Banking on Disagreement: Heterogeneous Credit Risk Assessments in Syndicated Lending*

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Abstract

Using confidential supervisory data, we measure disagreement among bank syndicate lenders about borrowers' credit risk by exploiting dispersion in probability-of-default (PD) estimates that banks report to the Federal Reserve for the same borrower-loan pair. Consistent with theory, disagreement is greater for larger loans and syndicates as well as disagreement about credit models. At origination, loans with higher disagreement driven by credit models but also banks' incentives or private information access carry significantly higher spreads, even after controlling for borrower and loan risk characteristics. Although disagreement does not affect the number of covenants, it lowers the likelihood that contracts include performance-pricing provisions, consistent with lenders seeking to avoid future coordination frictions. After origination, banks with more pessimistic PD assessments are more likely to exit the syndicate, and greater disagreement lowers the probability of loan amendments following both positive and negative shocks to borrower fundamentals. However, successful renegotiations narrow subsequent disagreement. Overall, our evidence shows that within-syndicate coordination frictions shape loan pricing, contract design, syndicate composition, and renegotiation outcomes.

Keywords: Syndicated bank lending, Bank disagreement, Probability of default estimates, Loan contracting
JEL Classifications: G21; G23; G32; M41

1. Introduction

Banks commonly form loan syndicates to share the risk of extending large loans to firms with uncertain investment opportunities. The literature emphasizes two main frictions that can arise in this process. The first stems from information asymmetry between the lead arranger and participant lenders. The lead arranger interacts directly with the borrower and leads the due diligence process, gaining an informational advantage over other syndicate members. This asymmetry creates an adverse selection problem, which is mitigated when the lead arranger retains a larger share of the loan as a signal of deal quality (Gorton and Pennacchi, 1995; Ball et al., 2008; Ivashina, 2009; Down et al., 2024; Leland and Pyle, 1977). The second friction, which is the focus of our study, arises from coordination challenges within the syndicate itself. Larger syndicates require greater communication and alignment when setting terms ex ante or when renegotiating ex post. In particular, lead arrangers must reconcile potentially divergent assessments among syndicate lenders regarding borrower credit risk (Berlin et al., 2020; Caskey et al., 2026; Gertner and Scharfstein, 1991).

We investigate the determinants of this disagreement and examine whether it has implications for loan contracting outcomes, both at origination and over the life of the loan. To do so, we use confidential supervisory data from the Federal Reserve's FR Y-14Q, which requires large U.S. bank holding companies to report internal one-year probabilities of default (PD) estimates for every corporate loan exceeding $1 million. We measure disagreement among banks in the syndicate as the range between the highest and lowest PD estimates reported by banks for the same borrower and at the same point in time. The median disagreement in our sample is economically meaningful at 0.51 percentage points, which is roughly 90% of the median PD.

To understand syndicate disagreement, we start by considering how syndicate banks arrive at their individual credit risk assessments. The extent to which banks differ in their credit risk estimation response to common signals will drive disagreement across banks, but banks' models are unobservable and proprietary. We attempt to capture banks' modeling differences by estimating a simple credit risk model for each bank. We conjecture that common borrower fundamentals such as profitability, leverage, and firm size are key inputs into this model and measure the association between these fundamentals and the bank's PD estimates across the bank's lending portfolio within an industry over time. We then use the estimated coefficients in our syndicated loan sample to generate an expected PD ($\widehat{PD}$) for every bank-borrower pair. We argue that these fitted PDs proxy for disagreement attributable to banks placing different weights on observable borrower fundamentals.

We document that, on average, the three key borrower fundamentals explain 54% of the variation in banks' PD assessments across industries within their portfolios, with pseudo R^2 ranging from 43% to 61%. These results indicate substantial heterogeneity in how banks translate observable borrower fundamentals into credit risk assessments. Heterogeneity arises not only across industries but also across banks within the same industry. For example, within the Transportation industry, the estimated weight placed on borrower profitability varies by approximately a factor of four across banks, based on an average of more than 3,000 borrower-PD observations per estimate. The estimates also appear highly persistent over time, with the serial correlation in banks' estimated weights ranging from 0.85 to 0.96, suggesting that the estimated coefficients capture, at least in part, differences in banks' underlying credit risk models.

We next examine what drives banks to deviate from their model–based assessments by focusing on four channels motivated by prior work documenting characteristics of banks that affect their information processing: bank industry specialization, the length of the bank-borrower relationship, bank capital constraints, and geographic proximity between the bank and borrower. Specifically, we test whether these characteristics affect the overall level of reported PD estimates and whether they influence the extent to which reported PDs align with model-based assessments reflected by $\widehat{PD}$. We highlight several findings that help us understand banks' credit risk assessment. We find that banks with longer borrower relationships report lower PDs on average, consistent with the accumulation of private soft information that leads banks to assess familiar borrowers as less risky. These banks also place greater weight on model-based assessments, suggesting that relationship lending reduces adverse selection concerns and makes the hard information embedded in these models more relevant for credit risk assessment. By contrast, less capital-constrained banks do not report systematically different PDs on average, implying that capital constraints do not materially affect reported PDs. However, it is the less capital-constrained banks, rather than the constrained banks, that place less weight on credit model–based assessments, which is inconsistent with an incentive-driven bias explanation. If incentive-driven bias were a dominant mechanism, one would expect the capital-constrained banks to place less weight on model-based assessments in order to understate risk and reduce regulatory capital pressure. Overall, these findings suggest that deviations from model-based assessments are driven primarily by information-related factors rather than distortions due to capital-related incentives, although we cannot fully rule out prior evidence showing that bias can affect PD estimates. (e.g., Plosser and Santos, 2018; Owens and Sokolowski, 2025).

Having investigated factors that lead banks to different PD assessments, we next aggregate these individual risk assessments and examine the determinants of disagreement at the syndicate level. Validating our model-based measure, we find that the range of our predicted PDs for syndicate banks (*Model Disagreement*) is strongly and positively associated with syndicate disagreement based on the actual PDs. We also find that larger loans and syndicates with more lenders exhibit greater disagreement, consistent with coordination costs increasing in larger lending groups (Caskey et al., 2026). Further, we find that syndicates in which the lead arranger reports a more pessimistic PD than the other lenders exhibit higher levels of disagreement. This finding suggests that at least some participant banks can detect potential adverse selection incentives on the part of lead arrangers. At the same time, we do not find evidence that lead arrangers mitigate disagreement by retaining a larger share of the loan and having greater "skin in the game." Taken together, the findings suggest that disagreement within syndicates reflects both differences in credit risk models (i.e., *Model Disagreement*) and differences attributable to other information sources. We next examine how these measures of disagreement relate to contracting outcomes.

Theory provides clear predictions for how disagreement is associated with contracting outcomes.

Models on multi-creditor financing show that when lenders hold differing signals or priors about borrower quality, reaching efficient collective decisions becomes costly (e.g., Gertner and Scharfstein, 1991; Bolton and Scharfstein, 1996). As a result, disagreement may delay deal completion, limit the inclusion of contingent contractual features (e.g., performance-based pricing), and affect loan pricing dynamics.[1] Disagreement is also likely to generate frictions after origination because loan amendments and covenant waivers often require near-unanimous lender consent, slowing the syndicate's response to new information and potentially causing some lenders to exit the syndicate (Aghion and Bolton, 1992; Caskey et al., 2026; Phillips et al., 2026). Overall, these arguments predict that lender disagreement increases borrowers' financing costs and reduces the frequency of ex post loan renegotiations.

We begin our analysis of the consequences of disagreement by examining the association between our disagreement measures and loan spreads at origination. We find that both measures are associated with higher loan spreads. A one-standard-deviation increase in model disagreement is associated with a 1.7% increase in loan spreads, while a one-standard-deviation increase in actual disagreement is associated with a 4.0% increase in loan spreads. These findings are consistent with both differences in credit risk models and other sources of disagreement—such as private information, incentive biases, or more advanced modeling choices not captured by our $\widehat{PD}$s—increasing borrowers' financing costs.

We next examine the association between disagreement and state-contingent contractual terms. We find that actual disagreement is associated with fewer performance-pricing provisions, whereas model disagreement is not significantly associated with the use of performance pricing. Neither measure is statistically significantly related to the use of covenants, although the estimated coeffi-

[1] Lead arrangers typically use "market-flex language," which allows them to adjust loan pricing (i.e., spreads and fees) based on lender demand (Leveraged Commentary & Data, 2024). This language also permits shifts in the allocation across loan tranches. Loans are usually launched with a range of spreads, and syndicate participants often make tiered commitments based on these spreads in a blind auction bidding process. For example, a participant might commit $25 million at a 275 basis point spread or $15 million at 250 basis points. Once all commitments are received, the arranger totals them and determines the final loan pricing. Greater heterogeneity in lender assessments can widen the dispersion in these bids.

cients are negative.[2] The evidence suggests that disagreement makes it more difficult for syndicate lenders to reach consensus on contingent contractual terms that may be harder to enforce ex post when lenders hold divergent views. We further examine whether disagreement predicts lender exit from the syndicate. We find that both model disagreement and actual disagreement predict the future exit of banks that assess borrower credit risk more pessimistically relative to other syndicate members over horizons ranging from one to four quarters ahead. These findings are also consistent with disagreement generating post-origination frictions, which are sufficiently meaningful to induce banks to leave the syndicate.

Next, we test whether disagreement constrains the syndicate's ability to renegotiate when borrower credit conditions change. Because amendments and covenant waivers typically require broad lender consent, persistent disagreement should increase coordination costs and delay collective responses (Aghion and Bolton, 1992; Roberts and Sufi, 2009). We proxy for changes in borrower credit conditions using changes in profitability, which capture fundamental shocks that are plausibly exogenous to lenders' prior assessments of borrower credit risk. Importantly, while lead arrangers may anticipate the level of disagreement within the syndicate at origination, the change in disagreement in response to borrower-specific profitability shocks reflects information that is likely unanticipated at the time of syndicate formation. This allows us to identify coordination frictions that arise from post-origination disagreement that could not have been fully contracted around ex ante, addressing concerns that disagreement and its consequences are a result of endogenous syndicate formation ex ante. Conditional on a profitability shock, both model disagreement and actual disagreement reduce the likelihood of amendment. The findings are consistent with theoretical predictions that heterogeneous assessments increase coordination costs (e.g., Gertner and Scharfstein, 1991; Bolton and Scharfstein, 1996; Berglöf and Von Thadden, 1994; Caskey et al.,

[2]If disagreement only reflected borrower risk, we would expect to observe both higher spreads and *more* covenants. Prior work also suggests that lenders trade off between price and non-price protections when contractual monitoring is costly or difficult to enforce (Sridhar and Magee, 1996; Costello and Wittenberg-Moerman, 2011; Donovan et al., 2024). While our results are directionally consistent with such a trade-off, we do not find statistically significant evidence supporting it.

2026).

We then examine what happens after amendments take place. For the subset of loans that are successfully renegotiated, actual disagreement declines in the quarters immediately following the amendment and remain lower for several subsequent periods. These findings suggest that while initial disagreement can impede collective action, successful renegotiation can partially resolve these frictions by realigning lenders' assessments of borrower risk once coordination is achieved.

The primary threat to our interpretation that disagreement increases coordination frictions in debt contracting is that the observed relation between disagreement and loan outcomes could reflect higher underlying borrower credit risk or general uncertainty rather than differences in lenders' assessments. Borrowers that are objectively riskier or operate in more volatile conditions might prompt greater dispersion in modeling and actual PD estimates and simultaneously face higher spreads or lower amendment success. We address this concern in several ways. First, we explicitly control for multiple dimensions of credit risk and market volatility by including borrowers' internal credit ratings, leverage, and profitability, as well as industry and idiosyncratic stock return volatility. The pricing and amendment results remain unchanged, indicating that disagreement does not merely proxy for riskier borrowers or for uncertainty in their operating environment. Second, we examine whether disagreement predicts future deterioration in loan performance or borrower default risk. We find no positive association between either of our measures of disagreement and subsequent declines in credit quality as reflected in loan defaults. Taken together, these analyses indicate that bank disagreement does not capture borrower shared uncertainty or underlying credit risk.

A related concern is that the observed PD dispersion may reflect differences in banks' internal rating methodologies rather than heterogeneous assessments of borrower-specific fundamentals. Banks vary in whether they adopt a through-the-cycle (TTC) approach, which smooths PD estimates across macroeconomic cycles, or a point-in-time (PIT) approach, which adjusts PDs more aggressively in response to current conditions. If our disagreement measure primarily captures TTC versus PIT heterogeneity, syndicates mixing both types of lenders would mechanically exhibit wider

PD dispersion during stressed periods, and this cyclical variation could confound our inferences about coordination frictions. We address this concern through two complementary tests. First, we construct bank-specific measures of PD cyclical sensitivity using each institution's complete FR Y-14Q portfolio and control for syndicate-level variation in rating cyclicality. Second, we test whether disagreement associations are concentrated in periods of macroeconomic stress by interacting our disagreement measures with indicators for high-stress quarters (unreported results). Across both approaches, we find that controlling for rating cyclicality leaves our core results unchanged, and disagreement associations remain stable across the business cycle. These patterns indicate that our measure captures heterogeneity in lenders' credit-risk assessments rather than mechanical differences driven by macroeconomic conditions in banks' rating methodologies.

Overall, we interpret our findings as consistent with bank-specific, information-driven disagreement affecting loan contracting outcomes. We acknowledge, however, that our empirical proxy relies on banks' reported PDs, which prior research has shown may be subject to bias (Plosser and Santos, 2018; Owens and Sokolowski, 2025). If such individual PD bias were the primary driver of our disagreement measure, then reported PDs would not reflect banks' true (i.e., actionable) credit risk assessments. In that case, actual disagreement would not be expected to systematically influence loan contracting outcomes. Consequently, any attenuation arising from biased PD reporting would bias our tests toward finding no effect. Our estimates should therefore be interpreted as a lower bound on the relationship between disagreement and loan contracting outcomes.

Our study advances the literature on coordination costs in lending by providing direct evidence of heterogeneity in credit risk assessment among syndicated loan lenders, as measured by the dispersion of their PD estimates, and by documenting its association with loan pricing, renegotiation outcomes, and syndicate composition. We also contribute by decomposing the disagreement in banks' reported PD estimates within the syndicate into a component attributable to model differences and a residual component reflecting private information and potentially incentive-driven biases, and by showing that both components independently affect contracting outcomes. Whereas prior research has largely inferred heterogeneity in lender assessments using indirect proxies such as loan structure or pricing (Gorton and Pennacchi, 1995; Ivashina, 2009; Ball et al., 2008; Caskey et al., 2026), we offer direct empirical validation of theoretical predictions that coordination frictions within lending syndicates have economically distinct and meaningful consequences. In particular, our findings show that frictions arising from disagreements on credit risk increase the cost of syndicated lending for borrowers, complementing recent theoretical work on heterogeneous lender types and syndicate amendment voting (Caskey et al., 2026).

