account market-wide shifts over time in the composition of borrowers and banks' lending and risk-taking profiles. The part of β_t^k corresponding to lender-specific variables capture factors such as rent-seeking behavior and bank-specific credit supply conditions that may influence the terms of the loan contract. Finally, time fixed effects α_t absorb all aggregate macroeconomic and financial conditions.

The size of the residual term in equation 1, which is orthogonal to the set of observables $\{X_{i,j,t}^k\}$ and dummy variables is proportional to the variation in discretion embedded into loan spreads. Consequently, we interpret a high residual variance as indicative of more discretion. This is a measure which may represent lender's qualitative judgment, market-power, other lender preferences, as well as lender private information.[11] To ensure that our estimates are not driven by differences in loan spreads compensating for other features of the loan contract, we may include the non-price terms of the loan contract as additional control variables. Further, to help ensure that the residual estimates capture discretion, we require that our set of explanatory variables $\{X_{i,j,t}^k\}$ along with the various dummy variable controls is sufficiently large so as to span public information. This motivates our approach to use as much data as feasible about borrowers and lenders and from various sources as explanatory variables.[12]

We then decompose the residual variance, discretion, into several factors as outlined in equation 2 where $Z_{i,j,t}^c$ include other terms of the loan contract to absorb unobserved differences arising from the non-price terms of the loan, bank-borrower relationship variables, and bank-specific factors. These capture bank-time specific de-

request.

[11]Private information in this context pertain only to those that determine the loan rate conditional on the loan being granted, an intensive margin.

[12]By extension, we do not make causal interpretations about coefficient estimates in equation 1. Rather, the emphasis of the approach is to ensure that estimates of the residual $\epsilon_{i,j,t}$ are orthogonal to publicly available information.

terminants such as institutional differences in preference for discretion, rent-seeking behavior, and banks' propensity to supply credit.[13] The set of dummy variables ρ_j are lender fixed effects. Finally, δ_t provides conservative estimates of time-variation in discretion that is orthogonal to public information and not driven by loan-, bank-, and borrower-specific factors.

2.2 Data description

The main challenge to this approach is to have a sufficiently rich set of explanatory variables to reasonably span all available public information pertinent to the loan contract terms. To fulfill this requirement we combine several datasets comprising balance sheet, credit rating, and stock market performance information for borrower characteristics, observable loan and lender characteristics as well as regulatory information for lender factors.

Our sample consists of syndicated (senior) term loans taken out by non-Financial and non-Utilities borrowers in the U.S. from lead lenders or arrangers also headquartered in the U.S. for the period 1987-2011 from the *Dealscan* dataset.[14] We then combine the loan data from *DealScan* with borrower balance sheet data from *Compustat* and borrower equity stock returns from *CRSP*.[15] In the matching, we aggregate time into quarters beginning the fourth quarter 1987 until the third quarter of 2011. To avoid endogeneiety, we use the *Compustat* and *CRSP* data that would have been available in the quarter prior to the loan date. This yields 11,173

[13]In the multiplicative heteroscedasticity framework by Harvey (1976), the factors driving the residual variance are additive in logs. Further, as shown in Harvey (1976), we can take the estimated squared residuals in the mean equation to approximate the variances and OLS estimates of the coefficients are consistent up to a scalar constant. Since we do not interpret the coefficient estimates in equation 1, we do not benefit from any potential efficiency gains of using maximum likelihood estimates.

[14]An earlier study by Strahan (1999) uses a similar dataset and interested readers may refer to it for a discussion on the average type of firm in the sample.

[15]The datasets are merged using the Chava and Roberts (2008) link data. We thank the authors for making this file publicly available.

unique loans made by 4,190 borrowers over 96 quarters and averaging 116.4 loans per quarter. The mean number of loans per borrower is 2.67 with a maximum of 26 loans. The average loan rate is 290 basis points over LIBOR, the average loan size is 198 million dollars, and an average maturity of 62 months.

From the *Compustat* and *CRSP* datasets, we include the log of total assets, the return on assets, the current ratio, interest coverage, the profit margin, the book to market value of equity, the leverage ratio, the quick ratio, the log of the market value of equity, the sales to total assets ratio, the ratio of total liabilities to the market value of total assets, the ratio of book to market value of total assets, and the ratio of property, plant, equipment, and inventories to total assets as a measure of asset tangibility. We also include two stock market performance ratios from *Compustat* - the year-on-year stock market return given by the growth rate of the closing price of the current calendar year over the closing price of the previous calendar year and a proxy for stock price volatility given by the difference between the highest and lowest price of the current year over the average between the closing price of the current and previous calendar year. We also observe and include short and long term S&P credit ratings which we have sorted into speculative and investment grade categories. A speculative grade is defined as lower than a BBB rating for long term and lower than $A3$ for short term ratings. We also include the first four moments of stock returns of borrower equity matched from the *CRSP* database. After merging the datasets, we are left with 6,744 loans with sufficient observations.

To control for lender characteristics, we define lender dummy variables for the most frequently occurring lenders in the dataset. Here, we only select the top 100 unique lenders by loans facilitated. We also associate a lead lender and her characteristics only to the loans for which we can identify a unique lead lender.[16]

[16]The lead lenders were identified according to their lender role descriptions with *Administrative agent* or *Syndication agent* as top priority and *Agent* or *Sole lender* in the absence of the previous two. See Sufi (2007) for a similar approach.

About 75 percent of the loans in the sample are matched to one of the identified lead lenders with the remaining 25 percent of loans were from lead lenders which do not occur frequently enough in the dataset. We then match these lenders to the Federal Reserve's Bank Consolidated Holdings database using institution names and loan dates.[17] Table 1 provides some statistics on the variables used.

[17] 51 of the identified lead lenders were matched to the Federal Reserve database.

Table 1: Summary statistics

	Mean	St. Dev.	p25	p50	p75
Loan variables					
Loan spread	290.5	154.1	200	275	350
Loan amount	197.8	509.2	15	62.37	200
Loan maturity	61.99	24.14	48	60	78
Secured loan	0.936	0.244	1	1	1
Syndication size	3.019	3.199	1	2	4
Number covenants	2.873	1.119	2	3	4
Covenant tightness	0.653	0.308	0.500	0.713	0.929
Loan purpose	N.A	N.A	N.A	N.A	N.A
Auditor opinion	N.A	N.A	N.A	N.A	N.A
Quarter-Year Dummy	N.A	N.A	N.A	N.A	N.A
Lender Dummy	N.A	N.A	N.A	N.A	N.A
Borrower variables					
Size (log TA)	5.960	1.858	4.690	5.950	7.236
Return on assets	0.103	1.122	0.0810	0.122	0.168
Current ratio	2.116	5.276	1.145	1.644	2.314
Interest coverage	51.53	921.3	1.993	3.939	8.880
Profit margin	-0.181	12.54	0.0691	0.120	0.187
Book to market	125.7	3972.3	0.310	0.521	0.853
Leverage	0.648	1.061	0.464	0.623	0.782
Asset tangibility	0.445	0.237	0.265	0.449	0.619
Age (years)	6.432	5.313	2.167	5.333	9.417
Quick ratio	1.552	5.259	0.747	1.091	1.593
Asset book to market	0.775	0.298	0.572	0.770	0.963
Stock return (FY)	5.434	398.8	-0.243	0.0517	0.396
Stock price range (FY)	0.838	0.929	0.469	0.671	0.987
Credit rating (long)	N.A	N.A	N.A	N.A	N.A
Credit rating (short)	N.A	N.A	N.A	N.A	N.A
Stock return (daily)	7.748	70.168	-26.06	11.46	46.04
Stock volatility (daily)	0.581	0.335	0.359	0.497	0.706
Stock skewness (daily)	-0.123	2.16	-0.32	0.159	0.593
Stock kurtosis (daily)	13.012	2.12	4.505	6.245	10.487
Industry dummy	N.A	N.A	N.A	N.A	N.A
Lender variables					
Lender EBITDA	3.612	4.634	0.371	1.950	5.229
Lender Net income	3.637	4.662	0.386	1.950	5.273
Lender Chargeoffs	0.345	0.538	0.0340	0.140	0.410
Lender Recoveries	0.0671	0.0809	0.0100	0.0390	0.0940
Lender Total assets	664.4	679.7	97.02	397.4	1178.3
Lender Total liabilities	609.3	620.5	89.20	367.5	1071.9
Lender Loss provision	9.783	10.25	3.762	7.090	9.028
Lender Tier 1 capital	49.50	43.36	14.33	38.57	74.98
Lender Tier 2 capital	26.78	16.22	15.50	26.48	37.70
Lender Risk-based capital	69.69	58.94	22.08	57.06	104.4
Lender Tier 1 Leverage ratio	6.640	1.443	5.920	6.290	7.040
Lender Tier 1 Risk-based capital ratio	9.070	1.801	8.200	8.470	8.920
Lender Risk-based capital ratio	12.67	1.928	11.54	12.04	12.77

Balance sheet variables in levels are in million US dollars. N.A. is Not Applicable. Industry codes are at the 2-digit SIC level. See the Appendix for further details. Covenant tightness is an index based on Murfin (2012).

