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Essays on Corporate Debt, Information, and Incentives

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ABSTRACT

The primary objective of this thesis is to contribute to the literature on corporate debt by examining how to protect creditor interests from both corporate and regulatory perspectives. My research relies on novel data collected from SEC filings, including proxy statements (Form DEF 14A) and syndicated loan contracts (Exhibits of Form 8-K, 10-Q, or 10-K).

The first chapter considers creditors' interests within the framework of corporate compensation design, which is a joint work with David M. Reeb and Wanli Zhao. It contributes to the compensation literature by offering new evidence of using debt-related performance metrics (DPMs), such as credit ratings and debt-to-EBITDA ratios, in executive compensation contracts as a strategic response to the agency costs of debt. Our study is among the first to identify and examine a comprehensive set of DPMs. We show that borrowers obtain less debt financing in periods of high market credit risk while using DPMs more frequently as a response. The likelihood of including DPMs increases after creditors' monitoring incentives increase due to debt maturity pressure or credit quality deterioration. Before new borrowing, either in the form of bonds or loans, firms tend to include DPM in the compensation contract. More importantly, we find that the borrowing costs decrease after DPM inclusion.

The second chapter, which is solo-authored, considers creditors' interests within the context of modern technology used for private information dissemination. I argue that technological advancements can mitigate communication and information processing frictions between syndication arrangers and participant lenders, thereby influencing the dynamics of the lending market. Specifically, I use novel data on the adoption of centralized digital platforms, which support document sharing and interaction among syndicate members during both formation and post-origination stages. Platform adoption has increased steadily since the early 2000s, with early adopters more likely to be arrangers previously involved in information-intensive deals. Exploiting staggered adoption, I find that platform use is followed by an increase in the arranger's syndicated lending volume, particularly to more leveraged borrowers. Syndicates become broader, with more geographically dispersed and first-time participants, and arrangers retain smaller loan shares. Default rates remain unchanged. The findings suggest that reducing communication and

processing frictions enables arrangers to scale financial intermediation without worsening loan performance.

The third chapter, which is solo-authored, considers creditors' interests within the setting of mandatory disclosure of syndicated loan contracts. While the SEC requires borrowers to publicly file these contracts, the broader implications for the lending market remain underexplored. Using SEC log file data, I document that disclosed contracts are actively accessed by outside lenders, with greater attention directed toward contracts involving riskier borrowers or larger loan arrangements. These search behaviors persist over time. I further investigate how these search behaviors influence subsequent contract designs. The results indicate that lenders' search history does not significantly impact pricing strategies but is associated with their covenant design, reflecting the unique value of SEC filings with full contract texts and detailed covenant structures. Overall, these findings highlight the informational role of disclosed loan contracts in SEC filings for outside lenders.

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Chapter 1: Debt-Based Incentives in Executive Compensation Contracts

ABSTRACT

We examine the inclusion of multiple debt performance metrics (DPMs) into executive compensation contracts as a strategic response to the agency cost of debt. Using a manually collected dataset, we find that approximately 19% of US publicly traded firms incorporated DPMs in their compensation contracts. The likelihood of including DPMs increases after creditors' monitoring incentives increase. To facilitate causal inferences, we use the exogenous default of lenders' other clients and observe that focal companies are more likely to include DPMs in compensation contracts when lenders focus more on the agency costs of debt. Further analysis suggests that shareholders incorporate more non-debt metrics in their incentive programs in response to DPM inclusion and request that DPM be included before corporate borrowing. We document a decrease in borrowing costs after firms include DPMs in compensation contracts. Our study highlights the importance of debt-related factors in executive compensation beyond cash flows.

Keywords: Debt Performance Metrics (DPMs), Executive Compensation, Agency Conflict

JEL Codes: G32, J33, G30

1. INTRODUCTION

Since the work of Jensen and Meckling (1976) and Myers (1977) explored the agency costs associated with external financing, there has been a prevailing view in governance theory that reconciling the agency conflicts between shareholders and creditors is crucial to reducing the cost of debt. One critical method of reducing these conflicts centers on using covenants in agreements between the firm and its creditors. Another approach centers on incorporating creditor interests in executive compensation contracts (John and John, 1993). Recent research emphasizes this compensation approach and documents that firms adjust CEO compensation in the event of covenant violation as debtholder interests become more salient (Akins et al. 2019; Balsam et al. 2018; Carter et al. 2020). Focusing on cash-flow-based performance metrics in CEO compensation contracts, Gong et al. (2022) argue that including cash flows in CEO compensation contracts motivates them to improve cash flows and reduce risk. Building on this literature, we use hand-collected data to provide new insights into how and when firms *explicitly* incorporate debt-related performance metrics into executive compensation across various types of firms. We identify a comprehensive set of debt-based performance measures.