We also extend the literature by examining syndicate membership dynamics and loan renegotiation during the post-contracting period. While prior research has explored the role of lead arrangers in mitigating information asymmetry at origination (Ball et al., 2008; Phillips, 2025), we show that lender disagreement persists beyond origination and has significant consequences for syndicate composition. Specifically, we document that banks with more pessimistic risk assessments are significantly more likely to exit the syndicate post-origination, leading to a self-selection process that gradually reshapes the syndicate's composition. Additionally, greater lender disagreement slows lenders' collective response to borrower shocks, suggesting that disagreement creates friction in the renegotiation process. Thus, bank disagreements not only raise borrowing costs but also reduce syndicate stability and affect loan terms in the post-contracting period.

2. Related Literature

Syndicated lending requires multiple lenders to coordinate on a common set of contractual terms, yet this process is shaped by two distinct frictions: information asymmetry between the lead arranger and participant lenders, and coordination frictions among lenders themselves. A substantial body of research examines the first friction and the role of the lead arranger in mitigating information gaps with and between participant lenders. Because the lead arranger has privileged access to borrower-specific information, it acts as the informational intermediary that structures the loan and communicates risk assessments to the syndicate. However, this advantage introduces an adverse selection problem because the lead arranger must convince less-informed participants that the loan is of sufficient quality to secure their capital commitments. Prior work shows that lead arrangers use contractual mechanisms such as covenants and collateral to alleviate this problem and reduce the information asymmetry premium imposed by participants (Gorton and Pennacchi, 1995; Sufi, 2007). Ivashina (2009) estimates that this premium accounts for roughly 4 percent of borrowers' total financing costs.

In addition, arrangers often retain a larger share of the loan as a credible signal of borrower quality. Consistent with signaling theory, lead banks increase their retained share when information problems are more severe (Sufi, 2007). Ball et al. (2008) further show that arrangers retain larger portions when accounting information has lower debt-contracting value, limiting participants' ability to assess borrower risk independently. Yet arrangers do not always act as neutral information intermediaries. Down et al. (2024) find that lead banks retain smaller loan shares when they possess private regulatory information (e.g., FDA inspections), indicating selective disclosure to participants. Consequently, participant lenders balance reliance on arranger signals with their own risk assessments, sometimes drawing on private information acquired through prior borrower relationships (Sufi, 2007).

While this literature provides extensive evidence on information asymmetry between arrangers and participants, less attention has been paid to the second friction of coordination challenges that arise among syndicate lenders themselves. Lenders may differ systematically in how they interpret identical information or apply internal credit models. More generally, assessment dispersion can stem from differences in internal modeling frameworks, portfolio constraints, prior lending relationships, or industry specialization (Berg and Koziol, 2017).[3] Regulatory guidance similarly

[3]For example, Agarwal and Hauswald (2010) show that geographic proximity affects private information collection; Stomper (2006) demonstrate that industry expertise allows banks to extract rents consistent with information advantages. Relationship lending also accumulates borrower-specific soft information (Bharath et al., 2007, 2011; Petersen and Rajan, 1994; Schenone, 2010; Liberti and Petersen, 2019). Banks may also differ in how they collect information produced externally about the borrower, such as stock prices, the media, or financial analysts (De George et al., 2025; Bushman et al., 2017; Binz et al., 2025; Call et al., 2022). Finally, bank health can influence monitoring intensity and contract design (Chodorow-Reich and Falato, 2022).

notes wide differences in banks' model-risk-management practices, reinforcing the expectation that credit assessments will vary even across sophisticated institutions.[4]

Theoretical work in corporate finance and contract theory highlights that coordination costs among multi-creditor capital structures are a fundamental constraint on efficient lending. When lenders must act collectively, each creditor internalizes only a fraction of the surplus from successful coordination but bears the full cost of negotiation delay or disagreement. Empirically, coordination frictions have been shown to increase with the number and diversity of creditors (Berlin et al., 2020; Caskey et al., 2026), consistent with the idea that lender heterogeneity complicates joint action.

At origination, theory argues that when lenders hold heterogeneous signals or priors about borrower quality, reaching efficient collective decisions becomes costly because each creditor has different continuation values and bargaining incentives (e.g., Gertner and Scharfstein, 1991; Bolton and Scharfstein, 1996). Greater heterogeneity can delay deal completion, increase loan spreads to compensate for negotiation risk, and constrain the inclusion of contingent features such as performance-based pricing.

After origination, coordination frictions can impede a syndicate's ability to respond efficiently to new borrower information. This collective-action problem can generate inefficient holdout behavior and under-investment in monitoring (e.g., Gertner and Scharfstein, 1991; Berglöf and Von Thadden, 1994; Bolton and Scharfstein, 1996). In addition, because amendments and covenant waivers often require near-unanimous consent, heterogeneous preferences increase renegotiation costs and slow contractual adjustments (Aghion and Bolton, 1992; Caskey et al., 2026). Empirical work confirms that amendments are frequent and economically important (Roberts and Sufi, 2009; Roberts, 2015; Nikolaev, 2018; Dou, 2020; Chen et al., 2025), yet we know relatively little about how disagreement within syndicates affects this process. Over time, these dynamics can lead to inefficient credit

[4] `https://www.occ.treas.gov/publications-and-resources/publications/comptrollers-handbook/files/model-risk-management/pub-ch-model-risk.pdf`

adjustments and value losses for both borrowers and lenders.[5]

Taken together, the literature suggests that divergent assessments of borrower risk can influence both the *ex-ante* design of loan terms and the *ex-post* flexibility to renegotiate and amend those terms. Our paper provides direct evidence on these coordination frictions by using supervisory data on banks' internal credit-risk assessments. In contrast to prior studies that infer heterogeneity from loan structure or pricing outcomes, we observe each bank's internal probability-of-default (PD) estimate for the same borrower and loan at the same time. These data allow us to quantify assessment dispersion, which we refer to as *bank disagreement*, and to examine how it shapes loan pricing, contract design, and renegotiation outcomes.

3. Data and Syndicate Disagreement Measurement

3.1. Stress Test Reporting and FR Y-14Q

Following the passage of the U.S. Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (Dodd-Frank Act), systemically important financial institutions in the U.S. became subject to annual supervisory stress tests. As part of the stress testing exercise, firms have been required to submit quarterly loan-level holdings data to the Federal Reserve in Form FR Y-14Q filings since 2012.[6]

We focus our analyses on Schedule H.1, which contains detailed information on banks' commercial and industrial (C&I) loans with a committed balance greater than or equal to $1 million (Caglio et al., 2022). In Schedule H.1, banks are also required to report certain fundamental characteristics of the borrower (as of the most recent trailing twelve months) as well as loan terms, loan performance, and their estimates of the borrower's credit risk. The vast majority of corporate

[5] Lenders recognize and react to this. For example, Berlin et al. (2020) identify that syndicated loan arrangements with bank facilities (e.g., revolving credit facilities and non-bank facilities, such as institutional term loans) concentrate control rights in the bank facility to reduce coordination frictions arising from disagreement among non-bank lenders.

[6] Financial institutions with total consolidated assets above $50 billion were subject to supervisory stress from 2011 until 2019. In 2019, the reporting threshold was raised to $100 billion.

lending in the U.S. (about 70%) is covered by these reporting requirements (Bidder et al., 2021; Howes and Weitzner, 2026), including syndicated lending facilities. Banks are required to report syndicated loan exposures as soon as they have signed a commitment letter to the borrower, even if the borrower has not countersigned. Banks are also required to report loan exposures that have been disposed of within the quarter of the current reporting period. Thus, we can capture syndicated loan data from banks, regardless of whether they intend to keep or sell their loan shares.

As part of the loan-level disclosures, banks must report a probability of default (PD) estimate for each borrower. This PD represents the likelihood that a borrower will default on their loan obligations *within one year*. The PD is a critical metric in assessing credit risk and reflects the bank's judgment of the borrower's financial health and ability to meet debt payments. Relatively higher PD estimates imply that the bank has assessed the borrower as being less creditworthy, indicating a greater risk of default. Conversely, lower PD estimates suggest that the bank views the borrower as relatively stable and financially sound, with a lower risk of default. These PD estimates serve as a key input in determining the loan's terms, such as the interest rate, collateral requirements, and covenants, with higher PDs typically leading to more stringent loan terms to compensate for the increased risk.

3.2. Sample

Our main sample is constructed by matching syndicated loan data from the FR Y-14Q, Schedule H.1 regulatory filings with loan information from LPC Dealscan over the period 2014:Q4 to 2025:Q2.[7] The FR Y-14Q filings provide detailed quarterly loan-level data reported by large bank holding companies and intermediate holding companies, while Dealscan contains syndicated loan contract data. By combining these datasets, we can analyze lender disagreement and its association with syndicated loan outcomes.

To match lenders across the two datasets, we conduct a hand-match of 35 FR Y-14Q parent

[7]We conduct the matching process with data starting in 2012:Q1, but restrict the sample to observations after 2014:Q4 later due to PDs being largely unpopulated prior to then.

banks to Dealscan lenders using bank names. Borrowers are matched using a name-cleaning process that standardizes borrower names by removing ancillary words such as "Corporation," "Inc.," and "Products." After standardizing the names, we conduct a fuzzy name match on borrower names using multiple string distance algorithms, including exact name matching, Jaro-Winkler string similarity, and Weighted Jaccard similarity.

After joining FR Y-14Q and Dealscan loans based on the matched lenders and borrowers, we apply three filters to ensure consistency between the datasets and confidence in the loan-level match of the sample. First, we impose that the reported facility types (e.g., credit lines, term loan A) across the two datasets must match exactly. Then, we retain matches where the origination date in FR Y-14Q is within 5 days of the tranche active date field in Dealscan. If the origination dates do not exactly align, we retain matches where the participation share, calculated as the committed amount in FR Y-14Q divided by the tranche amount in Dealscan, is within half a percentage point of the participation interest field reported in FR Y-14Q. Lastly, we remove matches where the borrower's four-digit industry code (NAIC or SIC) and three-digit ZIP code reported in FR Y-14Q and Dealscan never match during the lifetime of the loan.

We retain the data under two structures: (1) a sample of PD estimates at origination and (2) a time series of PD estimates from origination through the maturity of the syndicated loan. This allows us to examine the contractual consequences of ex ante and ex post disagreement, including a detailed examination of lender disagreement, loan pricing, and renegotiation outcomes. Table 1 Panel A shows our sample construction and attrition.

3.3. Syndicate Disagreement Measures

To capture disagreement across banks, we employ both (1) the bank's own reported PDs based on its internal credit risk rating models and (2) a bank's expected PDs based on an estimated first stage model. Using both measures allows us to proxy for different dimensions of how banks differ in assessments: *general* disagreement and *modeling* disagreement.

Two features of banks' reported PDs make them ideal for capturing *general* disagreement among syndicate banks. First, the Basel Committee framework requires that each bank within the syndicate independently reports its PD estimate based on its internal credit risk models to their regulators.[8] Such models incorporate current and historical quantitative data, forward-looking projections, and "soft" information gathered by loan officers about the borrower or similar borrowers. They also take into account factors such as industry conditions and macroeconomic trends. The excerpt below from the Basel III framework (CRE36:33) discusses a bank's use of relevant information in credit risk assessment:

"Credit scoring models and other mechanical rating procedures generally use only a subset of available information. Although mechanical rating procedures may sometimes avoid some of the idiosyncratic errors made by rating systems in which human judgment plays a large role, mechanical use of limited information also is a source of rating errors. Credit scoring models and other mechanical procedures are permissible as the primary or partial basis of rating assignments, and may play a role in the estimation of loss characteristics. Sufficient human judgment and human oversight are necessary to ensure that all relevant and material information, including that which is outside the scope of the model, is also taken into consideration, and that the model is used appropriately."

The second feature that makes bank-reported PDs ideal for capturing general disagreement within a bank syndicate is that banks have significant incentives to ensure accurate PD estimates. Systematic errors or bias in PD estimates can result in disciplinary actions by the Federal Reserve, including forced recognition of additional loss reserves and restrictions on dividend payments, among other consequences (Howes and Weitzner, 2026). The threat of regulatory enforcement,

[8] This requirement implies that banks use the Advanced Internal Ratings-Based approach to estimate PDs. Under this approach, banks can use their internal models to estimate PDs, subject to regulatory approval. This approach is generally employed by the large and internationally active banks. There is a second, Standardized or Non-Advanced approach, which does not allow banks to use internal models. Instead, they must rely on predefined risk weights for borrower categories provided by the regulator and based on external credit ratings when estimating PDs. The majority of banks in our sample use the Advanced approach. Controlling for the share of banks using the Advanced approach does not affect our findings.

along with the regular quarterly reporting of these estimates, ensures that they accurately and timely reflect banks' views on borrowers' credit risk profiles.[9]

Thus, we posit that cross-bank variation in bank-reported PD estimates for a given borrower captures heterogeneous inputs along three fronts: (i) each bank's prior interactions with and proprietary information about the borrower; (ii) discretionary modeling choices embedded in internal credit systems; and (iii) institution-specific constraints, including portfolio-diversification targets, sectoral risk appetites, and regulatory capital requirements.

We also estimate banks' *expected* PDs ($\widehat{PD}$) to capture disagreement that arises from banks' discretionary modeling choices. While we cannot directly replicate banks' internal credit risk models, we can quantify how borrower characteristics correlate with banks' PD assessments across their lending portfolios over time. After estimating this relationship between banks' PDs and borrower and loan characteristics within each industry and rolling period, we can apply these estimates to infer a PD estimate that we would expect a bank to assign to a borrower based on the bank's own implied modeling approach.

3.4. Expected PD Modeling

More specifically, to generate a bank's expected PD ($\widehat{PD}$) for a given borrower, we estimate a series of first stage models across each bank's within-industry lending portfolio (in FR Y-14Q, Schedule H.1) and year-quarter to extract how it may weight important observable hard information. For each firm i from industry k borrowing from bank b in quarter t, we estimate a fractional logit model on the sample of observations in bank b's portfolio of loans in industry k between quarters $t-12$ and $t-1$ (i.e., in the three years of available data in the bank's industry portfolio prior to

[9]Nonetheless, there are prior studies that show some evidence of strategic bias in PD estimates (e.g., Firestone and Rezende, 2016; Plosser and Santos, 2018). For example, Owens and Sokolowski (2025) find evidence of a discontinuity in bank PD ratings relative to external ratings around 0, with banks being relatively more optimistic than external rating agencies. Importantly, our study examines the range of PD estimates while controlling for the level of external ratings, allowing us to wash out any on-average bias affecting banks' ratings. Moreover, any differences in banks' preferences that bias their ratings would reflect their heterogeneity and could still lead to contracting frictions, to the extent they motivate the biased bank to pursue loan outcomes that fit its circumstances (Caskey et al., 2026).

quarter t). Specifically, we estimate the following model:

$$E(PD_{ibkt}|X_{ibkt}) = \frac{\exp X_{ibkt}\beta}{1+\exp X_{ibkt}\beta} \tag{1}$$

Here, X_{ibkt} denotes our chosen set of loan characteristics and borrower fundamentals used to predict PDs. This set always includes *ln(Committed Exposure)*, *Maturity*, *ROA*, *Size*, *Leverage*, *Private*, and *Industry Volatility*. We choose a fractional logit to better model and predict the distribution of PDs, which are bound between 0 and 1 and are often extremely right-skewed.[10] From this set of first stage models, we can then both (1) extract the imputed model weights, β, for each covariate for each bank b, industry k, and quarter t and (2) generate a predicted PD, $\widehat{PD}_{ibkt}$, for our sample of loans where we observe all variables of hard information used in the first stage model. Table 2 and Figure 1 show the first stage coverage by industry.