3. Discretion across time and institutions

3.1 Estimates of discretion

We use the loan spread as the dependent variable.[18] Further, we include other potentially endogenous variables such as a dummy variable for collateralized loans into the specification. Finally, we allow for the set of coefficients $\{\beta_t^k\}$ to vary over time. This helps address concerns that the composition of the borrower and lender pool may change over time and hence affect the variance of the residual.

We run three sets of two specifications. The first set comprise variables available for the full period whereas the second and third sets restrict the sample to loans post 2001. The baseline specification uses all borrower factors and only lender fixed effects. The expanded specification adds lender specific variables as well as additional terms in the loan contract including the number of members in the syndication, a secured loan dummy variable, and covenant variables. For the third set, the expanded specification includes other lender variables that become available post 2001 (e.g. regulatory capital ratios).[19] Table A.3 in the appendix provides the full list of variables used for each specification. To reduce dimensionality, the regression is done in two stages. We first run a regression of the loan spread and all remaining explanatory variables on the dummy variables for the lead lender, industry classification, loan purpose, and auditor's opinion on the financial statements in *Compustat*.

Before proceeding with the regression with time varying coefficients, we first run an ordinary least squares regression on equation 1 where all β^k coefficients are constant over time. Table 2 reports regression results. We run various specifications

[18]The loan spread is defined as the average interest rate of the loan considering all fees and charges less LIBOR. We also consider specifications using the spread in levels with similar results.

[19]We have also run regressions on specifications which exclude the non-price terms of the loan contract and have obtained similar estimates of time variation in squared residuals. These and other unreported results are available upon request.

including variables that have only become available since 2002. The specifications can explain between 45 to 63 percent of the variation in loan spreads.[20] This is similar to the results in an earlier study by Strahan (1999) on syndicated loan data from 1988-1998 who had an (un-adjusted) R-squared of between 41 to 45 percent and much higher than the 25 percent in Cerqueiro et al. (2011) who use survey data on small business loans. The expanded specifications yield better fits than the baseline and also for when the sample is restricted to include only loans post 2001.

[20]The first stage regression on dummy variables explains about 25 percent of the variation in loan spreads.

Table 2: Constant coefficients regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Loan amount	-0.135***	-0.138***	-0.097**	-0.165***	-0.157***	-0.122**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)
Loan maturity	0.075***	0.092***	0.030	0.081***	0.083***	0.015
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Loan to borrower size	0.108***	0.132***	0.119***	0.143***	0.150***	0.141***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Borrower ROA	-0.098**	-0.318***	-0.325***	-0.062	-0.278***	-0.285**
	(0.05)	(0.07)	(0.09)	(0.05)	(0.10)	(0.11)
Borrower tang. asset	-0.123***	-0.114**	0.034	0.010	0.053	0.084
	(0.04)	(0.05)	(0.06)	(0.05)	(0.07)	(0.08)
Borrower leverage	0.521***	0.564***	0.672***	0.508***	0.512***	0.568***
	(0.06)	(0.09)	(0.12)	(0.08)	(0.12)	(0.17)
Borrower rating: spec grade	0.099***	0.146***	0.075***	0.110***	0.166***	0.067**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Stock return mean	-14.361***	-17.792***	-19.957***	-14.302***	-15.889***	-17.931***
	(3.58)	(4.45)	(4.88)	(4.48)	(5.95)	(6.83)
Stock return variance	5.159***	4.637***	3.315***	4.763***	3.802***	3.219***
	(0.49)	(0.63)	(0.77)	(0.65)	(0.88)	(1.01)
Lender charge-offs		0.000***	0.000***		0.000***	0.000***
		(0.00)	(0.00)		(0.00)	(0.00)
Syndication size		-0.008***	-0.013***		-0.017***	-0.014***
		(0.00)	(0.00)		(0.00)	(0.00)
Secured loan			0.527***			0.496***
			(0.04)			(0.05)
Number covenants			0.020**			0.012
			(0.01)			(0.01)
Covenant tightness			0.190***			0.170**
			(0.05)			(0.07)
Lender Tier 1 capital ratio					0.072*	0.129**
					(0.04)	(0.06)
Borrower controls	Full	Full	Full	Full	Full	Full
Lender controls	Fixed Effect	Baseline	Baseline	Fixed Effect	Full	Full
Sample	Full	Full	Full	Post-2001	Post-2001	Post-2001
N	5341	3377	1955	3279	1992	1216
Partial R-squared	0.251	0.299	0.436	0.299	0.382	0.492
Overall R-squared	0.448	0.483	0.584	0.483	0.544	0.625

** $p < 0.10$, **$p < 0.05$, ***$p < 0.01$; Robust standard errors in parentheses; Time, Industry, Lender, Auditor opinion, Loan purpose, and Covenant fixed effects estimates omitted. Loan to Borrower size is the ratio of the loan amount to borrower total assets. Borrower Baseline controls include balance sheet and stock market information but not credit ratings. Lender Baseline controls contain only variables available over the full time sample. The full set of variables used in each specification may be found in Table A.3 of the Appendix. The partial R-squared reports the explained variation time fixed effects, borrower, lender, and loan variables after controlling for lender, 2-digit industry, auditor report, and loan purpose dummy variables. The aforementioned set of dummy variables explain about 26% of the variation in loan spreads.*

Since we have saturated the mean regression with many explanatory variables, we limit the presentation of estimates to the most relevant and statistically significant.[21] With constant coefficients, we find that loans of longer maturity and which are large relative to the size of the borrower feature higher loan spreads. We also find that secured loans, loans with covenants, and smaller syndications also feature higher spreads.

Next, we proceed with estimating time-varying parameters for the same set of specifications. We do not report the (up to) 41 time-varying parameter estimates although we note that there is some variation in the estimates over time. In Figure 1 we plot estimates of the log variance of non-public determinants to loan spreads.[22] We find substantial variation in the average log variance over time. Similar patterns are observed using estimates from the other specifications although at different scales. Further, although the inclusion of additional explanatory variables improves the model fit for 2002 and onwards (as in columns 4-6 of Table 2), the expanded specifications yields the same patterns as the baseline specification over the 2002-2011 period .

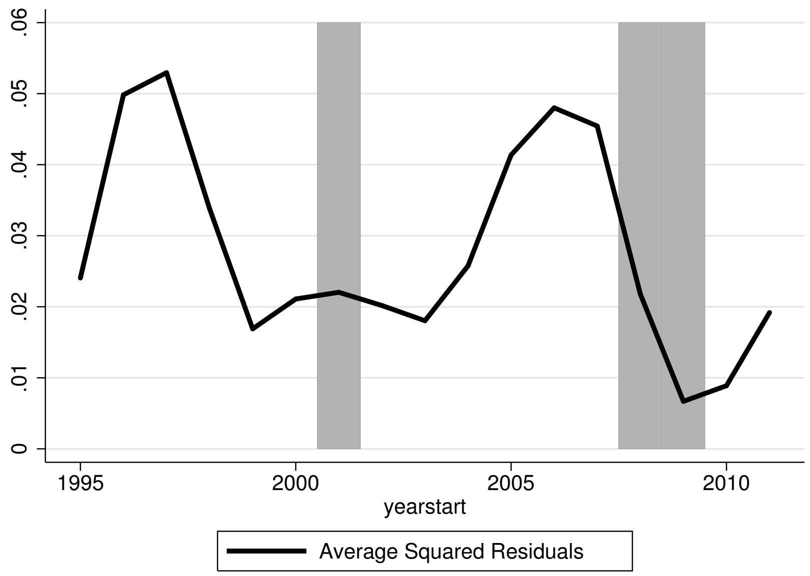
3.2 Determinants of discretion

To isolate time variation in screening activity and independent of changes in the composition of borrowers and lenders over time, we regress squares of the estimated residuals on a time trend or time fixed effects along with other controls as per equa-

[21] These, and other unreported results, are available upon request.