In this study, we define the incorporation of DPMs in compensation structures when firms: (1) plan to reward managers based on specific debt-related ratios (e.g., credit ratings); (2) determine managerial compensation based on debt-related targets (e.g., debt reduction, debt financing); and (3) plan to reward managers based on a financial metric with the explicit intention of addressing debt concerns. Prior studies often use data from IncentiveLab to provide insights into debt-related performance metrics. Our hand-collected data indicates that the IncentiveLab data does not include roughly 60% of debt-related performance metrics.

Table 1 illustrates the variety of DPMs firms in executive compensation contracts targeting creditors' interests. In contrast, prior work often relies on the presence of cash-flow metrics in prominent firms to capture the degree of debt-based compensation in an executive compensation contract (e.g., S&P 500). While cash flows gauge the repayment ability of the lender, they are also

related to other corporate decisions that benefit shareholders directly.[1] Our data collection shows that only roughly 20% of cash-flow metrics are debt-centric in the compensation contract. Furthermore, our analysis reveals that firm-level credit risk relates to our DPM measure but not non-DPM cash-flow metrics.

We argue that integrating debtholder interests through a wide variety of measures into the executive compensation contract has several advantages that complement the use of covenants. First, while covenants impose penalties on managers for non-compliance, compensation contracts reward managers for achieving specific performance targets, creating a favorable incentive structure. Second, debt holders may have divergent interests, making covenants costly to renegotiate due to the need for coordination among creditors. In contrast, debt-related performance metrics (DPMs) in compensation contracts mitigate these coordination problems and provide greater flexibility for adjustments. Third, incomplete contract theory highlights the difficulty of specifying creditor rights for every conceivable scenario. Debt covenants can reduce firm value by limiting the ability of corporate insiders to respond to unanticipated events. In contrast, because compensation contracts are inherently reward-based, they do not need to account for every potential contingency, thereby preserving managerial discretion and potentially increasing firm value.[2]

We collect DPMs from annual proxy statements. We gather every proxy statement from firms listed on major U.S. stock exchanges throughout the 2007-2020 proxy seasons using the EDGAR system. By applying manually synthesized regular expressions, we have identified DPM contracts, ultimately amassing a comprehensive dataset comprising 3,127 firm-years with DPM agreements. Based on our manually collected data, roughly 19% of US publicly traded firms have incorporated DPMs into their compensation contracts at least once between 2007 and 2020. This percentage increases to 43% when we focus on those firms participating in the primary debt markets. We

[1] Two examples illustrate this point about confounding shareholder and debtholder interests when relying on cash flows. CSX Corp. states that they select "cash flow" as a performance metric due to its high correlation with the company's stock price and its alignment with shareholders' interests. In contrast, American Axle & Manufacturing Holdings, Inc. notes they use "cash flow" due to its impact on liquidity and debt reduction (See Appendix A).

[2] Creditors can choose to increase interest rates. However, creditors may not want to raise interest rates as higher rates can heighten agency conflicts (Tirole, 2006). On the one hand, a higher interest rate diminishes the borrower's stake in projected profits, thereby motivating the borrower to engage in misconduct. On the other hand, higher interest rates tend to attract low-quality borrowers who are less affected by increased rates in a world of information asymmetry. Therefore, several alternative mechanisms, such as debt covenants, direct monitoring, and convertible debt, seek to balance the agency costs of different external claims. John and John (1993) further indicate that managerial compensation may play a role in achieving this balance.

notice a considerable change in DPM inclusion between 2007-2010 and 2017-2020, during which there were also significant fluctuations in supply-side lending strictness (as measured by the net percentage of banks tightening lending standards). In addition, our descriptive statistics show that DPMs typically concentrate on capital-based metrics, such as debt or leverage levels, borrower repayment ability, and the firm's credit rating, as shown in Table 1. In contrast, debt covenants focus more on performance-based metrics such as debt-to-cash flow ratios.[3]