Our first-stage models explain, on average, 54% of the variation in banks' PD assessments across industries, with pseudo R^2 ranging from 0.43 to 0.61. Table 2 also shows substantial heterogeneity in how banks translate observable borrower fundamentals into their credit risk assessments. This heterogeneity arises not only across industries but also across banks within the same industry. For example, within the Transportation industry, the estimated weight placed on borrower profitability varies by approximately a factor of four across banks, based on an average of more than 3,000 borrower-PD observations per estimate. These differences also appear highly persistent over time. The serial correlation in banks' estimated weights ranges from 0.85 to 0.96, suggesting that banks apply stable and institution-specific approaches when interpreting common borrower signals. This persistence is consistent with our interpretation that the estimated coefficients capture, at least in part, differences in banks' underlying credit risk models.

[10]The advantage of using a fractional logit in this specification is that (1) the model makes no assumptions about the underlying distribution and (2) the predicted values are always bound between 0 and 1.

3.5. Descriptive Statistics

Table 1 Panel B indicates substantial cross-lender dispersion in internal PDs even at origination: the main measure (*Max–Min PD*) has a median of about 0.51% and an interquartile range that implies meaningful heterogeneity across participating banks. For perspective, average default rates for syndicated loans are between 1% and 5% depending on the credit cycle (PitchBook, 2025). Our second measure, which compares estimated PDs and proxies for model-based disagreement (*Max–Min* $\widehat{PD}$), has a median of 1.47% and is larger in magnitude than our main measure. Facilities are economically large and multi-lender: the median number of reporting banks in FR Y-14Q is 3, while Dealscan reports a median of 8 lenders. The median all-in-drawn spread is 175 bps, and the median maturity is 4.8 years. Borrowers are profitable on average (median ROA $\approx$ 7%) and moderately levered (median leverage $\approx$ 0.31). Approximately 47% of the borrowers in the sample are private firms. Overall, the table confirms that disagreement is common at issuance and that it arises in sizable, multi-bank facilities where coordination costs are most likely to matter.

4. Understanding Model-Based versus Actual PD Estimates

To better understand disagreement across banks, we investigate the determinants of banks' reported PDs. Specifically, we examine the association between the bank-specific model-based PD estimate and the bank's reported PD estimate, as well as the factors that drive this association. Before we perform this analysis, we highlight that the bank-industry portfolios we use to generate the model weights that are used to compute the estimated PDs include many bilateral bank loans, which come from smaller firms than those that borrow in the syndicated loan market. As a result, we find that our predicted PDs are larger than the actual PDs. However, we are most interested in the association between the estimated and actual PDs rather than the actual predicted PD values.

The unconditional correlation between banks' estimated and reported PDs in our sample of loans at origination is positive at around 0.35. This shows a reasonable association between the estimated PDs and actual PDs, while leaving some room for first-stage error and the effect of factors unrelated to hard information. Additionally, the adjusted R-squared from regressing actual PDs on expected PDs is approximately 12%. While this explanatory power may seem low, regressing actual PDs on only bank-year-quarter fixed effects yields an adjusted R-squared of 8%, suggesting our estimated PDs are more closely tied to their reported counterparts.

To explore how banks typically deviate from their expected PD estimates, we focus on several factors that prior work indicates have a meaningful impact on the extent to which banks accumulate information affecting risk assessments. First, Blickle et al. (2026) find that banks can concentrate lending to a small number of industries, a lending behavior that reflects industry-specific knowledge. This would suggest that specialized banks use more industry-specific information in their risk assessment, rather than relying on more general risk models. Second, several studies find evidence consistent with banks creating an informational advantage when they have repeated relationships with borrowers, because they provide better loan terms (e.g., Petersen and Rajan, 1994; Bharath et al., 2011). Banks collect and use soft information from continuous direct access to clients (Campbell et al., 2019; Liberti and Petersen, 2019). Repeated lending relationships could place greater weight on key observable fundamentals, as these banks may have fewer adverse selection concerns. Alternatively, these banks may use their private information to a greater degree, and thus their reported PDs would rely less on the information predicted by their credit models. Third, with regards to banks' capital position, Plosser and Santos (2018) find evidence consistent with bank PD estimates incorporating bias due to capital-related incentives. In particular, they find that low-capital banks' PD assessments have less explanatory power for loan interest rates than those of high-capital banks. Their findings would predict that low-capital banks systematically report lower PDs and weigh hard information less in their risk assessments. Fourth, Agarwal and Hauswald (2010) finds that close proximity to the borrower enables lenders to collect soft information. If lenders rely more on soft information in lending decisions, they may underweight hard, model-based information. This would suggest that proximity to the borrower would attenuate the association between model-based PD estimates and the banks' actual PD estimates.

As stated above, we test whether each of these characteristics is associated with the reported PDs and whether they influence the degree to which reported PDs align with model-based assessments ($\widehat{\text{PD}}$). Table 3 reports these results. Columns (1)–(5) show that banks with industry specialization and longer borrower relationships report lower PDs on average, consistent with these banks accumulating private soft information that leads them to view familiar borrowers as less risky. Importantly, these same banks also place greater weight on their model-based assessments, suggesting that relationship lending reduces information asymmetries and makes the hard information embedded in credit models more relevant.

Starting from column (2), we interact estimates of PDs with indicators of industry specialization (*Ind Specialist*), relationship length (*Rel Length*), capital constraints (*Headroom*), and distance between the bank's and its borrower's headquarters (*Distance*). Column (2) shows that industry specialization does not provide further incremental information over and above an average effect (the coefficient on the interaction term between PD estimate and the indicator for industry specialization is not statistically significant). Column (3) shows that banks with longer relationships with a borrower (measured in years) put a higher weight on model-based assessments (the coefficient on the interaction term is positive and statistically significant).

In column (4), we report the results on how regulatory capital constraints affect banks' reported PDs. We measure capital constraints using regulatory headroom — the distance between a bank's actual capital ratio and the regulatory minimum, where lower headroom indicates tighter capital constraints. We find two key results. First, capital-constrained banks do not report systematically lower PDs on average, indicating that capital pressures do not bias the overall level of reported credit risk. Second, and more surprisingly, it is the less capital-constrained banks (those with more headroom) that place lower weight on model-based assessments, as shown by the negative and statistically significant interaction coefficient. This pattern is inconsistent with an incentive-driven bias explanation. If regulatory capital pressure drove banks to strategically understate risk, we would expect constrained banks to place less weight on model-based assessments in order to report lower PDs and reduce capital requirements. Instead, we observe the opposite: constrained banks rely more heavily on model-based assessments.

Overall, the evidence in this section points to bank-specific information, rather than strategic bias, as the primary driver of deviations between reported and model-implied PDs. Banks with stronger informational advantages appear to incorporate soft information into their risk assessments in ways that systematically affect reported PDs. Moreover, the evidence on regulatory capital constraints is inconsistent with an incentive-driven explanation in which constrained banks strategically understate risk. Nevertheless, we cannot fully rule out the possibility that bias affects PD estimates, as documented in prior work (e.g., Plosser and Santos, 2018; Owens and Sokolowski, 2025).

5. Determinants of Lender Disagreement

We turn to our main analyses next and examine which loan, borrower, and syndicate characteristics are associated with variation in lenders' credit-risk assessments at the syndicate level. Understanding these determinants provides descriptive evidence on how within-syndicate disagreement arises. Specifically, we estimate the following regression model:

$$\begin{aligned} \mathit{Disagreement}_l = {} & \beta_1 \ln(\mathit{Total\ Exposure})_l + \beta_2 \mathit{Maturity}_l + \beta_3 \mathit{Private}_l + \beta_4 \mathit{N\ Lender}_l \\ & + \beta_5 \mathit{Industry\ Return\ Volatility}_l + \beta_6 \mathit{ROA}_l + \beta_7 \mathit{Size}_l \\ & + \beta_8 \mathit{Leverage}_l + \beta_9 \mathit{High\ Share}_l + \beta_{10} \mathit{Lead\ Above}_l + \gamma_t + \gamma_b + \varepsilon_l, \end{aligned} \tag{2}$$

where we measure lender disagreement for loan l at origination using *Max–Min PD* and *Max-Min* $\widehat{PD}$. *Max–Min PD* is defined as the range between the highest and lowest internal PD estimates reported by syndicate members for the same borrower and loan in a given quarter. *Max-Min* $\widehat{PD}$ computes the range using our estimate of expected PD ($\widehat{PD}$). We use the range rather than the standard deviation to capture lender disagreement for two main reasons. First, the range directly reflects the distance between the most optimistic and most pessimistic risk assessments within the syndicate. Because lead arrangers must reconcile the views of these extreme participants, the range provides a more economically relevant measure of the coordination challenge than the standard deviation, which gives equal weight to all observations. Second, the number of banks reporting PDs varies across loans, often with only two or three observations per syndicate. In such cases, standard deviations can be less informative and more sensitive to sample size, whereas the range remains well-defined and comparable across syndicates.[11]

We estimate Equation (2) using a set of loan, borrower, and syndicate characteristics, controlling for year–quarter of origination and borrower-rating fixed effects. Standard errors are clustered at the loan level. Table 4 reports the results. Column (1) shows the results for the model-based estimated PD (modeling disagreement), while columns (2) and (3) show the results for our measure of within syndicate general disagreement—which we refer to as "disagreement" throughout the text. Disagreement is significantly higher for larger loans (*ln(Total Exposure)*) and a greater number of participating lenders (*N Lender*). These patterns indicate that larger and more diffuse syndicates exhibit wider dispersion in banks' internal risk assessments, consistent with greater heterogeneity in modeling approaches and credit-risk views when more institutions participate in underwriting.

Borrower fundamentals are also related to disagreement. General disagreement is higher for firms that are smaller (smaller *Borrower Size*), less profitable (lower *ROA*), and more leveraged (higher *Leverage*), suggesting that weaker fundamentals make credit risk harder to assess consistently across lenders. In contrast, disagreement shows no reliable association with loan maturity (*Maturity*) or private borrowers (*Private*), implying that these characteristics do not materially influence the alignment of lenders' PD estimates once borrower fundamentals are held constant. Importantly, our disagreement measures show no statistical association with borrower industry volatility (*Industry Return Volatility*), suggesting that disagreement is not driven by elevated uncertainty about borrower

[11] Our results are robust to using other measures of disagreement, including the standard deviation of PDs (*SD(PD)*), scaling *Max–Min PD* by the average PD of the borrower's associated internal rating, (*Max–Min PD (Scaled)*), or excluding PD estimates of the lead arranger.

industry performance.

From the set of indicators of the lead arranger's position, including *High Share* and *Lead Above*, only *Lead Above* is statistically significantly associated with disagreement among syndicate members. *High Share* is an indicator equal to one if the lead arranger has the highest share of the loan and zero otherwise. This captures loans where the lead arranger may need to keep more of the loan to offset adverse selection risks for participant lenders. *Lead Above* is an indicator equal to one if the lead arranger's PD is higher than the median PD of the syndicate and zero otherwise. This captures a potential adverse selection risk in which the lead arranger has a private assessment of the loan that is worse than that of the rest of the syndicate.

In column (3), we also control for a proxy capturing disagreement arising from differences in bank credit risk models using the expected PD disagreement measure with the bank-specific fitted PDs (*Max-Min* $\widehat{PD}$). In this specification, we find that model disagreement is strongly and positively associated with bank disagreement, and that syndicates in which the lead arranger reports a more pessimistic PD than the other lenders exhibit higher levels of disagreement. This latter finding suggests that at least some participant banks can detect potential adverse selection incentives on the part of lead arrangers. At the same time, we do not find evidence that lead arrangers mitigate disagreement by retaining a larger share of the loan.

Overall, the evidence from columns (1)–(3) indicates that lender disagreement within the syndicate is primarily explained by loan size, borrower fundamentals, and syndicate composition. Larger facilities and larger syndicates are associated with greater dispersion in perceived borrower risk, whereas stronger borrower performance is associated with greater consensus among lenders. Banks' own credit risk models also explain some of the dispersion. These findings suggest that disagreement within syndicates reflects both differences in credit risk models and differences in private information. This motivates our examination of the consequences of disagreement for contracting outcomes.

6. Consequences of Lender Disagreement at Loan Origination

We next examine whether bank disagreement is associated with variation in debt contract terms, focusing on two dimensions of syndicated loan design: pricing and non-price provisions. These tests assess whether dispersion in assessments among syndicate members is related to the structure of costs and contingencies in credit agreements.

6.1. Loan Pricing

We first assess whether greater lender disagreement is associated with higher loan spreads, which reflect the costs of coordination and heterogeneity in risk perceptions. The dependent variable is the natural logarithm of the all-in-drawn loan spread, and the key independent variables are *Max–Min PD* and *Max-Min* $\widehat{PD}$, which measure the range of internal probability-of-default (PD) estimates across syndicate lenders and potential model-based disagreement across syndicate members for the same borrower. Descriptively, Figure 2 shows a monotonic increase in the natural logarithm of the spread for each decile increase in disagreement (*Max–Min PD*), providing initial evidence that disagreement is associated with loan pricing. In our multivariate model, we control for borrower and loan characteristics, and include year–quarter of origination and borrower-rating fixed effects, clustering standard errors at the loan level.[12]

Table 5 reports the baseline results relating lender disagreement to loan pricing. Columns (1)–(3) show a positive and statistically significant association between dispersion in lenders' model-based disagreement (column 1) and internal PD estimates disagreement (columns 2-3) and loan spreads. Economically, facilities in which syndicate members hold more divergent views about borrower credit risk are priced at higher spreads. This pattern is consistent with a coordination-based pricing mechanism: when credit risk assessments are heterogeneous, lead arrangers must set spreads high enough to attract participation from the most conservative lenders, while also

[12]Our findings are robust to excluding the lead arranger from the estimates of the *Max-Min (PD)*.

compensating syndicate members for the additional costs of reaching agreement and monitoring under disagreement. In this sense, spreads reflect not only expected credit risk, but also the friction associated with aligning lenders with differing risk assessments. Column (3) shows that model-based and estimate-based measures of disagreement are positively associated with higher loan spreads, with the estimate-based measure having a more economically significant impact. Taken together, these results provide evidence that credit risk assessment heterogeneity within lending syndicates increases the cost of credit in syndicated loan markets.

6.2. Other Contractual Terms

We next examine whether lender disagreement influences non-price contract features that govern borrower behavior and monitoring, including the number of financial covenants and the use of performance-based pricing provisions. Both features require syndicate-wide agreement on borrower thresholds and monitoring mechanisms, so assessment dispersion could make such coordination more difficult.