[22] These are taken from a specification similar to column 2 of Table 2 but with time-varying coefficients.

Figure 1: Average unexplained variation in spreads



The solid line plots averages for the estimated $log(\hat{\epsilon}^2_{i,j,t})$ *in equation 1 and using the specification in column 2 of Table 2 but with time-varying coefficients. The gray bars represent recession periods identified using NBER dates.*

tion 2. We include as controls a dummy variable on whether a loan is collateralized (secured), the number of lenders participating in the syndication, the logs of the size and maturity of the loan, the number of and tightness of covenants in the loan contract, and the log of the size of the borrower in terms of sales. To incorporate potential relationship lending factors, we also include a set of dummy variables which take the value of one if the borrower has taken out a loan with the same lead lender in the previous quarter and for the previous year.[23] We also include several lender-specific factors to control for lender-specific factors such as rent-seeking behavior, propensity to provide credit, and differences in bank funding and regulatory costs. The results are reported in Table 3.[24]

[23]See for instance Petersen and Rajan (1994) and Santos and Winton (2008) on how prior relationship can affect the terms of a loan contract. Though not reported, we have also run regressions with dummy variables for loans up to the past three years.

[24]We use the residuals from the baseline specification of the mean spread regression (corresponding to column 2 of Table 2) with time-varying coefficients. Similar results are obtained with the residuals from the other specifications as well as specifications which exclude potentially endogenous terms of the loan contract.

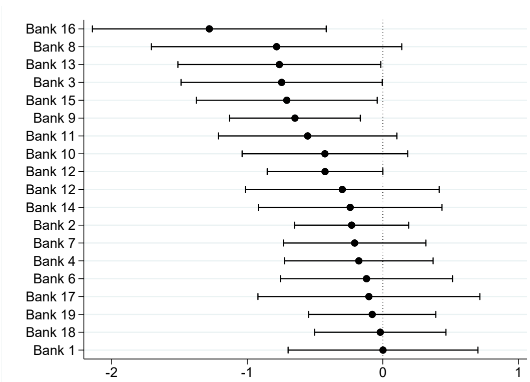
Table 3: Log variance regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Securedloan		-1.224***		-1.313***		-1.238***	-1.094**	-1.353***		-1.254***
		(0.22)		(0.22)		(0.24)	(0.55)	(0.26)		(0.23)
Borrower size		-0.052		-0.050		-0.068	-0.300	0.084		-0.094
		(0.12)		(0.13)		(0.13)	(0.20)	(0.17)		(0.12)
Loan amount		0.061		0.047		0.070	0.376**	-0.141		0.055
		(0.11)		(0.12)		(0.12)	(0.18)	(0.16)		(0.12)
Loan maturity		-0.248		-0.297		-0.377*	-0.317	-0.410		-0.282
		(0.19)		(0.19)		(0.20)	(0.27)	(0.27)		(0.19)
Syndication size		-0.049*		-0.051**		-0.053**	-0.068*	-0.030		-0.041
		(0.02)		(0.03)		(0.03)	(0.04)	(0.04)		(0.03)
Loan-to-Borrower size		0.301		0.367		0.287	0.252	0.455		0.374
		(0.32)		(0.36)		(0.35)	(0.45)	(0.59)		(0.35)
Number covenants		-0.030		-0.039		-0.046	-0.195	0.023		-0.019
		(0.09)		(0.09)		(0.09)	(0.14)	(0.12)		(0.09)
Covenant tightness		0.110		0.033		-0.100	-0.439	0.141		0.085
		(0.28)		(0.28)		(0.27)	(0.46)	(0.36)		(0.28)
Lender size			0.061	0.153*		-0.075	0.145	0.139		0.003
			(0.06)	(0.08)		(0.25)	(0.48)	(0.40)		(0.07)
Lender leverage			-7.102**	-6.377		-0.733	-14.253	12.317		1.150
			(3.50)	(4.80)		(7.03)	(11.51)	(11.50)		(4.14)
Lender profitability			3.201**	3.012		2.960	3.726	4.212		5.411**
			(1.30)	(2.30)		(2.71)	(5.22)	(3.80)		(2.39)
Lender charge-off ratio			-0.751	-1.486		-0.053	0.059	0.583		-2.742*
			(0.89)	(1.53)		(2.15)	(3.17)	(3.32)		(1.49)
Loan in previous quarter					-0.504	-0.280	0.186	-1.097***		-0.347
					(0.39)	(0.91)	(1.24)	(0.34)		(0.76)
Loan in previous year					-0.110	-0.354	-0.273	-0.350		-0.404
					(0.17)	(0.27)	(0.53)	(0.32)		(0.27)
Recession -2									-0.104	-0.627***
									(0.14)	(0.24)
Recession -1									0.046	-0.188
									(0.13)	(0.23)
Recession 0									-0.334**	-0.538*
									(0.15)	(0.30)
Recession +1									-0.776***	-0.680*
									(0.17)	(0.37)
Recession +2									-0.855***	-0.736**
									(0.17)	(0.33)
Time	Time FE	Time FE	Time FE	Time FE	Time FE	Time FE	Time FE	Time FE	Rec dummy	Rec dummy
Lender	Lender FE	None	None	None	Lender FE	Lender FE	Lender FE	Lender FE	Lender FE	None
Sample	Full	Full	Full	Full	Full	Full	Pre 2001	Post 2000	Full	Full
R-squared	0.0637	0.0857	0.0591	0.100	0.0645	0.128	0.173	0.142	0.0255	0.0678
N	3124	1024	2956	988	3124	988	392	596	3124	988

* $p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; *Robust standard errors in parentheses; Year, and Lender Fixed effects estimates omitted. Covenant tightness is an index based on Murfin (2012). Borrower and Lender size is in terms of log total assets. Lender leverage is total liabilities over total assets, Lender profit is net income to total assets; Lender charge-off ratio is the ratio of charge-offs to total assets. The variables* Loan in past X *are dummy equal to one if we observe a loan between the same borrower-lead arranger pair in the past* X *period. The variables* Recession X *are dummy variables equal to one if the loan was made* X *periods before or after the start of a recession year.*

The first column is the benchmark in which we only include time and lender fixed effects. Figure 2 plots the marginal effects of the estimated lender and year dummy variables along with their 95% confidence intervals. We do find some variation across lending institutions as exhibited in the left panel of Figure 2. For instance, Bank 16, a bank that has specialized in lending to hi-tech firms, appear to use significantly less discretion than other banks. We find much stronger evidence for time variation in discretion across banks. Our results provide a more nuanced interpretation of the finding in Cerqueiro et al. (2011) who document a decline in discretion over time using three five-year samples (centered on the years 1993, 1998, and 2003) of small business loan data. Here we find a hump-shaped pattern over non-recession periods where discretion is low before recessions and for some time after. The right panel of Figure 2 indicates that the patterns documented in Figure 1 remain after controlling for bank-specific behavior.

Figure 2: Discretion across time and institutions I



The figure plots marginal effects of lender identities from the regression in column 1 of Table 3. Lender fixed effects are estimated for identified lead lenders with at least 20 loan observations. The horizontal bars represent 95% confidence intervals.

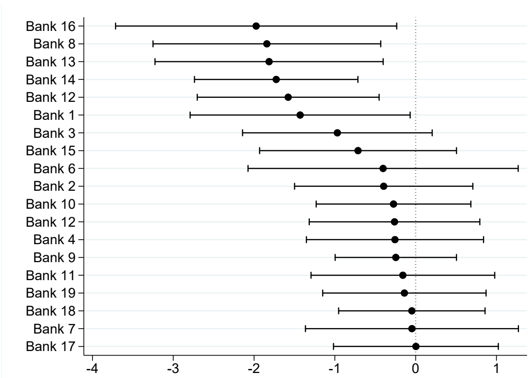
The figure plots marginal effects for year dummy variables representing the year a loan is made. The solid black line plots coefficient estimates from column 1 of Table 3. The red shaded area represents 95% confidence intervals. The gray bars represent recession periods identified using NBER dates.