We explore the reasons why firms include DPMs in their compensation contracts. We find examples showing that both shareholders (i.e., their concerns about liquidity) and lenders can incentivize the compensation committee's decisions to include DPMs.[4] We argue that including debt performance metrics (DPMs) in executive compensation contracts can be a viable solution to mitigate the agency cost of debt. Empirically, we find that borrowers are more likely to use DPMs in response to increases in their credit risks, as measured by their debt-to-EBITDA, expected default frequency, and credit rating.[5] We also note that in periods of high market credit risk, proxied by high Moody's Baa–Aaa credit spread, borrowers obtain less debt financing while using DPMs more frequently as a response. This evidence is consistent with the notion that lenders' demand for monitoring plays a crucial role in compensation contract design.

To facilitate causal inferences, we rely on the exogenous default of other clients of the same lender, motivated by prior research showing that recent defaults may prompt lenders to update their beliefs (Murfin, 2012). We define the treatment time as the lender's first experience of defaults. Our regressions only analyze the first treatment effects for a borrower, excluding companies without syndicated loans and defaulting companies. Our difference-in-difference results indicate that focal companies are more likely to include DPMs in their compensation contracts after the

[3] Interestingly, in some cases, borrowers select compensation performance metrics based on the covenants outlined in their debt contracts (see Appendix A Example 5).

[4] Before the Tax Cuts and Jobs Act (2017), a compensation plan's performance goals would only qualify for exclusion from the Section 162(m) deduction limitation of the Internal Revenue Code if the plan's material terms were disclosed to and approved by shareholders ahead of the payout. While it is common for a compensation plan's performance goals to (be required to) be disclosed to and approved by shareholders ahead of the payout, the compensation committee overall has substantial discretionary power in determining the inclusion of DPMs. The compensation committee exercises discretion if it believes such designs are in the company's and its shareholders' bests interests.

[5] Prior literature often relies on the presence of cash-flow metrics (CFM) to capture the degree of debt-based compensation and shows a positive association between the presence of CFM and credit risk. In the Online Appendix, we categorize contracts with cash-flow metrics (CFM) into DPMs and non-DPMs according to our definition. The results suggest that credit risk is related to our measure of DPM but is not related to non-DPM cash-flow metrics. The results are robust across our three credit risk measures.

lender's perception of future default likelihood increases. Specifically, our findings suggest that after lenders experience recent payment defaults in their portfolios, their current borrowers are more likely to incorporate DPMs in their compensation designs, even when defaulting borrowers are in different industries and geographic regions from the current borrower. We also address recent econometric concerns with staggered DID designs by showing robustness to using two alternative estimators: Callaway and Sant'Anna (2021) and the Stacked DID estimator. Overall, our results are robust across alternative DID estimators, as suggested by Baker et al. (2022).

Similarly, we posit that when the company has the principal's payment approaching the debt's maturity, we expect an increase in DPM inclusion in the compensation contract as the creditors become more concerned about the firm's risk-taking choice. Our empirical evidence supports the notion that debt maturity pressure influences DPM inclusion. We investigate the time series pattern of DPM inclusion relative to the maturity year of the "big payment". We observe that during the two years before the big payment, firms are more likely to include DPM or increase the number of DPMs in the compensation contract. In addition, as we move farther from the big-payment due year, we observe that firms are less likely to include DPM in the compensation contract.

Based on the argument that shareholders bear the agency cost of debt, shareholders should be expected to actively incorporate creditors' interests as it lowers the firm's capital cost. Against that backdrop, we next turn to explore the shareholders explicitly. In response to including DPMs, shareholders introduce more non-debt metrics into their incentive programs. This finding suggests that shareholders tend to balance the lower risk-taking incentives introduced by DPM.

We next explore the scenarios where shareholders may voluntarily demand DPM. We posit that when the firm and debt financing facilitate value-creation for the shareholders, shareholders are more willing to include DPM to mitigate the creditors' concern that managers choose riskier projects. Our findings suggest that before new borrowing, either in the form of bond or loan, firms tend to include DPM in the compensation contract, aiming to pledge the borrower's developing creditworthiness, and thus benefit from the diminished agency expenses of debt.