Table 6 presents the results. Columns (1), (2), and (3) show no significant relationship between lender disagreement and the number of financial covenants for both model-based (column 1) and actual (columns 2 and 3) disagreements. This suggests that when lenders diverge in their risk assessments, they do not systematically compensate by imposing additional restrictions. In contrast, columns (5)-(6) reveal a strong negative association between disagreement and the likelihood of including performance-based pricing provisions for the measure of actual disagreement, while the model-based disagreement does not seem to exhibit a significant relationship (as shown in column 4). When lenders disagree more about borrower risk, they appear reluctant to rely on pricing grids that require future consensus about performance triggers. Instead, arrangers adopt fixed-rate pricing to lock in compensation ex ante, reducing the potential for future disputes. This result complements the positive spread effect, indicating that disagreement not only raises borrowing costs but also leads contracts toward simpler terms.

Taken together, these findings show that lender disagreement has meaningful implications for how syndicated loans are priced and structured at origination. Greater dispersion in internal credit assessments leads to higher loan spreads and a lower likelihood of including contingent pricing mechanisms, consistent with the assessment heterogeneity increasing coordination costs among syndicate members. The evidence suggests that disagreement makes it more difficult for syndicate lenders to reach consensus on contingent contractual terms that may be harder to enforce ex post when lenders hold divergent views.

7. Disagreement and Ex Post Loan Outcomes

7.1. Bank Exits and Lender Disagreement

One implication of within-syndicate disagreement is that lenders with more pessimistic assessments of borrower creditworthiness may choose to withdraw rather than remain exposed to loans they perceive as underpriced relative to their internal models. To test this implication, we examine whether a lender's relative risk assessment predicts its likelihood of exiting the syndicate in the quarters following origination. Unlike prior analyses that focus on loan-level contract terms at issuance, this test is conducted at the bank–loan–quarter level, allowing us to trace how individual lender assessments translate into changes in syndicate composition.

We estimate a series of linear probability models in which the dependent variable, *Exit*, equals one if a bank exits the loan syndicate within the next n quarters and zero otherwise, where $n \in \{1,2,3,4\}$. The key independent variable, *PD Diff*, measures the difference between a syndicate bank's internal probability-of-default (PD) estimate and the average PD across all lenders in the same loan and quarter. $\widehat{PD}$ *Diff* captures the difference between a syndicate bank's PD and the average PD estimate (model-based disagreement). Positive (negative) values indicate that the lender is more pessimistic (optimistic) than the syndicate mean. A positive coefficient on *PD Diff*, therefore, implies that banks with relatively more pessimistic assessments are more likely to exit in subsequent quarters. We estimate the following equation:

$$Exit_{btl} = \beta_1 PD\ Diff_{btl} + \beta_2 \widehat{PD}\ Diff_{btl} + X_{lt}\Gamma + \gamma_t + \delta_b + \omega_r + \varepsilon_{btl}, \tag{3}$$

where $Exit_{btl}$ is an indicator for whether bank b in quarter t exits the syndicate for loan l within n quarters. The vector X_{lt} represents borrower and loan characteristics including *ln(Total Exposure)*, *Maturity*, *Private*, *N Lender*, *Industry Return Volatility*, *ROA*, *Size*, *Leverage*, *High Share*, and *Lead Above*. The specification includes year–quarter fixed effects (γ_t) to absorb macroeconomic shocks, borrower rating fixed effects to capture credit risk (ω_r), and bank fixed effects (δ_b) to capture time-invariant differences in each bank's exit propensity. Standard errors are clustered at the loan level.

Table 7A presents the results. Across all four exit horizons, the coefficients on *PD Diff* and on $\widehat{PD}$ *Diff* are positive and statistically significant at the 1% level, indicating that banks with more pessimistic internal credit risk assessments are consistently more likely to exit the syndicate within one to four quarters. Intuitively, when a lender views the borrower as riskier than its syndicate peers, continued participation becomes less attractive: the lender faces higher perceived downside risk while being constrained by contract terms and collective decision-making. Exiting the syndicate allows pessimistic banks to reduce exposure and avoid future coordination frictions, particularly in settings where renegotiation or active monitoring may be required. These results are consistent with assessment heterogeneity driving endogenous sorting within syndicates, as lenders with divergent risk assessments adjust their participation over time.

We also estimate the likelihood of bank exit using a Cox proportional hazards model with time-varying covariates to determine whether *PD Diff* influences the instantaneous risk of bank exit. In particular, we estimate the following model:

$$h(t) = h_0(t) \cdot \exp(\beta_1 PD\ Diff_{btl} + \beta_2 \widehat{PD}\ Diff_{btl} + X_{lt}\Gamma), \tag{4}$$

This model assumes the hazard rate of bank exit at quarter t is the product of the baseline hazard rate, $h_0(t)$, and the function of risk factors X_{lt}, which include time-varying loan and borrower characteristics following prior analyses. Note that β_1 represents the log hazard ratio for *PD Diff*. Given the results from Table 7A, we would expect β_1 to be greater one, suggesting that banks with higher relative pessimism about the borrower have a higher hazard of exiting the syndicate.

Table 7B presents the results of the hazard model. Across bank and borrower stratifications, the logged hazard ratio on *PD Diff* and on $\widehat{PD}$ *Diff* is above one and statistically significant, reinforcing the claim that banks with more pessimistic internal assessments are consistently more likely to leave.

These results support the view that both model and actual disagreement impose ongoing coordination frictions in syndicated lending. When lenders interpret borrower risk differently, pessimistic banks are more likely to withdraw, leaving a more homogeneous, optimistic group of lenders behind. Over time, this sorting process reduces within-syndicate heterogeneity and likely facilitates smoother coordination in subsequent renegotiations.

7.2. Fundamental Shocks, Lender Disagreement, and Amendments

Next, we test whether within-syndicate disagreement constrains the syndicate's ability to amend loan contracts following shifts in borrower fundamentals. In particular, borrowers' changes in operating performance provide natural settings in which the incentive to renegotiate terms is heightened, either because improving conditions lead borrowers to request more favorable terms or deteriorating conditions prompt lenders to tighten covenants or seek additional protections. We therefore treat these events as measures of fundamental shocks that increase the expected probability of contract renegotiation. Importantly, while loan terms and syndicate characteristics are likely endogenously related to disagreement at origination, the change in disagreement in response to borrower-specific profitability shocks reflects information that is likely unanticipated at the time of syndicate formation. This allows us to identify coordination frictions that arise from post-origination disagreement that could not have been fully contracted around ex ante.

We estimate the following linear probability model at the loan–quarter level:

$$
\begin{aligned}
Amendment_{lt+1} = &\beta_1 Disagreement_{lt} + \beta_2 Shock_{lt} + \\
&\beta_3 \left(Disagreement_{lt} \times Shock_{lt} \right) + X_{lt}\Gamma + \gamma_t + \gamma_b + \varepsilon_{lt},
\end{aligned} \tag{5}
$$

where the dependent variable, $Amendment_{t+1}$, equals one if the loan l in quarter t is renegotiated in the following quarter $(t+1)$ and zero otherwise. *Disagreement* is measured using either *Max–Min PD*, the range between the highest and lowest internal PDs across syndicate members or *Max-Min* $\widehat{PD}$, the range between internal probability estimates. *Shock* captures exogenous shifts in borrower fundamentals and is measured in two ways:(i) the year-over-year change in industry-level ROA (ΔROA) and (ii) the absolute value of that change ($|\Delta ROA|$), which captures the magnitude of both positive and negative performance shocks. X_{lt} includes loan and borrower characteristics following prior analyses. All specifications include year–quarter fixed effects (γ_t) and borrower-rating fixed effects (γ_b), and standard errors are clustered at the loan level.

Table 8 presents the results. Across all specifications, the coefficient on *Disagreement* × *Shock* is negative, albeit not always statistically significant. In particular, for the measure of model-based disagreement, the coefficient on the absolute value of the shock is statistically significant, while for the syndicate-based disagreement, the coefficient on the change in ROA is statistically significant. These results overall indicate that when the borrower's fundamentals change, whether improving or deteriorating, loan syndicates marked by greater internal disagreement are less able to act in the subsequent quarter. Intuitively, this finding captures the idea that heterogeneity among lenders creates collective-action frictions. In syndicates where member banks hold different risk assessments (high *Max–Min PD*), each creditor may have its own view of how urgent or necessary a contract amendment is. When fundamentals deteriorate, some lenders may push for tighter covenants or collateral, while others, believing the borrower remains in good financial condition, prefer to maintain existing terms to avoid jeopardizing the relationship. Conversely, when fundamentals improve, more optimistic lenders may favor relaxing covenants or repricing downward, while more conservative members resist concessions. The greater the dispersion in assessments, the harder it becomes to reach the unanimous consent typically required for amendments in syndicated loans.

Taken altogether, these results demonstrate that disagreement not only increases ex-ante contracting frictions but also generates persistent ex-post coordination costs.

7.3. Loan Amendments and the Resolution of Bank Disagreements

We next analyze how disagreement evolves following amendments to assess whether renegotiations help resolve coordination frictions within lending syndicates. Theoretical models suggest that amendments serve as coordination mechanisms through which lenders share information, update assessments, and realign their credit assessments (Aghion and Bolton, 1992). If so, disagreement should decline in the quarters following a successful amendment, as syndicate members converge on a common view of borrower creditworthiness.

Descriptively, Figures 3A and 3B reveal a clear and systematic pattern in lender disagreement around loan amendments. In the periods leading up to amendments, both average default risk and dispersion in lenders' PD estimates rise sharply, consistent with deteriorating borrower fundamentals that heighten uncertainty and exacerbate coordination frictions among syndicate members. As firm conditions worsen, lenders not only reassess risk upward but also diverge more in their views about the severity and implications of that risk. Following an amendment, however, disagreement declines even though average default risk remains elevated. This pattern suggests that the amendment process itself (through information sharing, negotiation, and the formal resolution of contractual terms) helps align lenders' assessments, reducing heterogeneity in risk assessments without immediately improving the borrower's underlying credit quality.

In additional tests, we estimate the following regression model at the loan–quarter level:

$$Disagreement_{lt} = \beta \, Quarters\ After\ Amend_{lt} + X_{lt}\Gamma + \gamma_t + \gamma_b + \varepsilon_{lt}, \tag{6}$$

where the dependent variable, *Disagreement*, is measured using either *Max–Min PD*, defined as the range between the highest and lowest internal PD estimates across syndicate members for the same borrower and loan. The key independent variable, *Quarters After Amend*, captures the number of quarters since the amendment, taking zero during the quarter of the amendment. We restrict the sample to loan-quarter observations that occur exactly during an amendment or in the one to three quarters immediately following it, which effectively imposes a within-loan design. Due to this sample restriction, *Quarters After Amend* can take values equal to 0, 1, 2, or 3. We also control for the model-based disagreement (*Max-Min* $\widehat{PD}$). The vector X_{lt} includes the same loan and borrower controls used in prior analyses, and all specifications include year–quarter and borrower-rating fixed effects with standard errors clustered at the loan level.

Table 9 presents regression results that complement the descriptive patterns shown in Figures 3A and 3B. Each column corresponds to a different post-amendment window, with the number of quarters in each sample indicated at the top of the table. In all three specifications, the coefficient on quarters after amendment is negative and statistically significant, which is generally strong evidence that lender disagreement systematically declines in the periods following a loan amendment. Economically, this result implies that, conditional on elevated credit risk, the amendment process itself helps reduce heterogeneity in lenders' risk assessments. Renegotiations require syndicate members to exchange information, update expectations, and agree on revised contractual terms, which appears to promote assessment convergence. The magnitude and persistence of the estimated decline suggest that amendments function as effective coordination mechanisms rather than merely reflecting short-lived adjustments or mechanical changes in syndicate composition.

It is unlikely that bank-wide modeling practices will change in response to an amendment from a single borrower. However, we find that even after controlling for model-based disagreement, actual disagreement is reduced after an amendment. This pattern suggests that the renegotiation process itself facilitates information sharing and consensus formation among syndicate lenders. Overall, these findings suggest that while initial disagreement can impede collective action, successful renegotiation can partially resolve these frictions by realigning lenders' assessments of borrower risk once coordination is achieved.

8. Robustness

8.1. Future Credit Risk

A natural alternative interpretation of our findings is that lender disagreement reflects differential foresight about future borrower deterioration rather than coordination frictions. In this view, banks assigning higher internal PDs may simply be more accurate in anticipating subsequent increases in credit risk, implying that disagreement captures genuine heterogeneity in borrower fundamentals rather than inefficiencies in aggregating information within the syndicate. To assess this possibility, we examine whether disagreement predicts (1) subsequent changes in the syndicate's average assessment of borrower credit risk and (2) realized loan default. By testing these implications, we evaluate whether disagreement primarily reflects the superior forecasting ability of some banks in the syndicate or instead operates through coordination frictions.

We first estimate the following regression model at the loan origination level:

$$\Delta Avg\,PD_l = \beta\,Disagreement_l + X_l\Gamma + \gamma_t + \varepsilon_l, \tag{7}$$

where the dependent variable, Δ*Avg PD*, is the change in the syndicate's average internal PD over the next $k \in \{1,2,3,4\}$ years from origination for loan l. The variable *Disagreement* is measured using *Max–Min PD* and (*Max-Min* $\widehat{PD}$) at origination. The control vector X_i includes borrower and loan characteristics consistent with prior specifications, and all models include year–quarter of origination fixed effects with standard errors clustered at the loan level.

Table 10 reports the results. The coefficient on actual *Disagreement* is negative and statistically significant for the one-, two-, and three-year windows, indicating that higher disagreement at origination does not predict subsequent deterioration in borrower credit quality. If anything, loans characterized by greater initial disagreement experience smaller increases (or larger declines) in the syndicate's average PD over subsequent years. This pattern runs counter to an informed-pessimism interpretation, under which disagreement would be expected to precede worsening fundamentals. Instead, the results suggest that disagreement reflects differences in assessments rather than superior forecasting ability, and that lenders with more conservative assessments are not systematically more accurate in predicting future credit risk. Our proxy for model-based disagreement shows negative coefficients across all horizons, but statistically significant differences only for one- and three-year changes in estimates of average PDs following an amendment. Taken together, these findings support our interpretation of disagreement as a coordination friction rather than a proxy for unobserved borrower risk.

While the preceding analysis shows that disagreement does not forecast subsequent increases in lenders' average assessments of borrower credit risk, it remains possible that disagreement predicts adverse realized outcomes that are not fully captured by banks' subsequent PD revisions. To further examine this possibility, we test whether disagreement at origination is associated with future realized loan defaults by estimating the following regression model at the loan origination level:

$$\mathbb{1}\{Default_l\} = \beta\, Disagreement_l + X_l\Gamma + \gamma_t + \varepsilon_l, \tag{8}$$

where the dependent variable, $\mathbb{1}\{Default_l\}$, is an indicator for whether the borrower defaults within the lifetime of the loan or within $k \in \{1,2,4\}$ years from origination for loan l. The variable *Disagreement* is again measured using *Max–Min PD* and (*Max-Min* $\widehat{PD}$) at origination. The vector X_l includes borrower and loan characteristics consistent with prior specifications, and all models include year–quarter of origination fixed effects with standard errors clustered at the loan level.