Columns two to four of Table 3 replace the lender fixed effects with borrower and loan characteristics, lender characteristics, and borrower, loan, and lender characteristics respectively. Here we find that, consistent with the findings in Cerqueiro et al. (2011) on small business loans, secured loans entail less discretion. We also find that discretion is decreasing in the number of lenders in the syndication. These results confirm the findings in Sufi (2007) who find that the size of the syndication is related to the degree of information asymmetry between borrowers and lenders. On the other hand, we find that larger and more profitable lead lenders are associated with more discretion whereas highly leveraged lead lenders tend to use less discretion.

In columns five to eight of Table 3, we test the hypothesis that past lending relationships (with the lead lender) influence discretion. We find that for the full sample (columns five and six), past lending relationships do not appear to have statistically significant effects on discretion. On the other hand, when we restrict the sample to loans that have been made before 2001 in column seven and during and after 2001 in column eight, we do find that past lending relationships (in the previous quarter) tend to lower discretion after 2001. This result may be related to the passing of Regulation FD (Fair Disclosure) in August of 2000 which prohibited public institutions from disclosing previously non-public information to certain parties without making it available to the general public as well.

We revisit the robustness of the variations in discretion across time after accounting for borrower, lender, and loan-specific factors that may explain variations in discretion. In Figure 3, we plot the marginal effects of time and lender fixed effects from the regression in column 6 of Table 3 along with their 95% confidence intervals. We find similar patterns as in Figure 2 which leads us to conclude that there are institutional and business cycle features to discretion that cannot be explained by borrower, lender, and loan characteristics. The estimates suggest an attenuated hump-shaped pattern for discretion over expansions mirroring that of Figure 1. There appears to be a downward trend around recession start dates which bottoms out two years after the start of a recession. Interestingly, and consistent with the theoretical literature on bank screening and private information production, discretion appears to decline before the start of a recession.

Figure 3: Discretion across time and institutions II



The figure plots marginal effects of lender identities from the regression in column 6 of Table 3. Lender fixed effects are estimated for identified lead lenders with at least 20 loan observations. The horizontal bars represent 95% confidence intervals.

The figure plots marginal effects for year dummy variables representing the year a loan is made. The solid black line plots coefficient estimates from column 6 of Table 3. The red shaded area represents 95% confidence intervals. The gray bars represent recession periods identified using NBER dates.

We investigate further the time dimension to discretion by looking around NBER recession dates. In columns nine and ten of Table 3, we replace the time fixed effects with dummy variables around NBER recession dates. The results suggests that discretion declines around recessions where the effect is strongest at two years after the start of a recession. We find that discretionary activity is lowest a couple of years after the start of a recession and increases thereafter during an expansion. Further, it begins to decline up to two years prior to the start of the next recession. We do not make causal interpretations of the results. Rather, our goal is to document and establish when and for which loans is there evidence of higher or lower discretion.

We have used a broad range of specifications and a comprehensive set of explanatory variables over several dimensions of the loan contract to estimate the degree of discretion across institutions and time. Further, we have also allowed for many of our estimated coefficients to vary over time. To further address the concern that changes in the log-variance of the residual may be due to changes in the composition of the borrower pool that are not captured by our time-varying coefficients approach, we repeat the exercise for a sub-sample of more homogeneous borrowers.

Due to the reduction in sample size, we focus on variations of discretion in the time dimension for this exercise. The resulting estimates of the log-squared residual and our measure for discretion are reported in Figure 4. See Appendix B for other details of the exercise. The left panel of Figure 4 is analogous to Figure 1 while the right panel is analogous to the right panel in Figure 2.

Figure 4: Discretion based on homogeneous sub-sample

(a) Average unexplained variation in spreads

(b) Time fixed effects

The solid line on the left panel plots averages for the estimated $\log(\hat{\sigma}^2_{i,j,t})$ *in equation 1 and using the specification in column 3 of Table B.5. The gray bars represent recession periods identified using NBER dates. The right panel plots estimates of time fixed effects in equation 4 using the smaller but more homogeneous borrower sample along with the 95% confidence interval as the red shaded area.*

4. Private information in discretion

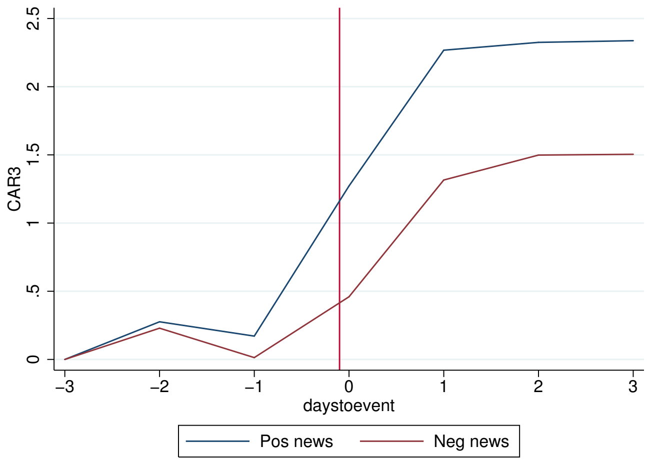
The previous section has provided estimates of bank discretion. It has also characterized how discretion has varied across lending institutions and time. In this section we test the hypothesis that discretion contains variation that represents the private information that bank's have acquired about their borrowers. To do so, we are going to link discretionary behaviour by banks with borrower fundamentals. In particular, we show that the stock market disproportionately reacts positively to discretionary behavior representing positive news about borrowers upon the granting of loans. Further, we link discretionary activity to unforecasted future borrower earnings performance and show that our measure of discretion can explain analyst forecast errors of future earnings - evidence that banks' discretionary behaviour incorporates information that professional analysts are not privy to even when analyst forecasts were made after the loans have been made.

4.1 Stock market evidence that discretion reflects borrower fundamentals

We now address the concern that our measure of discretion represents mostly idiosyncratic variation in the terms of a loan contract. To verify whether or not this is the case, we look at the stock market's valuation of the borrowers' equity following these loans and in relation to the discretion component of the loan spread. In particular, we use an event study approach to evaluate the hypothesis that the residual reflecting discretion contains previously private information about the borrower that becomes priced into the value of the borrowers equity following the loan agreement. To test this hypothesis, we construct abnormal stock market returns on the equity of each borrower around syndicated loan dates and test whether, aside from a loan announcement effect, loans with a negative residual (a loan rate that is lower than that predicted by publicly observable factors) in the regressions leads to larger abnormal returns around the loan event. We find evidence for this effect which suggests that indeed, the residual contains previously non-public information which is subsequently priced into the borrowers equity following the loan event.

Figure 5 plots the average cumulative abnormal returns on borrower equity from three days before to three days after each loan. The blue line depicts average cumulative abnormal returns for borrowers who obtained a negative residual in the loan spread regressions (a lower interest rate than predicted by observables) which constitutes positive information about the borrower quality while the red line represents the averages for borrowers who obtained a positive residual. Intuitively, the

Figure 5: Cumulative abnormal returns



residual represents deviations of the loan spread from that predicted by publicly observable factors. Hence, if stock market participants consider this deviation as informative about the borrowers' conditions, the stock market performance of the borrowers' equity following the loan agreement should partially depend on the estimated residual. To do this, we estimate the sensitivity of the cumulative abnormal returns of the borrower's stock price to the estimated residual in the days following the loan issuance.[25]

We combine the estimated residuals with the daily returns data from *CRSP* and are able to match 2,204 loan events for which we have returns data and do not observe another loan in the preceding 125 trading days for each event. We date each loan event using the loan issue date. The literature has typically used loan announcement dates culled from various media sources although several (e.g. Harvey et al. 2004, Focarelli et al. 2008, Li and Ongena 2015) use the loan issue date as we do. The use of loan issue dates may potentially underestimate the effects if the loan details are observed by the market at a loan announcement date significantly

[25] See James (1987); Lummer and McConnell (1989); Billet et al. (1995); Fields et al. (2006) and Ongena et al. (2014) for examples of earlier work on the stock market response to loan announcements.

different from the loan issue date[26]. The potential underestimation bias may be less severe for the loan spread variable we consider as typical news announcements may not include the full terms of the loan contract.

We first generate a predicted series for each equity return by estimating a Fama-French factor model using daily return data from one year before up to three days prior to each loan event.[27] That is we estimate

$$\begin{aligned} \hat{R^e_{i,t}} &= \hat{\alpha_i} + \hat{\beta_{i,1}} Mkt^e_t + \hat{\beta_{i,2}} SMB_t + \hat{\beta_{i,3}} HML_t \\ AR_{i,t} &= R^e_{i,t} - \hat{R^e_{i,t}} \end{aligned}$$

where $R^e_{i,t}$ are excess returns of borrower i at time t and Mkt^e_t, SMB_t, and HML_t are the Fama-French size and book-to-market factors. We then compute abnormal returns around the loan event by subtracting the Fama-French model predicted returns from the actual daily returns. We Winsorize the abnormal returns and compute the cumulative abnormal return for two event windows, from one day before to the loan date ($CAR10$) and from one day before to one day after the loan event ($CAR11$).

$$CAR_{i,\tau,T} = \sum_{s=-\tau}^{T} AR_{i,t+s}$$

The following table reports summary statistics for our CAR estimates.

[26] This appears to be a small matter in the event study analysis of Harvey et al. (2004) using bond and syndicated debt issuances between 1980 to 1997 for emerging market issuers.

[27] Daily Fama-French factors are obtained from Kenneth French's website on 07 May 2014

Table 4: CAR sample means

	CAR10		CAR11	
	Positive news	Negative news	Positive news	Negative news
Mean	0.9040	0.5389	1.6592	1.3935
St. dev	0.2170	0.2233	0.3265	0.3389
Obs	1083	1095	1056	1056

The test consists of estimating a predicted relationship between the sign of the our measure for private information (the residual) and abnormal stock market returns. The prediction is that the cumulative abnormal returns are systematically higher for loans with a lower spread than predicted by publicly available information. Consequently, we expect a negative relationship between our measure of discretion and abnormal returns. In the regression,

$$CAR_{i,t,T} = \alpha + \beta\hat{\epsilon}_i + \gamma X_i + \mu_i$$

we expect β is negative and where X_i are a set of controls which include the size (in log total assets), book-to-market value, and leverage ratio of the borrower, along with the ratio of the loan amount to total assets of the borrower, the log maturity of the loan, the log size of the loan, and a dummy variable if the loan took place during a recession. Table 5 reports the regression results.

Table 5: CAR regressions

	CAR10			CAR11		
	(1)	(2)	(3)	(4)	(5)	(6)
Residual	-0.652	-0.885**	-0.777*	-0.992	-1.387*	-1.450*
	(0.437)	(0.443)	(0.448)	(0.710)	(0.734)	(0.741)
Constant	0.709***	4.537	3.896	1.507***	6.254	7.781
	(0.156)	(2.770)	(6.683)	(0.236)	(4.225)	(6.247)
Controls	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes
R-squared	0.000986	0.0278	0.0686	0.00104	0.0285	0.0750
N	2178	2178	2178	2112	2112	2112

** $p < 0.10$, **$p < 0.05$, ***$p < 0.01$; Robust standard errors in parentheses; Control variables are borrower log total assets, borrower book-to-market value, borrower leverage ratio, ratio of loan to borrower total assets, log maturity of the loan, log size of the loan, and a dummy variable if the loan took place in a recession period; Coefficents on controls not reported but included in the specifications of columns (2), (3), (5) and (6).*

The regressions results broadly confirm our hypothesis.[28] We find that a negative residual, positive news about the borrowing firm, generates strong stock market responses.

4.2 Analyst forecast evidence that discretion reflects borrower fundamentals

In a second exercise, we show that analysts forecasts, made around the loan dates in our sample, of borrower earnings several years into the future could be improved by using the residuals estimated in our regressions. Such evidence suggests that indeed the residuals we estimate constitute (previously) private information that lenders have about the borrower that professional analysts were not aware of at around the time of the loan. In particular, we show that a negative residual - positive private

[28]At larger event windows (e.g. more than three days) the results are not statistically different from zero although with the right signs. We also find that the inclusion of our control variables can explain away the loan announcement effect in that the constant coefficient is no longer statistically significantly different from zero once we include control variables.

information about the borrower - predicts a positive forecast surprise, an earnings outcome higher than what analysts have forecasted.

The test makes use of analyst forecasts of key borrower performance indicators made around the time of the loan issue date. If indeed the residual contains private information accessible only to the lenders, then these residuals should be able to explain some fraction of surprises (forecast errors) in analyst forecasts of firm fundamentals made prior to but relatively close to the loan issue date.[29]

To implement the test we take analyst level forecasts of net income (NET), pre-tax income (PRE), and earnings per share (EPS) around loan issue dates from the IBES analyst forecast database.[30] We take all loan events in our sample for which we do not observe a syndicated loan in the preceding 125 business days and are able to match to analyst-level forecasts of net and pre-tax income of the respective borrowers in a (+/-) 90 calendar day window around each borrower-loan date. We take all forecasts confirmed accurate (review date) within this window and limit forecasts to those reviewed at least 30 calendar days before the forecast period end date. Forecast surprises are calculated using the actual values also available in the IBES dataset. After matching with IBES, we end up with 386 unique loan events identified by borrower and loan date for which we have 6,156 forecast surprises from 843 unique analysts.

We test the following hypotheses: (1) A negative residual, constituting positive private information, leads to a positive surprise (the actual being higher than the

[29]See Boubakri et al. (2015) for evidence on the role of analysts as information providers and aggregators.

[30]To mitigate potential confounding effects of higher leverage that arise from more borrowing, we focus on measures independent of financing structure and provide evidence using both pre-tax and net income measures. We use forecasts for Fiscal Year 3 which is the longest horizon forecast available with sufficient observations for the analysis. Similar results are obtained with Fiscal Year 2.

forecast). In the regression,

$$Surprise = \alpha + \beta_0 Residual + \epsilon$$

β_0 is negative; and (2) that the negative effect is stronger (present) for forecasts made before the loan date than for those made after the loan date. In the regression,

$$Surprise = \alpha + \beta_0 Residual + \beta_1 Before + \beta_2 Residual * Before + \epsilon$$

where $Before$ is a dummy variable indicating the forecast was made prior to the loan date, β_2 is negative.

The second hypothesis takes into account potentially unobserved (and unaccounted for) factors that may bias the estimated coefficient β_0. Consequently, the identifying assumption in the test for the sign of β_2 is that there is no other unobserved factor - aside from the loan itself - which systematically changes the relationship between forecast surprises and the residual measure for private information around the date of the loan event. To test the second hypothesis, we define the dummy variable $0before$ with the loan date as the cutoff. Further, to take into account potential information leakage or advanced notices, we also define an alternative dummy variable $5before$ which has five days before the loan date as the cutoff.[31] The regression results are reported in Table 6.

[31] Note that all observations for net and pre-tax income forecasts occur after the passing of Regulation Fair Disclosure in which analysts may not have preferential treatment in terms of advanced releases of or private information.

Table 6: Surprise Regressions

	Net income surprise			Pre-tax income surprise			EPS surprise		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Residual	-93.552***	-63.982**	-64.067**	-88.341*	-37.727	-39.563	-2.113**	-1.977	-2.133*
	(29.84)	(31.76)	(30.75)	(51.06)	(51.35)	(50.67)	(1.03)	(1.27)	(1.26)
Residual by 0 before		-51.818**			-85.410**			-0.203	
		(25.05)			(37.35)			(0.79)	
Residual by 5 before		-33.355***			-50.925***			-0.286	
		(8.73)			(17.43)			(0.69)	
Dummy 0 before			-55.503**			-88.982**			0.058
			(24.75)			(37.74)			(0.77)
Dummy 5 before			-29.110***			-41.761**			-0.077
			(9.21)			(18.29)			(0.66)
R2	0.931	0.932	0.932	0.927	0.928	0.928	0.824	0.824	0.824
N	875	875	875	883	883	883	1010	1010	1010

* $p < 0.10$, **$p < 0.05$, ***$p < 0.01$; *Robust standard errors in parentheses; Analyst and industry fixed effects not reported but included in all specifications. Sample contains unsecured loans and for which borrowers have not made a loan with the same lead arranger in the past 3 years.*

The results strongly confirm the hypotheses. The estimated coefficients in the first row confirm the first hypothesis where a negative residual induces a positive performance surprise in terms of both Net Income and Pre-Tax Income. The estimated coefficients in the second rows of columns 2 and 5 and third row of columns 3 and 6 confirm the second hypothesis for net income and pre-tax income forecasts where forecast surprises before the loan issue date exhibit a stronger negative correlation between the surprise component (forecast error) and our estimate of private information. On the other hand, we do not find statistically significant effects for earnings per share. Note that the regression results reported in columns 3, 6, and 9 take into account potential leakage of information with respect to the loan up to five days prior to the loan issue date.