Table 11 reports the results. Across all horizons, the coefficient on *Disagreement* is statistically insignificant for both actual and model-based measures of disagreement. Overall, these estimates indicate that higher disagreement at origination does not predict a greater likelihood of realized loan default. If anything, the point estimates suggest the opposite. Combined evidence in Tables 10 and 11 highlights that these findings are difficult to reconcile with an informed-pessimism interpretation in which disagreement reflects superior foresight about future borrower credit risk deterioration. Instead, taken together, the results support our interpretation of disagreement as reflecting assessment heterogeneity and coordination frictions among lenders rather than unobserved differences in underlying borrower fundamentals.

8.2. Through-the-Cycle vs. Point-in-Time Rating Methodologies

A potential concern with our interpretation is that observed PD dispersion may reflect differences in banks' internal rating philosophies rather than heterogeneous interpretations of borrower creditworthiness. Specifically, banks vary in whether they adopt a through-the-cycle (TTC) or point-in-time (PIT) approach to credit risk assessment. TTC banks estimate PDs that remain relatively stable across macroeconomic cycles, smoothing through transitory shocks to capture long-run default probabilities. In contrast, PIT banks adjust their PDs more aggressively in response to current macroeconomic conditions and near-term information. These differences in rating philosophy are well documented in regulatory guidance and can generate persistent dispersion in PD estimates even when banks observe identical borrower information.

If our disagreement measure primarily captures TTC vs. PIT heterogeneity rather than coordination frictions, this would have important implications for our results. First, syndicates mixing TTC and PIT lenders would mechanically exhibit wider PD dispersion during stressed periods, when PIT banks' estimates rise sharply while TTC banks' estimates remain relatively flat. Because loan spreads, contract terms, and renegotiation activity also vary with macroeconomic conditions, the observed associations between disagreement and these outcomes could reflect cyclical patterns rather than coordination costs. Second, in response to fundamental shocks to borrowers' creditworthiness, PIT lenders may update their assessments more rapidly than TTC lenders, creating temporary dispersion precisely when amendments are most likely, even if coordination itself is unimpaired.

We address this concern through two complementary empirical approaches. First, we construct bank-specific measures of PD cyclical sensitivity using each bank's complete FR Y-14Q C&I portfolio. For each bank independently, we (1) estimate the responsiveness of borrower-level PDs to three macroeconomic indicators, including the Federal Funds rate, the VIX, and the unemployment rate, and (2) use borrower fixed effects to absorb time-invariant differences in credit quality. We measure sensitivity using the current quarter level, the lagged level, and the quarter-over-quarter change for each indicator, yielding nine bank-specific "beta" coefficients that capture each institution's degree of PIT methodology. Banks with higher positive betas exhibit greater PD cyclicality and thus operate closer to a PIT philosophy. We then aggregate these bank-level measures to the syndicate level, computing the average sensitivity, standard deviation, and range (max–min) across syndicate members. If TTC/PIT differences drive our results, controlling for syndicate-level variation in rating cyclicality should substantially attenuate our disagreement coefficients.

Across all specifications, including controls for the average, dispersion, and range of bank-level cyclical sensitivities, leaves our core findings unchanged. The coefficient on disagreement in the spread regression remains positive, statistically significant, and economically similar in magnitude. This pattern holds regardless of which macroeconomic indicator we use to measure PD sensitivity or whether we control for the level, lag, or change in that sensitivity. These results indicate that our disagreement measure captures variation in lenders' credit assessments beyond systematic differences in rating cyclicality.

Second, we test whether the effects of disagreement are concentrated in periods of macroeconomic stress, when TTC and PIT rating philosophies would diverge most sharply. We interact our disagreement measure with indicators for high-stress quarters, defined as periods in the top 10% or top 25% of changes in the Federal Funds rate, VIX, or unemployment rate. If TTC/PIT heterogeneity drives our pricing results, the disagreement premium should be significantly larger during stressed periods when PIT banks' PDs spike relative to TTC banks. However, we find that interactions are uniformly small and statistically insignificant. The main effect of disagreement on loan spreads is stable across both calm and stressed macroeconomic environments, further supporting our interpretation that dispersion reflects persistent differences in how banks assess borrower-specific risk rather than mechanical differences in rating cyclicality.

Taken together, these tests provide strong evidence that our disagreement measure captures genuine heterogeneity in lenders' credit-risk assessments rather than differences in rating philosophy. While banks certainly vary in their sensitivity to macroeconomic conditions, this variation does not explain the pricing premium, contractual patterns, or renegotiation frictions we document. Instead, our results reflect coordination costs that arise when syndicate members interpret the same borrower information differently, consistent with our core interpretation that assessment dispersion creates inefficiencies in debt contracting.

9. Conclusion

This study investigates how disagreement among lenders shapes the structure and dynamics of syndicated lending. Drawing on confidential supervisory data from the Federal Reserve's stress testing program, we construct direct measures of assessment dispersion based on variation in banks' internal probability-of-default (PD) estimates for the same borrower. We show that disagreement arises systematically with observable loan and borrower characteristics and has meaningful consequences for both contract design and syndicate behavior. Loans characterized by greater lender disagreement carry higher spreads at origination, exhibit higher rates of lender withdrawal, and are less likely to be renegotiated when borrower conditions change. Moreover, disagreement declines after renegotiation, suggesting that amendments serve as coordination mechanisms that enable lenders to reconcile differing risk assessments.

Several caveats should be considered when interpreting our findings. First, our analysis focuses on large bank holding companies subject to the Federal Reserve's stress testing requirements. These institutions dominate the syndicated loan market, and thus, our evidence may not generalize to smaller or non-bank lenders, whose internal risk-assessment practices and coordination mechanisms may differ. Second, although the FR Y-14Q data provide an unusually rich view of banks' internal credit assessments, we cannot fully disentangle whether disagreement arises from differences in the ability to process information, private information collection, or institutional preferences. Our findings should therefore be interpreted as reflecting the overall effect of heterogeneity in lenders' assessments rather than any single underlying channel. Third, while our empirical design holds the borrower, loan, and macroeconomic environment constant, we cannot entirely rule out all alternative explanations related to unobservable uncertainty or risk factors. Nonetheless, by considering our results across multiple settings, including quasi-exogenous fundamental shocks and post-amendment assessment alignment, we believe our evidence as a whole is most consistent with coordination costs arising from lender disagreement imposing frictions in debt contracting during and after loan origination.

Subject to these caveats, our results contribute to a growing literature on information frictions in credit markets by providing the first direct evidence on the consequences of within-syndicate credit risk assessment heterogeneity. Unlike prior studies that infer informational asymmetries from syndicate structure or pricing patterns, we observe lenders' internal assessments of borrower credit risk and isolate the effects of disagreement. In doing so, we show that disagreement itself represents an independent and meaningful source of coordination costs in syndicated lending.

Future research could extend these findings along several dimensions. A first avenue is to examine how persistent within-syndicate disagreement may affect borrowers' activities. For example, do firms whose lenders hold more dispersed risk assessments exhibit greater investment conservatism, higher precautionary cash holdings, or delayed adjustment to new information? Such analysis would clarify whether coordination frictions in credit markets translate into under-investment or inefficient capital allocation at the firm level. A second avenue of future work could explore how disagreement may shape information flows and borrower disclosure incentives, both toward lenders and to external capital markets, as borrowers may strategically adjust transparency when faced with divided creditors. A third direction is to investigate the contractual and institutional design features that may mitigate the costs of dispersed lender assessments. Finally, the dynamics we document raise broader implications for systemic and macro-financial stability. In periods of heightened macroeconomic or policy uncertainty when banks' models and forecasts diverge most, collective lender inaction could amplify credit rigidity and propagate distress across interconnected institutions. Future work integrating measures of credit risk assessment dispersion into models of credit supply cyclicality or financial network resilience (e.g., Acharya et al., 2013) could help assess the aggregate significance of these coordination frictions.

Declaration of Generative AI and AI-Assisted Technologies in the Manuscript Preparation Process

During the preparation of this work, the authors used Claude and ChatGPT to assist with copyediting and code development. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content.

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A. Variable definitions

Variable	Definition	Source
PD	A bank's reported internal one-year probability of default (PD) of the syndicated loan	FR Y-14Q, Schedule H.1
$\widehat{PD}$	A bank's predicted PD on the syndicated loan, which is based on (1) a first stage model of the bank's rating philosophy using its own within-industry loan portfolio and (2) applying the model on the the borrower's current fundamentals	FR Y-14Q, Schedule H.1 and authors calculations
Max-Min PD	The difference between the maximum and minimum reported PD on the syndicated loan across banks within the syndicate at a given point in time in percentage points	FR Y-14Q, Schedule H.1 and authors calculations
Max-Min $\widehat{\text{PD}}$	The difference between the maximum and minimum predicted $\widehat{\text{PD}}$ of a loan across banks within the syndicate at a given point in time in percentage points	FR Y-14Q, Schedule H.1 and authors calculations
PD Diff	The difference between a bank's reported PD estimate and the average reported PD estimate across banks in the syndicate in percentage points	FR Y-14Q, Schedule H.1 and authors calculations
$\widehat{PD}$ *Diff*	The difference between a bank's fitted PD estimate and the average fitted PD estimate across banks in the syndicate in percentage points	FR Y-14Q, Schedule H.1 and authors calculations
ln(Total Exposure)	Loan size measured as the natural logarithm of the loan amount	Dealscan
Maturity	Loan maturity (in years)	FR Y-14Q, Schedule H.1
Private	An indicator variable which is equal to one if a borrower is a private firm and zero otherwise	FR Y-14Q, Schedule H.1 and authors calculations
N Lender	The number of lenders for which there is a reported PD estimate for the syndicated loan	FR Y-14Q, Schedule H1 and authors calculations
ROA	The ratio of the borrower's net operating income to total assets	FR Y-14Q, Schedule H.1 and authors calculations
Size	The natural logarithm of the borrower's total assets	FR Y-14Q, Schedule H.1 and authors calculations
Leverage	The ratio of the borrower's total debt to total assets	FR Y-14Q, Schedule H.1 and authors calculations
Industry Return Volatility	The standard deviation of the firm's industry's daily stock returns across one quarter (lagged by one year), aggregated to the three-digit NAICS.	CRSP Daily Stock File and authors calculations
High Share	An indicator variable which takes the value of one if the lead arranger holds the highest exposure of a given loan in a syndicate and zero otherwise	FR Y-14Q, Schedule H.1 and authors calculations
Lead Above	An indicator variable which takes the value of one if the lead arranger's PD for a given loan is above the median PD of the syndicate and zero otherwise	FR Y-14Q, Schedule H.1 and authors calculations
Borrower Rating	The minimum (most pessimistic) rating across each syndicate banks' internal risk ratings of the borrower (where each banks' internal risk rating system has been mapped to a unified system)	FR Y-14Q, Schedule H.1
ln(Interest Rate Spread)	Interest rate spread for the syndicated loan	Dealscan
Number of Financial Covenants	The number of financial covenants for the syndicated loan	Dealscan
Performance Pricing	An indicator variable equal to one if the syndicated loan has a performance pricing provision and zero otherwise	Dealscan
Bank Exits Within n Qtrs	An indicator equal to one if the bank in quarter *t* leaves the loan syndicate in the next *n* quarters and zero otherwise	FR Y-14Q, Schedule H.1 and authors calculations
Δ*ROA*	The year-over-year change in ROA for the borrower's industry (3 digit NAICS)	FR Y-14Q, Schedule H.1 and authors calculations
$\|\Delta ROA\|$	The absolute year-over-year change in ROA for the borrower's industry (3 digit NAICS)	FR Y-14Q, Schedule H.1 and authors calculations
$Amendment_{t+1}$	An indicator equal to one if the loan is renegotiated in the next quarter and zero otherwise	FR Y-14Q, Schedule H.1 and authors calculations
Quarters After Amend	The number of quarters since an amendment, which equals 0 if the quarter observed is an amendment quarter	FR Y-14Q, Schedule H.1 and authors calculations
Δ *Avg PD in n Years*	The difference between the syndicate's average reported PD *n* years from origination and the syndicate's average reported PD at origination	FR Y-14Q, Schedule H.1 and authors calculations
Default within n years	An indicator equal to one if the lead arranger reports the loan as 90 days past due, reports nonzero charge-offs, or reports a non-accrual date once *n* years after origination and zero otherwise	FR Y-14Q, Schedule H.1 and authors calculations
$\mathbb{1}\{\textit{Ind Specialist}\}$	An indicator equal to one if the borrower's industry is the first or second top industry by the number of loans or volume of loans for a bank in a given quarter	FR Y-14Q, Schedule H.1 and authors calculations
Rel Length	The length of the relationship between the bank and borrower in years	FR Y-14Q, Schedule H.1 and authors calculations
Headroom	The banks' CET1 Ratio - capital Requirements for each quarter in percentage points	FR Y-9C and authors calculations
Distance	The distance between the bank's and the borrower's headquarters in kilometers	FR Y-14Q, Schedule H.1 and authors calculations

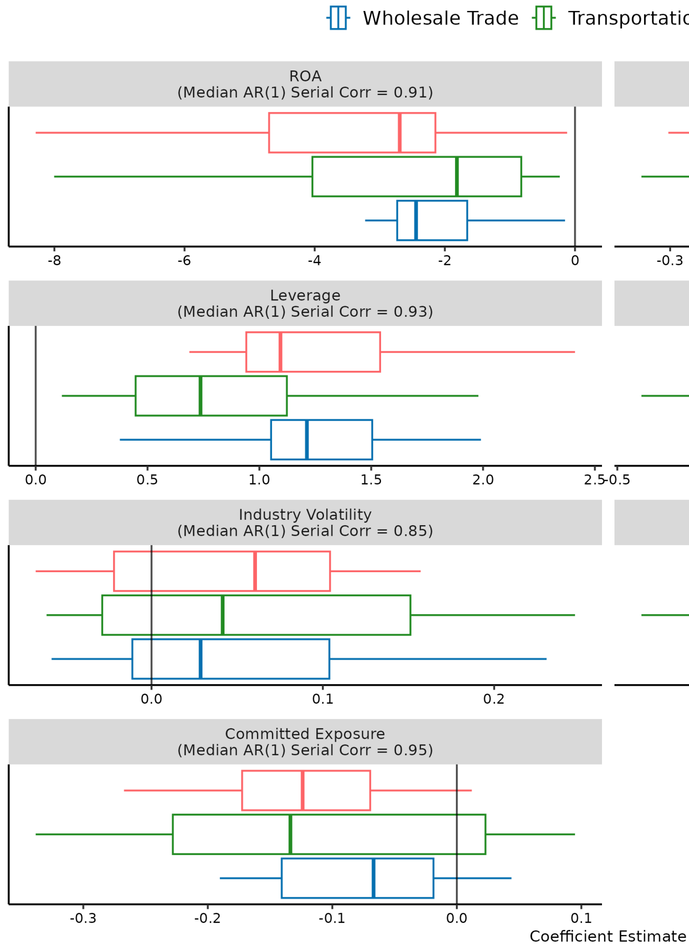


Figure 1: First Stage Coverage by Industry

This figure displays the boxplots of the imputed weights on our first stage covariates for three industries with good first stage coverage: Wholesale Trade, Transportation, and Manufacturing. The box plots display the distribution of imputed weights by bank. We remove the weights of banks in the bottom 10th and top 90th percentiles for each covariate. The median AR(1) serial correlation in the weights for these industries for each covariate is displayed in the grey ribbon. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.