4.3 Private information across time

We have previously shown that discretion in the setting of the loan rate in the syndicated loan market was priced into the borrower's equity by the stock market and can help explain future borrower earnings that professional analysts were unable to forecast. This suggests that at least some part of discretion reflects material and private information about borrower fundamentals that the lenders have obtained in the process of giving out the loan. In many ways, our methodology of using all publicly available information across many sources as explanatory variables in the setting of loan spreads and using the resulting residual as a measure of discretion lends itself to the hypothesis that our measure is related to private information that lenders have acquired about their borrowers.

Given that our regressions are sufficiently flexible and use a very broad set of variables, one could argue that our residuals which capture discretion already satisfy the requirements for classification as private information.[32] Our measure of discretion is estimated after controlling for multiple sources of variation from borrowers, lenders and the other terms of the loan contracts themselves. By focusing on the time fixed effects in the log-variance regression, we have also produced a measure of discretion over time which controls for institutional, lender-specific, loan-specific, and borrower-specific factors that may arise due to rent-seeking and risk-taking behavior by banks as well as differences in banks' cost of funding and propensity to provide credit.

To formally verify the hypothesis that our measure of discretion relates to private information, we conduct the following exercise. We use a proxy variable (see e.g. Botsch and Vanasco, 2018) which relates to unobserved borrower fundamentals and is orthogonal to information available to the public even after the loan has been made and test how this relates to the loan spread. Average analyst forecast surprises (errors) using forecasts of firm outcomes made soon after a loan event emerges as

[32]Our regression analysis incorporates as many publicly observable variables across all potential dimensions relevant to the loan contract in our specifications. In particular, our use of credit ratings and moments of daily stock market returns provides additional channels for public information from any other source not in our dataset to be accounted for in our specification. Finally, since we allow for parameter estimates to vary over time, our estimates are less likely to capture other explanations such as changing borrower composition or risk attitudes by lenders.

an ideal candidate for such a proxy variable. Such forecasts should embed publicly available information in the days following a loan event potentially including the terms of the loan contract. Consequently, forecast surprises (i.e. forecast errors) of firm outcomes for future fiscal years should be informative about firm fundamentals while being orthogonal to publicly available information soon after each loan event.

To tease out the private information component to discretion, we conduct a proxy variable regression to confirm that indeed part of the changes in the loan rate are due to private information. In this regression, we take average analyst forecast surprises of borrower earnings per share two fiscal years after the loan year using analyst forecasts made between 5 and 90 days after the loan date.[33] This ensures that the forecast surprises are correlated with future firm fundamentals and, these surprises are orthogonal to public information available around the loan dates including information about the loans themselves.

First, since these forecasts are made after the loan events, the forecast errors or surprises are exogenous and unpredictable to public information available during and soon after the loan event. Second, and for the same reason, we can rule out reverse causality in that the forecasts themselves should incorporate the forecasted effects of the loan and its terms themselves on future firm fundamentals such that the forecast surprise contains only information beyond what these expected effects are. Thus, the estimated correlation between forecast surprises and the loan rate should reflect lenders' private information about these firm fundamentals. We run the following regression on the log loan rate of a loan by borrower i from lender j at time t,

$$logspread_{i,j,t} = \alpha_j + \theta_t + \gamma_k + \beta IV_{i,j,t+h} + \delta X_{i,j,t} + \epsilon_{i,j,t} \tag{3}$$

[33] We choose the longest forecast horizon, Fiscal Year 2, which provides us with enough observations to do the analysis. We restrict the analysis to earnings per share forecasts as forecasts of net and pre-tax income would severely reduce sample size and restrict our sample to starting from the year 2003 and onwards.

where the first three parameters are lender, time, and industry fixed effects and X are a set of additional controls. The coefficient β reflects how the loan rate loads on our proxy variable for future firm fundamentals that cannot be forecasted with public information. The inclusion of time, lender, and industry fixed effects allow us to exclude common (systemic) variations in the future that affect borrower earnings from confounding our estimates of the β coefficient.

We test the following hypothesis, a positive forecast surprise signifying positive future borrower fundamentals not in the forecasters' information set leads to a reduction of the loan rate if the lender has some private information about borrower fundamentals such that the coefficient β in equation 3 is negative. The results are reported in Table 7.

Table 7: Loan spread regressions with analyst forecast surprises

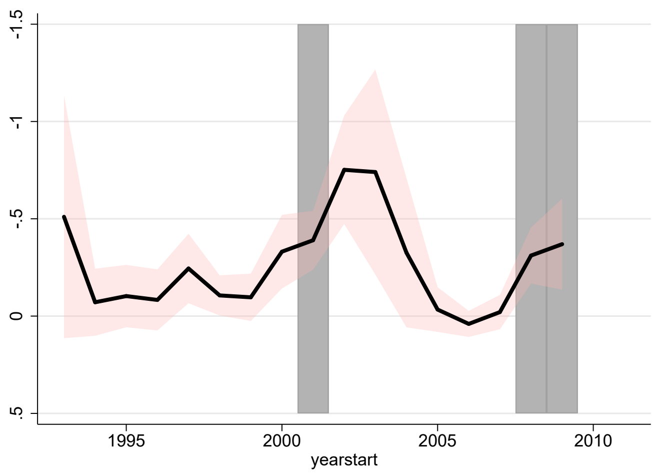
	(1)	(2)	(3)
	l_allindrawn	l_allindrawn	l_allindrawn
	b/se	b/se	b/se
Surprise FY2	-0.020**	-0.019**	-0.018**
	(0.01)	(0.01)	(0.01)
Loan-to-Borrower size		0.049**	0.071***
		(0.02)	(0.03)
Rating: Spec grade		0.101**	0.157***
		(0.04)	(0.05)
Syndication size		-0.019***	-0.012*
		(0.01)	(0.01)
Stock return: mean		-23.347**	-23.979**
		(9.73)	(9.79)
Stock return: variance		11.410***	10.597***
		(1.60)	(1.61)
Stock return: kurtosis		-0.003***	-0.003***
		(0.00)	(0.00)
Covenant tightness			0.100**
			(0.04)
Loan amount			-0.051**
			(0.02)
Loan maturity			0.033
			(0.05)
Fixed effects	All	All	All
R-squared	0.310	0.433	0.440
N	958	958	958

* $p < 0.10$, **$p < 0.05$, ***$p < 0.01$; *Robust standard errors in parentheses; Other coefficient estimates are omitted in the table. All regressions include a recession year dummy. All fixed effects include year, lender, and industry fixed effects. Lender fixed effects are based on the lead lender identity for lead lenders with at least 15 loans in the sample. Industry fixed effects are at the one digit SIC level.*

As the results indicate, positive forecasts surprises (better firm outcomes than predicted) in terms of earnings per share for up to two years ahead of the loan event are associated with lower loan rates indicating that lenders do have some private information about their borrowers.

To assess time variation in private information production, we estimate a regression with our proxy variable and year fixed effects over a a rolling window sample of five years. We plot the estimated coefficients on the proxy variable along with its 95% confidence interval in Figure 6. Note that a larger coefficient in absolute value implies more private information and the vertical axis scale has been reversed such that a higher point in the figure reflects more private information.

Figure 6: Rolling window estimates of private information



The figure plots coefficient estimates on analyst forecast surprises in a regression which includes year fixed effects similar to column 1 of Table 7 and using a rolling window sample of five years. The red shaded area represents 95% confidence intervals. The gray bars represent recession periods identified using NBER dates.

We find that the magnitude of the coefficient tends to be low during a boom and picks up during and soon after recessions.