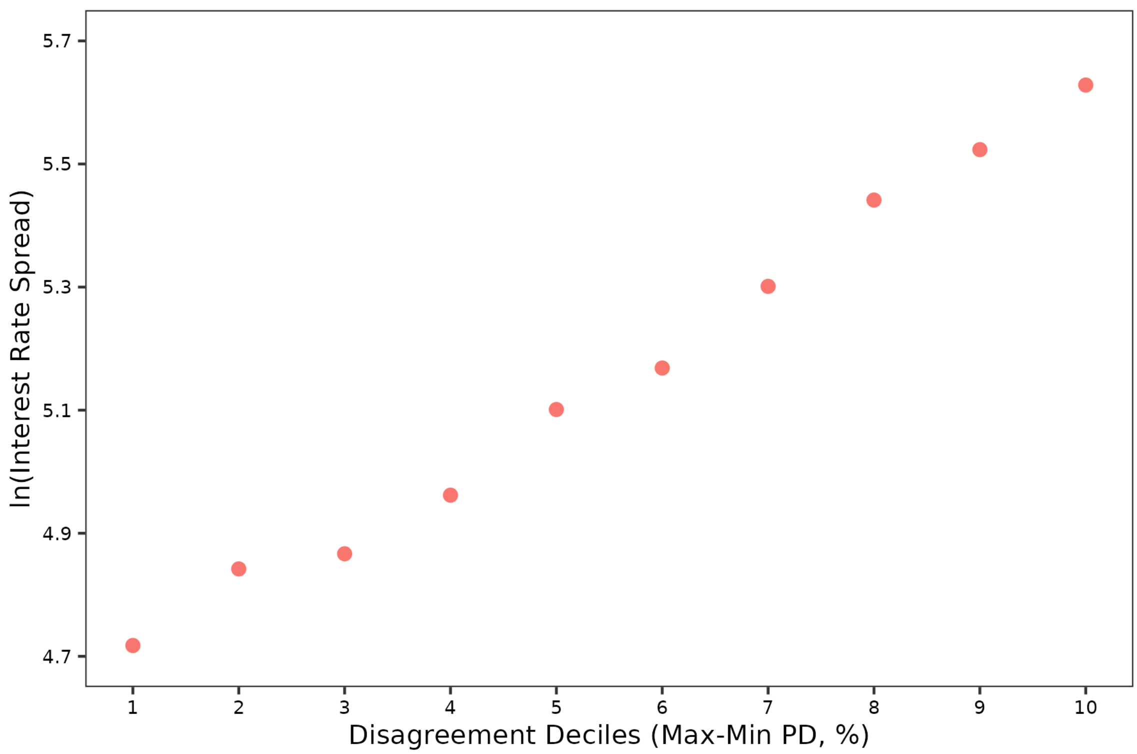
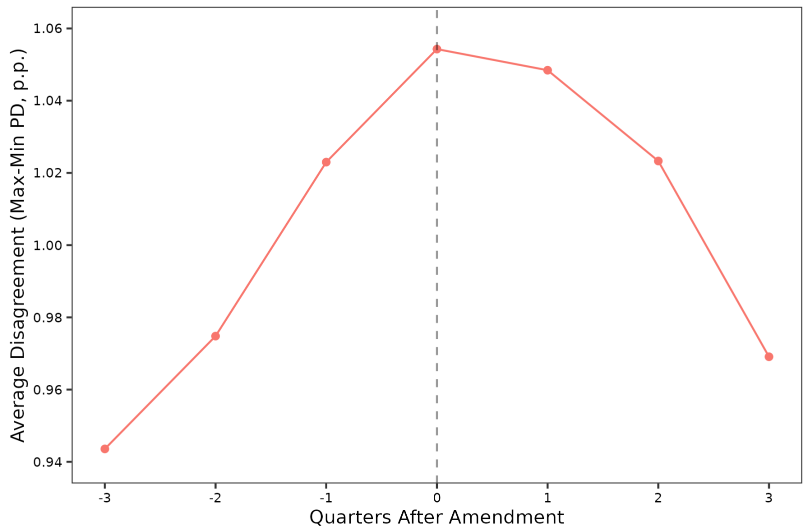
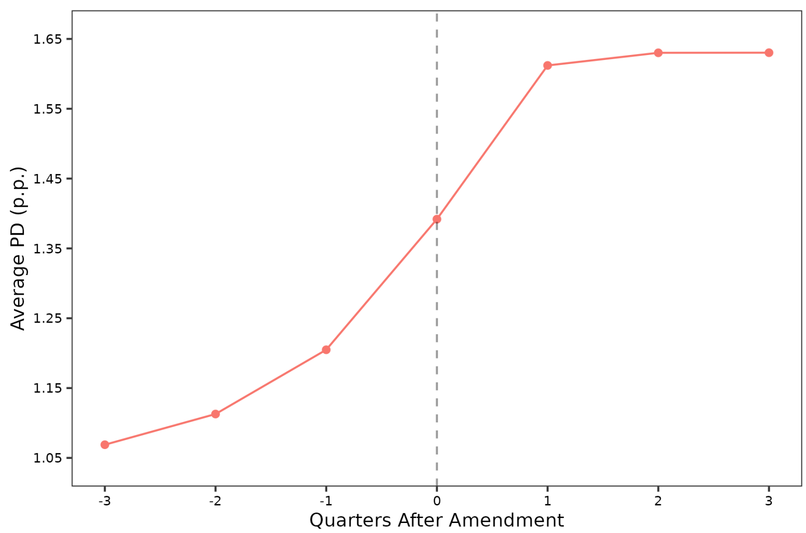


Figure 2: Average Spread (logged) across Disagreement Quantiles

This figure plots the average logged interest rate spread across each decile of our measure of disagreement, *Max-Min PD*. The analysis is conducted at the loan origination level. We take the logged interest rate spread to be the natural logarithm of the all-in-drawn spread from Dealscan. We take quantiles of *Max-Min PD*, which measures lender disagreement by taking the range between the highest and lowest probability of default (PD) estimates among syndicate members. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.



(A) Disagreement around Amendments



(B) Credit Risk Assessment around Amendments

Figure 3: Disagreement and Credit Risk Assessment around Amendments

Panel A plots the average level of disagreement around the quarters before, during, and after an amendment. Panel B plots the average credit risk assessment of the borrower around the quarters before, during, and after an amendment. The analysis is conducted at the loan-time level. Our measure of disagreement is *Max-Min PD*, which measures lender disagreement by taking the range between the highest and lowest probability of default (PD) estimates among syndicate members. We measure the average credit risk assessment as the average probability of default (PD) estimate across syndicate members. We define an amendment in FR Y-14Q as a change in the origination date or renewal date as consistent with the reporting form. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.

Table 1: Sample and Descriptive Statistics

This table presents our sample construction in Panel A and the summary statistics for variables used for the analyses in the paper in Panel B, Panel C, and Panel D. Note that for Panel A, we conduct the matching process with data starting in 2012:Q1, but restrict the sample in the main analysis to after 2014:Q4 due to PDs being largely unpopulated prior to then. Descriptive statistics are calculated whenever there are non-missing data available. The sample descriptives are at the loan origination level. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.

Panel A: Sample Construction

Description	Number of observations
Matching Sample	
Starting sample of FR Y-14Q, Schedule H.1 (2012:Q1-2025:Q2)	19,365,017
Starting sample of LPC Dealscan (2012:Q1-2025:Q2)	1,306,188
Name-matched sample of Dealscan - FR Y-14Q	8,758,009
Filtered match sample of Dealscan - FR Y-14Q	1,039,369
Panel Level Collapsing	
Starting sample	1,039,369
Filter where # of Lenders reporting PDs >= 2	830,897
Collapse to Syndicate × BHC × Year-Quarter level	628,929
Collapse to Syndicate × Year-Quarter level	153,404
Filter where Max-Min PD <= 10%	146,178
Filter to originations	7,077
Filter to observations with fundamentals	4,992

Panel B: Descriptive Statistics (at Origination)

	Count	Mean	SD	P25	Median	P75
Disagreement						
Max-Min PD	7077	1.06	1.39	0.18	0.51	1.33
Max-Min $\widehat{\text{PD}}$	3470	3.20	6.42	0.75	1.47	2.81
Credit Risk and Lead Arranger						
Lead Arranger's PD	5609	1.09	3.32	0.16	0.45	1.10
Avg PD	7077	1.04	1.24	0.23	0.57	1.32
Borrower Rating	7077	6.02	1.10	5.00	6.00	7.00
High Share	6609	0.85	0.36	1.00	1.00	1.00
Lead Arranger's Share	6609	0.28	0.82	0.10	0.18	0.32
Lead Above	6431	0.54	0.50	0.00	1.00	1.00
Loan Characteristics						
ln(Total Exposure)	7077	5.61	1.54	4.61	5.70	6.62
Interest Rate Spread	5723	203.09	109.26	125.00	175.00	250.00
Maturity	7077	4.02	1.27	3.20	4.74	4.90
N Lender	7077	3.73	2.19	2.00	3.00	5.00
N Lender (DS)	7077	9.71	7.34	4.00	8.00	13.00
Borrower Fundamentals						
ROA	5485	0.10	0.13	0.04	0.07	0.13
Borrower Size	5627	20.29	4.07	19.27	20.81	22.43
Leverage	5429	0.35	0.24	0.18	0.31	0.47
Private	7077	0.47	0.50	0.00	0.00	1.00
Industry Return Volatility	7077	0.91	0.51	0.61	0.80	1.04
Future Credit Risk						
ΔAvg PD 4 Years After Origination	7077	0.62	3.01	-0.10	0.00	0.18
$\mathbb{1}$(Ever Default)	6620	0.01	0.07	0.00	0.00	0.00

Panel C: Descriptive Statistics (Bank × Loan Origination Level)

	Count	Mean	SD	P25	Median	P75
Bank's PD	27665	0.83	1.22	0.14	0.35	0.98
Bank's $\widehat{\text{PD}}$	14494	1.83	2.44	0.58	1.13	2.07
$\mathbb{1}\{\text{Ind Specialist}\}$	29879	0.44	0.50	0.00	0.00	1.00
Rel Length	29369	4.14	4.27	0.00	3.25	7.25
Headroom	29656	3.53	2.12	1.95	2.94	4.62
Distance	27826	14.91	12.50	5.08	11.12	22.81

Panel D: Descriptive Statistics (Loan × Quarter Level)

	Count	Mean	SD	P25	Median	P75
Disagreement						
Max-Min PD	146178	1.02	1.48	0.15	0.45	1.16
Max-Min $\widehat{\text{PD}}$	92373	3.20	6.16	0.76	1.48	2.86
Credit Risk and Lead Arranger						
Lead Arranger's PD	116036	1.39	6.31	0.15	0.37	1.04
Avg PD	146178	1.10	1.99	0.20	0.46	1.12
Borrower Rating	146178	6.10	1.04	6.00	6.00	7.00
High Share	132191	0.83	0.37	1.00	1.00	1.00
Lead Arranger's Share	132191	0.28	1.03	0.10	0.17	0.29
Lead Above	127565	0.52	0.50	0.00	1.00	1.00
Loan Characteristics						
ln(Total Exposure)	146178	5.76	1.45	4.83	5.86	6.75
Maturity	141523	3.06	1.20	2.22	3.18	4.05
N Lender	146178	3.76	2.18	2.00	3.00	5.00
N Lender (DS)	146178	9.61	6.98	5.00	8.00	13.00
Borrower Fundamentals						
ROA	122989	0.09	0.11	0.03	0.06	0.11
Borrower Size	124069	21.30	2.39	20.05	21.45	22.73
Leverage	122253	0.37	0.23	0.23	0.35	0.48
Private	146178	0.40	0.49	0.00	0.00	1.00
Industry Return Volatility	145481	0.96	0.54	0.65	0.82	1.06
Amendments and Shocks						
Quarters After Amend	80619	0.45	0.89	0.00	0.00	0.00
Δ ROA	146146	0.00	0.04	-0.02	-0.00	0.02
$\lvert\Delta ROA\rvert$	146146	0.02	0.03	0.01	0.02	0.03

Table 2: First Stage Coverage by Industry

This table display the coverage and explanatory power of the first stage models across banks in each industry. Within each bank-industry, we take the average Pseudo R^2 and *N Obs* across periods where estimation is possible.

		Pseudo R^2		N Obs	
Industry	N Banks	Mean(Median)	P10 to P90	Mean(Median)	P10 to P90
Average Across Industries	20	0.54 (0.56)	0.39 to 0.67	2598 (1675)	369 to 6283
11: Agriculture	12	0.51 (0.50)	0.41 to 0.63	1477 (631)	171 to 3413
21: Mining	22	0.47 (0.44)	0.35 to 0.62	1359 (1025)	219 to 2472
22: Utilities	21	0.53 (0.56)	0.41 to 0.71	1616 (1319)	446 to 3088
23: Construction	22	0.57 (0.57)	0.42 to 0.70	2948 (2633)	218 to 6663
31: Manufacturing (Food, Textiles, and Apparel)	23	0.60 (0.63)	0.50 to 0.70	2519 (1577)	585 to 5607
32: Manufacturing (Chemicals, Paper, and Petroleum)	25	0.60 (0.62)	0.48 to 0.73	3693 (2699)	645 to 9752
33: Manufacturing (Metals, Machinery, and Equipment)	25	0.61 (0.62)	0.48 to 0.72	6499 (4487)	1196 to 18140
42: Wholesale Trade	23	0.60 (0.61)	0.50 to 0.69	7363 (4204)	600 to 21132
44: Retail Trade (Specialty)	22	0.61 (0.66)	0.48 to 0.73	5787 (2896)	405 to 11937
45: Retail Trade (General Merchandise)	22	0.55 (0.57)	0.41 to 0.68	1093 (509)	305 to 2502
48: Transportation	24	0.54 (0.54)	0.42 to 0.68	3020 (2156)	283 to 7303
49: Warehousing and Postal	14	0.43 (0.40)	0.22 to 0.60	361 (256)	139 to 743
51: Information	22	0.58 (0.60)	0.48 to 0.68	1929 (1425)	486 to 4764
52: Finance	10	0.46 (0.50)	0.13 to 0.67	1272 (1132)	166 to 2359
53: Real Estate	22	0.56 (0.59)	0.38 to 0.66	5058 (2475)	512 to 10228
54: Professional Svcs.	23	0.60 (0.61)	0.51 to 0.69	3802 (2265)	651 to 11286
55: Management	12	0.45 (0.52)	0.19 to 0.61	729 (350)	124 to 1735
56: Admin.	21	0.56 (0.57)	0.42 to 0.68	1687 (1325)	265 to 4001
61: Education	9	0.46 (0.46)	0.34 to 0.56	481 (352)	194 to 951
62: Health Care	23	0.54 (0.55)	0.40 to 0.71	2767 (1603)	339 to 6273
71: Entertainment	18	0.54 (0.54)	0.44 to 0.66	1054 (747)	148 to 2379
72: Accommodation	22	0.54 (0.55)	0.36 to 0.69	2394 (1728)	240 to 6062
81: Other Svcs.	19	0.55 (0.59)	0.32 to 0.67	857 (720)	154 to 1725

Table 3: Understanding Model-Based versus Actual PD Estimates

This table presents fractional logit regression results examining the role banks' discretion plays in PD estimates. The analysis is conducted at the bank × loan origination level. The dependent variable is *PD*, which captures the bank's probability of default (PD) estimate of the borrower immediately after loan origination. $\widehat{PD}$ is the predicted PD from a result of a first stage model estimated at the bank-industry-time level, which captures the PD explained by hard information and banks' modeling decisions. All regressions include year-quarter fixed effects. Standard errors are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.

Dep Var:	Bank's PD				
Interaction Var:		$\mathbb{1}${Ind Specialist}	Rel Length	Headroom	Distance
	(1)	(2)	(3)	(4)	(5)
Bank's $\widehat{PD}$	9.664***	9.437***	6.766***	11.988***	9.401***
	(7.38)	(6.23)	(4.36)	(6.24)	(8.10)
Bank's $\widehat{PD}$ × Interaction Var		0.008	0.008***	-0.008**	0.000
		(0.56)	(4.56)	(-1.99)	(0.45)
$\mathbb{1}${Ind Specialist}	-0.100*	-0.121**	-0.093*	-0.105*	-0.100*
	(-1.85)	(-2.27)	(-1.84)	(-1.94)	(-1.84)
Rel Length	-0.020***	-0.020***	-0.041***	-0.020***	-0.020***
	(-2.92)	(-2.92)	(-5.71)	(-2.90)	(-2.91)
Headroom	0.010	0.010	0.010	0.031	0.010
	(0.33)	(0.34)	(0.34)	(0.99)	(0.32)
Distance	-0.002	-0.002	-0.002	-0.002	-0.002
	(-0.61)	(-0.62)	(-0.60)	(-0.64)	(-0.62)
ln(Total Exposure)	-0.086***	-0.087***	-0.086***	-0.087***	-0.086***
	(-5.69)	(-5.93)	(-6.38)	(-6.02)	(-5.69)
Maturity	0.088***	0.088***	0.093***	0.085***	0.088***
	(4.02)	(4.04)	(3.88)	(3.84)	(4.03)
Private	0.113	0.113	0.117	0.112	0.113
	(1.29)	(1.28)	(1.37)	(1.28)	(1.28)
Industry Return Volatility	1.902	1.946	1.219	2.138	1.959
	(1.00)	(1.00)	(0.56)	(1.17)	(1.05)
ROA	-2.660***	-2.653***	-2.708***	-2.696***	-2.658***
	(-13.09)	(-13.20)	(-13.31)	(-13.39)	(-13.07)
Borrower Size	-0.100***	-0.098***	-0.099***	-0.100***	-0.100***
	(-7.19)	(-6.56)	(-7.10)	(-7.33)	(-7.25)
Leverage	0.832***	0.827***	0.838***	0.826***	0.833***
	(7.79)	(8.02)	(7.72)	(7.89)	(7.81)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.043	0.043	0.044	0.043	0.043
N	11,333	11,333	11,333	11,333	11,333

Table 4: Determinants of Bank Disagreement

This table presents regression results examining the determinants of lender disagreement in syndicated loans. The analysis is conducted at the loan origination level. The dependent variable is our disagreement measure, *Max-Min PD* or *Max-Min* $\widehat{\text{PD}}$, which measures the extent of disagreement among syndicate members regarding borrower credit risk. *Max-Min PD* captures the range between the highest and lowest probability of default (PD) estimates among syndicate members. *Max-Min* $\widehat{\text{PD}}$ is formulated similarly but uses $\widehat{\text{PD}}$. Loan and borrower characteristics are included as independent variables. All regressions include year-quarter and borrower rating fixed effects. Standard errors are clustered at the loan level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.

Dep Var:	Max-Min $\widehat{\text{PD}}$	Max-Min PD	
	(1)	(2)	(3)
ln(Total Exposure)	0.793***	0.063***	0.052***
	(5.33)	(4.31)	(2.68)
Maturity	-0.503***	0.013	0.010
	(-4.01)	(1.00)	(0.61)
Private	0.003	0.015	0.004
	(0.01)	(0.38)	(0.08)
N Lender	0.319***	0.048***	0.047***
	(5.44)	(6.55)	(5.06)
Industry Return Volatility	18.408	3.107	2.817
	(0.40)	(1.10)	(0.89)
ROA	-1.425	-0.540***	-0.814***
	(-0.89)	(-4.50)	(-5.00)
Borrower Size	-0.931***	-0.034***	-0.021*
	(-7.02)	(-3.76)	(-1.65)
Leverage	3.262***	0.288***	0.110
	(4.26)	(3.86)	(1.21)
High Share	-0.253	0.027	0.040
	(-0.97)	(0.79)	(0.96)
Lead Above	0.485**	0.033	0.082**
	(2.36)	(1.15)	(2.26)
Max-Min $\widehat{\text{PD}}$			0.019***
			(3.98)
Year-Quarter FE	Yes	Yes	Yes
Borrower Rating FE	Yes	Yes	Yes
R^2	0.186	0.525	0.561
N	3,232	4,992	3,232

Table 5: Bank Disagreement and Interest Rates

This table presents regression results examining the relationship between lender disagreement and syndicated loan interest rate spreads. The analysis is conducted at the loan origination level. The dependent variable is *ln(Interest Rate Spread)*, which captures the natural logarithm of the loan's interest rate spread. *Max-Min PD* measures lender disagreement, which represents the range between the highest and lowest probability of default (PD) estimates among syndicate members. *Max-Min* $\widehat{PD}$ is formulated similarly but uses $\widehat{PD}$. Loan and borrower characteristics are included as controls. All regressions include year-quarter and borrower rating fixed effects. Standard errors are clustered at the loan level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.

Dep Var:	ln(Spread)		
	(1)	(2)	(3)
Max-Min $\widehat{PD}$	0.003***		0.003**
	(2.71)		(2.21)
Max-Min PD		0.034***	0.029***
		(5.71)	(4.27)
ln(Total Exposure)	-0.063***	-0.071***	-0.064***
	(-9.73)	(-14.41)	(-9.96)
Maturity	0.036***	0.042***	0.036***
	(5.64)	(7.90)	(5.62)
Private	0.066***	0.067***	0.065***
	(4.15)	(4.98)	(4.14)
N Lender	-0.020***	-0.018***	-0.021***
	(-6.92)	(-7.43)	(-7.33)
Industry Return Volatility	0.752	-0.115	0.667
	(0.71)	(-0.12)	(0.66)
ROA	-0.016	-0.080	0.006
	(-0.30)	(-1.51)	(0.11)
Borrower Size	-0.007*	-0.010***	-0.006*
	(-1.92)	(-3.73)	(-1.76)
Leverage	0.169***	0.233***	0.166***
	(5.76)	(9.92)	(5.67)
High Share	0.003	-0.019	0.001
	(0.17)	(-1.48)	(0.09)
Lead Above	0.036***	0.030***	0.034***
	(2.96)	(3.08)	(2.81)
Year-Quarter FE	Yes	Yes	Yes
Borrower Rating FE	Yes	Yes	Yes
R^2	0.624	0.607	0.627
N	2,797	4,392	2,797

Table 6: Bank Disagreement and Contractual Terms

This table presents regression results examining the relationship between lender disagreement and two contractual features of syndicated loans: the Number of Financial Covenants and Performance Pricing. The analysis is conducted at the loan origination level. The dependent variable in Columns (1) - (3) is the *Number of Financial Covenants*, which captures the total count of financial covenants in the loan agreement. In Columns (4)-(6), the dependent variable is *Performance Pricing*, an indicator equal to one if the loan includes a pricing provision that adjusts the interest rate based on the borrower's performance and zero otherwise. *Max-Min PD* measures lender disagreement, which represents the range between the highest and lowest probability of default (PD) estimates among syndicate members. *Max-Min $\widehat{PD}$* is formulated similarly but uses $\widehat{PD}$. Loan and borrower characteristics are included as controls. All regressions include year-quarter and borrower rating fixed effects. Standard errors are clustered at the loan level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.

Dep Var:	Number of Financial Covenants			$\mathbb{1}$\{Performance Pricing\}		
	(1)	(2)	(3)	(4)	(5)	(6)
Max-Min $\widehat{PD}$	-0.000		-0.000	0.000		0.001
	(-0.09)		(-0.04)	(0.30)		(0.78)
Max-Min PD		-0.011	-0.005		-0.019***	-0.021***
		(-1.22)	(-0.44)		(-4.63)	(-4.68)
ln(Total Exposure)	0.012	-0.005	0.012	0.031***	0.022***	0.032***
	(1.16)	(-0.53)	(1.19)	(5.56)	(4.72)	(5.77)
Maturity	0.014	0.008	0.014	-0.001	-0.003	-0.000
	(1.40)	(0.98)	(1.41)	(-0.12)	(-0.68)	(-0.08)
Private	-0.417***	-0.510***	-0.417***	-0.140***	-0.200***	-0.140***
	(-14.54)	(-20.02)	(-14.54)	(-11.52)	(-17.93)	(-11.55)
N Lender	0.034***	0.042***	0.034***	0.021***	0.024***	0.022***
	(4.72)	(6.99)	(4.69)	(5.83)	(8.08)	(6.08)
Industry Return Volatility	-2.096**	-1.999**	-2.084**	-2.074***	-1.628**	-2.016***
	(-2.39)	(-2.35)	(-2.37)	(-2.97)	(-2.22)	(-3.05)
ROA	-0.147**	-0.085	-0.150**	0.067	0.096***	0.050
	(-2.20)	(-1.50)	(-2.24)	(1.62)	(2.81)	(1.22)
Borrower Size	-0.014**	-0.018***	-0.015**	0.003	-0.001	0.002
	(-2.17)	(-3.51)	(-2.18)	(0.95)	(-0.45)	(0.81)
Leverage	0.038	0.032	0.039	0.018	-0.004	0.021
	(0.92)	(0.94)	(0.94)	(0.81)	(-0.19)	(0.92)
High Share	-0.032	0.011	-0.032	-0.036**	0.002	-0.036**
	(-1.00)	(0.40)	(-0.99)	(-2.06)	(0.13)	(-2.01)
Lead Above	0.030	0.001	0.030	0.014	0.019**	0.016
	(1.27)	(0.05)	(1.28)	(1.21)	(1.98)	(1.36)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.157	0.206	0.157	0.239	0.267	0.242
N	3,232	4,992	3,232	3,232	4,992	3,232

Table 7A: Disagreement with Syndicate and Bank Exit (Linear Probability Model)

This table presents regression results examining the relationship between lender disagreement and the likelihood of a bank exiting the syndicate within one to four quarters. The analysis is at the bank-quarter-loan level and includes all quarterly observations for the loan that are available post origination. The dependent variable is an indicator equal to one if a bank in quarter *t* exits the syndicate within the number of quarters associated with each column and zero otherwise (*Bank Exits Within the Next n Qtrs*). *PD Diff* captures the difference between a syndicate bank's probability of default (PD) estimate and the average PD estimate across all lenders in the syndicate. $\widehat{PD}$ *Diff* captures the difference between a syndicate bank's PD and the average PD estimate across all lenders in the syndicate. Loan characteristics, including *ln(Total Exposure)*, *Maturity*, *Private*, *N Lender*, borrower financial variables such as *ROA*, *Size*, and *Leverage*, and lead arranger signaling variables such as *High Share* and *Lead Above* are included as controls. All regressions include the fixed effects listed at the bottom of the table. Standard errors are presented in parentheses and clustered at the lender level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1% and 99% level and are defined in Appendix A.

Dep Var:	Bank Exits Within the Next-			
	1 Qtr	2 Qtrs	3 Qtrs	4 Qtrs
	(1)	(2)	(3)	(4)
PD Diff	0.001***	0.002***	0.002***	0.002***
	(3.43)	(4.04)	(4.41)	(4.28)
$\widehat{PD}$ Diff	0.002***	0.002***	0.002***	0.002***
	(7.17)	(6.23)	(5.93)	(5.38)
ln(Total Exposure)	0.001	0.000	0.000	0.000
	(0.89)	(0.35)	(0.28)	(0.22)
Maturity	-0.019***	-0.027***	-0.032***	-0.036***
	(-32.08)	(-31.13)	(-29.69)	(-28.36)
Private	-0.006***	-0.006***	-0.007***	-0.006**
	(-4.28)	(-3.37)	(-2.69)	(-2.15)
N Lender	0.003***	0.005***	0.007***	0.008***
	(9.29)	(10.32)	(10.91)	(11.24)
Industry Return Volatility	-0.033	-0.033	-0.032	-0.037
	(-0.77)	(-0.57)	(-0.41)	(-0.46)
ROA	0.022***	0.032***	0.039***	0.046***
	(4.00)	(3.98)	(3.79)	(3.64)
Borrower Size	0.001**	0.002***	0.003***	0.004***
	(2.45)	(3.30)	(3.47)	(3.64)
Leverage	-0.002	-0.003	-0.004	-0.004
	(-0.80)	(-0.79)	(-0.79)	(-0.80)
High Share	-0.006***	-0.004*	-0.002	-0.001
	(-3.90)	(-1.87)	(-0.73)	(-0.37)
Lead Above	0.002	0.002	0.003	0.004
	(1.47)	(1.49)	(1.58)	(1.60)
Bank × Year-Quarter FE	Yes	Yes	Yes	Yes
Borrower Rating FE	Yes	Yes	Yes	Yes
R^2	0.0947	0.104	0.112	0.117
N	289,148	289,148	289,148	289,148

Table 7B: Disagreement with Syndicate and Bank Exit (Cox Hazard Model)

This table presents results examining the relationship between lender disagreement and the likelihood of a bank exiting using a Cox hazard model. The analysis is at the bank-quarter-loan level, and we define the failure event as the quarter during which a bank exits the syndicate prematurely. *PD Diff* captures the difference between a syndicate bank's probability of default (PD) estimate and the average PD estimate across all lenders in the syndicate. $\widehat{PD}$ *Diff* captures the difference between a syndicate bank's probability of default (PD) estimate and the average PD estimate across all lenders in the syndicate. Loan characteristics, including *ln(Total Exposure)*, *Maturity*, *Private*, *N Lender*, borrower financial variables such as *ROA*, *Size*, and *Leverage*, and lead arranger signaling variables such as *High Share* and *Lead Above* are included as controls. All regressions include the fixed effects listed at the bottom of the table. Standard errors are presented in parentheses and clustered at the lender level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.