Combined with the previous exercise, these results link our estimates of private information to both market expectations about borrower value (abnormal stock market returns) as well as directly to un-forecasted future borrower profitability (analyst forecast surprises). Further, since lenders may appropriate some of the information rents, the loan spread may only partially reflect private information collected.[34] This implies that our estimates are a lower bound and we are only capturing the extent to which private information is revealed by the terms of the loan contract. Similarly, since our procedure is potentially subject to a selection bias in that we only observe loans that have been granted, it may be the case that public and private information has already been used to reject borrowers who would then not appear in our datasets. Under this scenario, the residual variance is only indicative of the intensive margin to information production in fine-tuning the terms of the loan contract whereas we do not account for the extensive margin or the production and use of private information to reject or accept loans. Thus, our results are again potentially underestimating total private information production and use in credit markets.

5. Conclusion

In this paper we assessed the extent to which discretion is used and revealed in the pricing of syndicated term loans. Using two decades of U.S. loan data by a host of lenders and borrowers and across multiple data sources, we constructed a measure of discretion by decomposing the variation in loan spreads into that which can be explained by public and private information components. We find that discretion varies across time and institutions. It is lower for secured loans, loans granted by large loan syndications, and for loans with smaller and highly leveraged lead lenders. Consistent with the interpretation of our measure as private information, positive signals from our index generate both a positive stock market response after loan events and can predict favorable analyst forecast surprises on

[34] See Rajan (1992). Screening and private information provide banks monopoly rents (Dell'Ariccia and Marquez, 2004). Nevertheless, as Bouckaert and Degryse (2006) show, banks may have incentives to disclose some of their privately produced information such that the terms of credit may also reflect this information.

future borrower conditions. We find that our measure exhibits a hump-shaped pattern over economic booms where it is typically low shortly before, during, and in the years following a recession. These findings complement the existing theoretical literature and lend support to cyclical macro-prudential policies. These results open new areas of research in the conduct of financial regulation. Our index may have potential applications in the measurement of both institutional-level risk-taking as well as risk buildup. These are interesting extensions beyond the scope of this paper and are left for future work.

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Appendices

A. Data descriptives

Table A.1 provides an overview of the data used and their source while Table A.2 describes the variables used in detail. Table A.3 describes which variables were used in the regression specifications. In all cases, the dependent variable is the (log) spread in terms of the average interest rate (all fees and charges as a percent of the loan amount) less LIBOR although similar results were obtained with the spread in levels. For the loan spread, loan maturity, and loan amount variables, summary statistics in Table 1 are reported on the levels although the regression specification have these variables in logs.

Table A.1: Data sources overview

	Dealscan	Compustat	CRSP	FRB BHC
Date variable	Quarter date of loan	Balance sheet as of quarter prior to loan date	Average from previous year	As of quarter of loan date
ID variable	Borrower and Lender ID	Borrower ID†	Borrower ID	Lender ID‡
	Facility amount	Log of total Assets	Mean	EBITDA
	Maturity	Leverage ratio (Total Debt to Assets)	Standard deviation	Net Income
	Spread over libor (fees and rates)	Return on Assets (Operating income over total Assets)	Skewness	Charge offs on C&I loans
	Secured debt dummy	Interest coverage (Operating income over interest payments)	Kurtosis	Recoveries on C&I loans
	Loan primary purpose	Profit margin (Operating income over Sales)		Total assets
	Number of lenders	Current ratio		Total liabilities
	Syndication composition	Book to market value of equity and total Assets		Allowance for loan losses**
	Covenant count	Asset tangibility ratio		Tier 1 Capital**
	Covenant tightness index*	Log of market value of Equity		Tier 2 Capital
		Sales to total Assets ratio		Total risk-based capital**
		Firm age in years		Average total assets for leverage capital**
		Stock return (y-o-y)		Tier 1 leverage ratio**
		Stock vol: scaled high-low from previous year		Tier 1 risk-based capital ratio
		SIC Industry code of borrower		Total risk-based capital ratio**
		Stock price (low,high,beginning, and end)		
		S & P Long term ratings		
		S & P Short term ratings		

† Matching based on Chava and Roberts (2008), updated August 2012.

‡ Manually matched lender names and loan dates using the National Information Center Institution database of the Federal Reserve System.

* The index is constructed based on Murfin (2012).

** The data is available beginning 2002.

Asset tangibility ratio refers to Property, Plant, Equipment and Inventories over total assets.

Stock return moments from CRSP are computed using the daily returns in the preceding four quarters to the loan date.

The Federal Reserve Bank Holding Company dataset is available at the Federal Reserve Bank of Chicago http://www.chicagofed.org/applications/bhc/bhc-home.

Table A.2: Variable description

Name	Unit	Transformation	Description
Loan Variables			
Loan spread (log)	Basis points	log	Average fees and all charges over LIBOR
Loan amount (log)	USD millions	log	Total loan facility amount
Loan maturity (log)	months	log	Loan facility maturity in months
Secured loans	Binary	none	Dummy variable if loan is secured
Syndication size	Count	none	Number of participants in syndication
Number covenants	Count	none	Number of covenants in facility (package)
Covenant tightness	Index	none	Ex-ante probability of covenant violation
Borrower Variables			
Size (log TA)	log USD Million	log	Log of total assets
Return on assets	Ratio	none	Operating income before depreciation over total assets
Current ratio	Ratio	none	Current assets over current liabilities
Interest coverage	Ratio	none	Operating income before depreciation over interest expense
Profit margin	Ratio	none	Operating income before depreciation over sales
Book to market	Ratio	none	Book over market value of equity
Leverage	Ratio	none	Total liabilities over total assets
Asset tangibility	Ratio	none	Net property, plant , and equipment plus inventory over total assets
Age (years)	years	none	Age in years from IPO date to current balance sheet date
Quick ratio	Ratio	none	Current assets less inventories over current liabilities
Asset book to market	Ratio	none	Book over market value of total assets
Stock return (FY)	Percent	none	Current year closing stock price over previous year closing stock price
Stock price range (FY)	Index	none	Current year stock highest closing less current year lowest closing over average of current and previous year closing stock price
Credit rating (long)	Categorical	Three grades	S&P long term domestic issuer credit rating
Credit rating (short)	Categorical	Three grades	S&P short term domestic issuer credit rating
Stock return (daily)	(annualized) Percent	none	Average of daily stock returns in a four quarter period prior to loan quarter
Stock volatility (daily)	(annualized) Percent	none	Variance of daily stock returns in a four quarter period prior to loan quarter
Stock skewness (daily)	(annualized) Percent	none	Skewness of daily stock returns in a four quarter period prior to loan quarter
Stock kurtosis (daily)	(annualized) Percent	none	Kurtosis of daily stock returns in a four quarter period prior to loan quarter
Lender Variables			
Lender EBITDA	USD thousands	none	Income before extraordinary items and other adjustments
Lender Net Income	USD thousands	none	Net income
Lender Chargeoffs	USD thousands	none	Charge-offs on Commercial and Industrial loans to US addressees
Lender Recoveries	USD thousands	none	Recoveries on Commercial and Industrial loans to US addressees
Lender Total assets	USD thousands	none	Total assets
Lender Total liabilities	USD thousands	none	Total liabilities
Lender Loss provision	USD thousands	none	Allowance for loans and losses for the previous calendar year-end
Lender Tier 1 capital	USD thousands	none	Tier 1 capital
Lender Tier 2 capital	USD thousands	none	Tier 2 capital
Lender Risk-based capital	USD thousands	none	Total qualifying capital under risk-based capital guidelines
Lender Tier 1 leverage	Percent	none	Tier 1 capital over adjusted total assets
Lender Tier 1 risk-based capital ratio	Percent	none	Tier 1 capital less low-level recourse deduction, divided by risk-weighted assets
Lender Risk-based capital ratio	Percent	none	Total risk-based capital over risk-weighted assets