	Hazard of Bank Exit		
	(1)	(2)	(3)
PD Diff	1.031***		1.031**
	(2.79)		(2.40)
$\widehat{PD}$ Diff		1.085***	1.091***
		(8.67)	(9.58)
ln(Total Exposure)	1.027	1.071**	1.051*
	(1.15)	(2.48)	(1.80)
Maturity	0.511***	0.468***	0.471***
	(-43.18)	(-40.02)	(-39.62)
Private	0.520***	0.587***	0.584***
	(-10.98)	(-7.95)	(-7.97)
N Lender	1.079***	1.082***	1.095***
	(8.69)	(7.92)	(9.11)
Industry Return Volatility	0.854***	0.933*	0.923**
	(-4.70)	(-1.93)	(-2.25)
ROA	1.774***	2.044***	1.878**
	(2.74)	(3.04)	(2.57)
Borrower Size	0.935***	0.968*	0.957**
	(-4.21)	(-1.70)	(-2.32)
Leverage	0.972	1.036	1.017
	(-0.32)	(0.34)	(0.16)
High Share	0.749***	0.696***	0.717***
	(-5.78)	(-6.36)	(-5.89)
Lead Above	1.019	1.069	1.044
	(0.45)	(1.38)	(0.90)
Bank Strata	Yes	Yes	Yes
Borrower Rating Strata	Yes	Yes	Yes
R^2			
N	376596	289976	289150

Table 8: Disagreement, Borrower Shocks, and Amendment Timing

This table presents regression results examining the relationship between lender disagreement and the likelihood of a loan amendment. This analysis is conducted at the loan × quarter level, where the loan is aggregated to the syndicate level. The dependent variable is an indicator equal to one if the loan in quarter t undergoes renegotiation in quarter $t+1$ and zero otherwise ($Amendment_{t+1}$). *Disagreement* captures disagreement among syndicate lenders regarding borrower credit risk using our measures, *Max-Min PD* and *Max-Min* $\widehat{PD}$. *Shock* takes on a different type of shock to borrower conditions by column. In Columns (1) and (3), *Shock* reflects ΔROA, which is the year-over-year change in the aggregate ROA for the borrower's industry. In Columns (2) and (4), *Shock* reflects $|\Delta ROA|$, which now takes the absolute year-over-year change in the aggregate ROA for the borrower's industry. Loan characteristics, including *ln(Total Exposure)*, *Maturity*, *Private*, *N Lender*, borrower financial variables such as *ROA*, *Size*, and *Leverage*, and lead arranger signaling variables such as *High Share* and *Lead Above* are included as controls. All regressions include year-quarter and borrower rating fixed effects. Standard errors are presented in parentheses and clustered at the loan level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.

Dep Var:	$Amendment_{t+1}$			
Disagreement Measure:	Max-Min $\widehat{PD}$		Max-Min PD	
Shock Type:	Δ ROA	|Δ ROA|	Δ ROA	|Δ ROA|
	(1)	(2)	(3)	(4)
Disagreement	-0.001**	-0.000	0.004***	0.006***
	(-2.15)	(-0.45)	(3.79)	(4.19)
Disagreement × Shock	-0.006	-0.013**	-0.044**	-0.062**
	(-1.29)	(-2.00)	(-2.41)	(-2.06)
Shock	0.069*	0.225***	0.098**	0.281*
	(1.82)	(3.69)	(2.51)	(4.33)
ln(Total Exposure)	0.017***	0.017***	0.016***	0.016***
	(9.88)	(9.78)	(10.92)	(10.80)
Maturity	-0.042***	-0.042***	-0.040***	-0.040***
	(-33.92)	(-33.98)	(-35.12)	(-35.19)
Private	-0.003	-0.003	-0.005	-0.005
	(-0.60)	(-0.62)	(-1.18)	(-1.24)
N Lender	0.021***	0.021***	0.021***	0.021***
	(19.58)	(19.70)	(21.38)	(21.55)
Industry Return Volatility	0.019	0.014	0.015	0.010
	(0.20)	(0.14)	(0.17)	(0.11)
ROA	0.015	0.011	0.026	0.021
	(1.08)	(0.78)	(1.97)	(1.60)
Borrower Size	-0.003**	-0.003*	-0.002**	-0.002**
	(-1.96)	(-1.89)	(-2.11)	(-2.06)
Leverage	-0.022***	-0.021***	-0.026***	-0.024***
	(-2.90)	(-2.81)	(-3.72)	(-3.53)
High Share	-0.006	-0.006	-0.007*	-0.008*
	(-1.36)	(-1.39)	(-1.76)	(-1.81)
Lead Above	-0.002	-0.002	-0.001	-0.001
	(-0.64)	(-0.64)	(-0.24)	(-0.21)
Year-Quarter FE	Yes	Yes	Yes	Yes
Borrower Rating FE	Yes	Yes	Yes	Yes
R^2	0.057	0.057	0.054	0.055
N	78,568	78,568	103,635	103,635

Table 9: Disagreement After Amendments

This table presents regression results examining the dynamics of disagreement in the quarters immediately after a successful loan amendment. This analysis is conducted at the loan × quarter level, where the loan is aggregated to the syndicate level. The dependent variable is our measure of loan disagreement, *Max-Min PD*. *Max-Min* $\widehat{PD}$ measures model-based disagreement. *Quarters After Amend* captures the number of quarters after an amendment. Loan characteristics, including *ln(Total Exposure)*, *Maturity*, *Private*, *N Lender*, borrower financial variables such as *ROA*, *Size*, and *Leverage*, and lead arranger signaling variables such as *High Share* and *Lead Above* are included as controls. All regressions include year-quarter and borrower rating fixed effects. Standard errors are presented in parentheses and clustered at the loan level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.

Dep Var:	Max-Min PD		
	0-1 Qtrs After	0-2 Qtrs After	0-3 Qtrs After
	(1)	(2)	(3)
Quarters After Amend	-0.029*	-0.029***	-0.026***
	(-1.93)	(-3.09)	(-3.77)
Max-Min $\widehat{PD}$	0.010***	0.011***	0.010***
	(5.46)	(5.97)	(5.48)
ln(Total Exposure)	0.016	0.010	0.009
	(1.27)	(0.78)	(0.76)
Maturity	-0.046***	-0.046***	-0.045***
	(-4.35)	(-4.44)	(-4.51)
Private	-0.006	-0.021	-0.027
	(-0.16)	(-0.64)	(-0.83)
N Lender	0.045***	0.043***	0.043***
	(8.75)	(8.72)	(8.89)
Industry Return Volatility	1.085	1.286	1.547
	(1.03)	(1.33)	(1.61)
ROA	-0.565***	-0.525***	-0.521***
	(-4.70)	(-4.54)	(-4.64)
Borrower Size	-0.005	-0.002	-0.004
	(-0.65)	(-0.30)	(-0.59)
Leverage	0.221***	0.189***	0.179***
	(2.86)	(2.62)	(2.61)
High Share	0.014	0.026	0.040*
	(0.56)	(1.12)	(1.76)
Lead Above	0.027	0.027	0.026
	(1.15)	(1.19)	(1.14)
Year-Quarter FE	Yes	Yes	Yes
Borrower Rating FE	Yes	Yes	Yes
R^2	0.583	0.581	0.576
N	16,554	20,451	23,610

Table 10: Disagreement and Changes in Reported Credit Risk

This table presents regression results examining the relationship between lender disagreement at origination and credit risk assessment of the borrower in the future. The analysis is conducted at the loan origination level. The dependent variable is Δ*Avg PD*, which is the difference between the average internal PD of the borrower after *n* years of origination—denoted at the top of each column—and the average internal PD of the borrower at origination. In other words, Δ*Avg PD* is the change in average PD of the borrower after *n* years. *Max-Min PD* measures lender disagreement at origination, which represents the range between the highest and lowest probability of default (PD) estimates among syndicate members. *Max-Min PD* is formulated similarly but uses PD. Loan and borrower characteristics are included as controls. All regressions include year-quarter and borrower rating fixed effects. Standard errors are presented in parentheses and clustered at the loan level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1% and 99% level and are defined in Appendix A.

Dep Var:	ΔAvg PD after-							
	-1 Yr		-2 Yrs		-3 Yrs		-4 Yrs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max-Min PD	-0.056***		-0.068*		-0.159***		0.040	
	(-3.39)		(-1.72)		(-2.89)		(0.37)	
Max-Min $\widehat{PD}$		-0.005**		-0.003		-0.028***		-0.013
		(-2.19)		(-0.49)		(-3.29)		(-0.69)
Borrower Rating	-0.030**	0.013	-0.119***	-0.035	-0.292***	-0.209**	-0.242	-0.390*
	(-2.31)	(1.00)	(-3.61)	(-1.50)	(-3.31)	(-2.12)	(-1.60)	(-1.90)
ln(Total Exposure)	-0.048***	-0.041***	-0.075**	-0.091**	-0.133**	-0.089	-0.045	-0.003
	(-3.71)	(-2.63)	(-2.32)	(-2.54)	(-2.52)	(-1.17)	(-0.57)	(-0.03)
Maturity	0.009	0.011	0.040	0.062**	0.095	0.075	0.108	0.044
	(0.65)	(0.77)	(0.98)	(2.09)	(1.63)	(1.22)	(1.27)	(0.37)
Private	0.067**	0.079**	0.084	0.151*	-0.037	-0.043	0.063	0.171
	(2.10)	(2.07)	(1.09)	(1.76)	(-0.29)	(-0.27)	(0.35)	(0.67)
N Lender	-0.003	-0.004	-0.037***	-0.028**	-0.075***	-0.063***	-0.048*	-0.053
	(-0.65)	(-0.70)	(-2.99)	(-2.05)	(-3.81)	(-2.74)	(-1.85)	(-1.29)
Industry Return Volatility	0.526	1.509	12.587*	12.942*	5.863	9.778	-1.860	1.214
	(0.33)	(0.90)	(1.68)	(1.73)	(0.57)	(0.88)	(-0.12)	(0.08)
ROA	-0.126	-0.136	-0.381	-0.242	-0.264	0.050	0.424	1.041
	(-1.15)	(-0.95)	(-1.50)	(-0.73)	(-0.82)	(0.10)	(0.45)	(0.61)
Borrower Size	-0.003	-0.014	-0.017	-0.019	0.032	-0.036	-0.015	-0.006
	(-0.39)	(-1.58)	(-0.92)	(-1.06)	(1.29)	(-0.88)	(-0.26)	(-0.07)
Leverage	-0.010	0.033	-0.095	0.151	0.143	0.303	0.300	0.660
	(-0.16)	(0.46)	(-0.64)	(0.92)	(0.64)	(1.02)	(0.71)	(1.07)
High Share	-0.029	-0.048	0.067	-0.032	-0.011	0.100	0.057	0.211
	(-0.99)	(-1.38)	(1.22)	(-0.42)	(-0.09)	(0.97)	(0.35)	(0.97)
Lead Above	0.046*	0.048	0.174***	0.135*	0.134	0.056	0.060	0.007
	(1.84)	(1.53)	(2.81)	(1.92)	(1.42)	(0.45)	(0.39)	(0.03)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.054	0.060	0.043	0.042	0.049	0.051	0.048	0.059
N	4,332	2,783	3,468	2,783	2,579	1,525	1,673	841

Table 11: Disagreement and Default

This table presents regression results examining the relationship between lender disagreement at origination and borrower default. The analysis is conducted at the loan origination level. The dependent variable is *Default within n Years*, which is an indicator if the lead arranger has reported the loan as default within *n* years after origination—with *n* denoted at the top of each column. We define the loan as reported as default if the lead reports it 90 days past due, reports nonzero charge-offs, or reports a non-accrual date. *Max-Min PD* measures lender disagreement at origination, which represents the range between the highest and lowest probability of default (PD) estimates among syndicate members. *Max-Min* $\widehat{PD}$ is formulated similarly but uses $\widehat{PD}$. Loan and borrower characteristics are included as controls. All regressions include year-quarter and borrower rating fixed effects. Standard errors are presented in parentheses and clustered at the loan level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1% and 99% levels and are defined in Appendix A.

Dep Var:	Default Within-							
	-Lifetime		-4 Yrs		-2 Yrs		-1 Yr	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max-Min PD	-0.001		-0.001		0.001		0.000	
	(-0.46)		(-1.54)		(0.78)		(0.19)	
Max-Min $\widehat{PD}$		0.001		0.001		0.000		0.001
		(1.47)		(1.03)		(0.85)		(1.08)
Borrower Rating	-0.006**	-0.005**	-0.001	0.002	-0.001	-0.001	-0.003	-0.003
	(-2.22)	(-2.26)	(-1.34)	(0.93)	(-1.05)	(-1.11)	(-1.44)	(-1.49)
ln(Total Exposure)	-0.001	-0.001	-0.000	-0.003	-0.000	-0.001	-0.001	-0.001
	(-0.62)	(-0.97)	(-0.51)	(-0.91)	(-0.39)	(-1.00)	(-1.05)	(-0.88)
Maturity	-0.002	-0.001	0.001*	0.003*	-0.001	0.001	-0.001	-0.000
	(-1.59)	(-0.61)	(1.66)	(1.69)	(-0.35)	(1.24)	(-0.98)	(-0.24)
Private	0.003	-0.000	0.004	0.007	0.003	0.001	0.004	0.001
	(1.08)	(-0.03)	(1.43)	(1.40)	(0.88)	(0.28)	(1.40)	(0.33)
N Lender	0.000	0.000	0.001	0.002	0.001	0.001	0.001	0.001
	(0.51)	(0.47)	(1.46)	(1.38)	(0.95)	(1.24)	(0.87)	(0.89)
Industry Return Volatility	0.009	0.014	-0.012	-0.130	0.078	0.070	0.030	0.055
	(0.09)	(0.15)	(-0.62)	(-1.00)	(0.65)	(0.53)	(0.25)	(0.45)
ROA	-0.005	0.005	0.016	0.045	0.002	0.012	-0.003	0.010
	(-0.79)	(0.45)	(1.41)	(1.41)	(0.31)	(0.99)	(-0.38)	(0.95)
Borrower Size	0.001**	0.001**	0.000	0.002	0.000*	0.001	0.001**	0.001
	(2.56)	(2.02)	(0.47)	(1.10)	(1.79)	(1.24)	(2.44)	(1.59)
Leverage	0.001	0.003	0.012	0.021	0.005	0.011	0.003	0.006
	(0.28)	(0.48)	(1.10)	(1.19)	(0.75)	(1.17)	(0.50)	(0.88)
High Share	-0.002	-0.000	0.003	0.006	0.003	0.004	-0.002	0.001
	(-0.63)	(-0.06)	(1.36)	(1.36)	(1.28)	(1.08)	(-0.49)	(0.34)
Lead Above	-0.001	-0.001	-0.003*	-0.007*	0.002	0.002	0.000	0.001
	(-0.69)	(-0.39)	(-1.76)	(-1.88)	(0.89)	(0.69)	(0.08)	(0.22)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.022	0.025	0.030	0.056	0.019	0.024	0.018	0.020
N	4,993	3,233	1,673	841	3,468	2,159	4,332	2,783