Table A.3: Regression specifications

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable					
Loan spread* (bps)	Yes	Yes	Yes	Yes	Yes	Yes
	Explanatory variables					
First stage variables						
Lender dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Auditor's opinion dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Year (Quarter) dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Loan-specific variables						
Loan amount* (millions)	Yes	Yes	Yes	Yes	Yes	Yes
Loan maturity* (months)	Yes	Yes	Yes	Yes	Yes	Yes
Syndication size	No	Yes	Yes	No	Yes	Yes
Secured loan	No	No	Yes	No	No	Yes
Number covenants	No	No	Yes	No	No	Yes
Covenant tightness	No	No	Yes	No	No	Yes
Borrower-specific variables						
Size (log TA)	Yes	Yes	Yes	Yes	Yes	Yes
Return on assets	Yes	Yes	Yes	Yes	Yes	Yes
Current ratio	Yes	Yes	Yes	Yes	Yes	Yes
Interest coverage	Yes	Yes	Yes	Yes	Yes	Yes
Profit margin	Yes	Yes	Yes	Yes	Yes	Yes
Book to market	Yes	Yes	Yes	Yes	Yes	Yes
Leverage	Yes	Yes	Yes	Yes	Yes	Yes
Asset tangibility	Yes	Yes	Yes	Yes	Yes	Yes
Quick ratio	Yes	Yes	Yes	Yes	Yes	Yes
Asset book to market	Yes	Yes	Yes	Yes	Yes	Yes
Stock return (FY)	Yes	Yes	Yes	Yes	Yes	Yes
Stock price range (FY)	Yes	Yes	Yes	Yes	Yes	Yes
Credit rating (long)	Yes	Yes	Yes	Yes	Yes	Yes
Credit rating (short)	Yes	Yes	Yes	Yes	Yes	Yes
Stock return (daily)	Yes	Yes	Yes	Yes	Yes	Yes
Stock volatility (daily)	Yes	Yes	Yes	Yes	Yes	Yes
Stock skewness (daily)	Yes	Yes	Yes	Yes	Yes	Yes
Stock kurtosis (daily)	Yes	Yes	Yes	Yes	Yes	Yes
Lender variables						
Lender EBITDA	No	Yes	Yes	No	Yes	Yes
Lender Net income	No	Yes	Yes	No	Yes	Yes
Lender Chargeoffs	No	Yes	Yes	No	Yes	Yes
Lender Recoveries	No	Yes	Yes	No	Yes	Yes
Lender Total assets	No	Yes	Yes	No	Yes	Yes
Lender Total liabilities	No	Yes	Yes	No	Yes	Yes
Lender Loss provision	No	No	No	Yes	Yes	Yes
Lender Tier 1 capital	No	No	No	Yes	Yes	Yes
Lender Tier 2 capital	No	No	No	Yes	Yes	Yes
Lender Risk-based capital	No	No	No	Yes	Yes	Yes
Lender Tier 1 Leverage ratio	No	No	No	Yes	Yes	Yes
Lender Tier 1 Risk-based capital ratio	No	No	No	Yes	Yes	Yes
Lender Risk-based capital ratio	No	No	No	Yes	Yes	Yes
Sample	Full Sample	Full Sample	Full Sample	Post-2001	Post-2001	Post-2001

** The regression specifications use logs.*

B. Homogeneous borrower sub-sample regression

In this section we perform the same analysis as in Section 3 to obtain estimates of private information production over time but with a more homogenous sample of borrowers. This is done to address concerns that the time-varying coefficient approach adopted in the main analysis is not sufficient to take into account the time-varying composition of borrowers. To do so we limit the sample into borrowers who obtain only secured loans, have a speculative grade credit rating, and are above the mean size (log Total Assets). These choices were made so as to make the borrower pool for each year more homogeneous without severely limiting the sample size. This limits our sample to 2,571 loans of which we end up with between 805 to 1,423 observations for our regression analyses. The following table reports the mean and variance of the loan spread, credit rating, dummy for collateralized loan, and borrower size before and after we limit the sample.

Table B.4: Borrower characteristics

	Full sample				Homogeneous borrowers sub-sample			
	mean	sd	min	max	mean	sd	min	max
Borrower size (log TA)	5.9597	1.8580	-5.5215	13.5896	7.3731	1.0109	5.9503	13.0733
Credit rating (Inv/Spec Grade: 1/-1)	-0.4796	0.5549	-1.0000	1.0000	-1.0000	0.0000	-1.0000	-1.0000
Secured Loan Dummy	0.9362	0.2445	0.0000	1.0000	1.0000	0.0000	1.0000	1.0000
Observations	11173				2571			

The homogeneous borrowers sub-sample are limited to borrowers above the mean size (in log Total Assets), with a Speculative grade credit rating, and whose loan is secured by collateral.

A severe limitation of this sub-sample regression with more homogeneous borrowers is that we cannot implement a time-varying coefficient regression. In addition, we have to limit the span of explanatory variables into 17 borrower control variables, 7 lender control variables, 7 loan contract variables as well as lender, industry, and year fixed effects. The following table reports regression results that are comparable to the first three columns of Table 2 in the main text.

Table B.5: Constant coefficient regressions: homogenous borrowers sub-sample

	(1)	(2)	(3)
Borrower Current Ratio	-0.105***	-0.072**	-0.082***
Borrower Interest Coverage	0.000***	0.000***	0.000***
Borrower Profit margin	-0.020***	-0.022***	-0.046
Borrower Asset tangibility	0.150***	0.195***	0.210***
Borrower Quick Ratio	0.102***	0.070**	0.077***
Borrower Stock return-mean	-21.386***	-21.104***	-26.612***
Borrower Stock return-variance	6.481***	7.036***	7.199***
Borrower Stock return-kurtosis	-0.001***	-0.002***	-0.001**
Lender Charge-offs on CI loans		0.000***	0.000***
Lender Total Assets		-0.000**	-0.000***
Lender Total Liabilities		0.000**	0.000***
Syndication Size		-0.011***	-0.012***
Covenant Tightness			0.173**
Fixed effects	Full	Full	Full
Sample	Full	Full	Full
Partial R-squared	0.297	0.338	0.373
Overall R-squared	0.449	0.481	0.509
N	1423	969	805

* $p < 0.10$, **$p < 0.05$, ***$p < 0.01$; *Time, Industry, Lender, Auditor opinion, Loan purpose, and Covenant fixed effects estimates as well as for selected coefficient estimates which are not significantly different from zero have been omitted. The specifications explains between and 45 and 51 percent of total variation in log spreads.*

Using the regression results from column 3 of Table B.5, we plot estimates of the average squared residuals in the left panel of Figure 4 and is comparable to Figure 1 in the main analysis. The general patterns we find in the full sample hold for the sub-sample with more homogeneous borrowers. We also proceed in the same manner as in the main text to calculate our discretion index. We report the regression results for equation 2 using the homogeneous sub-sample in Table B.6.[35] As in the main analysis, the first column is the benchmark with both time and lender fixed effects. Columns two to four replace the lender fixed effects with lender-specific variables. Column three uses the same specification as in column two but uses only loans from 2002 onwards. Finally column four expands the set of lender variables to include those available since 2002 such as bank risk-based capital ratios and loss provisions. The resulting estimates are plotted in the right panel of Figure 4.

Table B.6: Log variance regressions: homogenous borrowers sub-sample

	(1)	(2)	(3)	(4)
Size (log TA)	-0.0347	-0.0723	-0.168	-0.192
Loan amount	-0.300	-0.180	-0.208	-0.169
Loan maturity	-0.320	-0.681*	-0.536	-0.491
Syndication size	-0.000465	-0.00160	0.00311	0.00371
Loan to borrower size	-0.262	-0.491	-1.198	-1.225
Number covenant	-0.0136	0.0435	0.0680	0.0497
Covenant tightness	0.525	0.527	0.640	0.639
Lender total assets		-0.00575	0.0727	0.111
Lender leverage		16.07*	24.02**	22.49
Lender profitability		-6.347**	-9.856***	-10.10***
Lender charge-off ratio		11.36***	14.79***	13.10***
Lender loss provision ratio				63.44
Lender risk-based capital ratio				-0.0467
Time	Time FE	Time FE	Time FE	Time FE
Lender	Lender FE	None	None	None
Sample	Full	Full	Post-2001	Post 2001
R-squared	0.111	0.133	0.162	0.169
N	400	385	270	270

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; *Lender leverage is total liabilities over total assets, Lender profit is net income to total assets; Lender Charge-off ratio is the ratio of charge-offs to total assets, and similarly for the loss provision ratio.*

[35] The smaller sample size limits our specification and we only use lender fixed effects for the 12 most frequently occurring lead lenders.

The resulting estimates for the average squared residuals and our measure for discretion are similar to those in Figures 1 and 2 in the main text suggesting that our results are not being driven by changes in the composition of borrowers over time.

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