To further explore the benefit of DPM on the firm's borrowing cost, we compare the firm's borrowing cost between their two consecutive financing activities, focusing on a sample of firms with multiple financing during the sample period. We find that if the firm includes DPM in the

compensation contract before funding, the same firm's borrowing cost decreases substantially more than the counterparts that do not include DPM. Further, this real effect of DPM only manifests in loan borrowing, not borrowing from the bond market, consistent with the notion that bondholders are more easily diversified in the secondary than lenders, and lenders have greater access to private information about the firm operation than bondholders.

Our hypothesis centers on the risk-shifting explanation (Jensen and Meckling, 1976; see also John and John, 1993), while the results so far could also be consistent with the debt overhang theory (Myers, 1977). Shareholders concerned with large levels of existing debt deterring future investment could also choose to include DPMs in the compensation contract. In this scenario, lowering the immediate debt costs is a secondary outcome. Our descriptive results point to this explanation because "debt reduction" is a significant component of DPMs (refer to Table 1). We show that credit risks and debt maturity pressure can lead the borrower to include "debt-reduction" DPMs and other types of DPMs. However, we do not observe significant increases in "debt-reduction" DPMs when lenders change their perception of future default risk. Instead, we do observe such increases in other types of DPMs. These findings suggest shareholders, rather than lenders, may use the managerial compensation mechanism to address debt overhang concerns.[6] Nevertheless, all results do not rule out the possibility of a risk-shifting explanation.

In our last set of results, we explore the real activity consequence of DPMs. Using Trinity Industries as an example (see Appendix A Example 1), after incorporating "credit rating" DPMs for the performance period 2010-2012, the company maintained its target level of "BB+" and then achieved the investment-grade "BBB-" in May 2013, indicating a reduction in the company's credit risk following the introduction of DPMs. Empirically, we show that firms decrease their future R&D intensity and SG&A when they have DPMs in the compensation contract. The negative associations suggest managers are less likely to take risky investments in the presence of DPMs. Alternatively, shareholders may have predicted the low-growth opportunities and thus are more

[6] Another way to mitigate the debt overhang problem is to renegotiate past debt contracts (Myers, 1977). DPMs may facilitate more favorable terms during debt renegotiation, such as extending the maturity date, which could ultimately alleviate underinvestment concerns. A case in point is American Axle & Manufacturing Holdings, Inc., which established its 2010 threshold award level for net operating cash flow based on projections submitted to lenders during the amendment of their senior credit agreements and refinancing all senior debt maturities through 2014 (See Appendix A Example 6).

likely to approve the inclusion of DPMs in the previous years. In this context, DPMs are a mechanism that shareholders use to limit overinvestment in risky projects.

Prior studies show that compensation policy is associated with the agency cost of debt (Duru et al. 2005; Billett et al. 2010; Bizjak et al. 2019; Li et al. 2020). Including DPMs in executive compensation agreements helps mitigate these costs, which can also be addressed through alternative mechanisms, such as debt covenants between borrowers and lenders and inside debt included in managerial compensation (Sundaram and Yermack, 2007).[7] Our study contributes to the compensation literature by offering direct evidence of how and when firms *explicitly* incorporate debt-related performance metrics into executive compensation, complementing prior research by exploring another form of incorporating debtholders' interests into managerial compensation design. Intuitively, DPMs target debtholders' concerns more directly than stock-based performance metrics. Our hand-collected data show that firms include various debt-related factors far beyond cash flow measures.

Interestingly, we find that credit risk is related to DPM but not to non-DPM cash flow metrics. While recent studies have attempted to provide evidence on the consideration of agency cost of debt in executive compensation designs, the majority of them only focus on the scenario when the lenders exercise their control rights (i.e., around loan covenant violations), as seen in Balsam et al. (2018), Akins et al. (2019), and Armstrong et al. (2023).[8] We document that debt considerations in compensation designs occur not only during contingencies (e.g., covenant violations or financial distress) but also at normal times. For instance, we find that debt factors are more likely to be included in compensation designs before significant payments and debt issuances. More interestingly, compensation still serves as a channel to address lenders' concerns even when perceived but not actual credit risk changes. Against this backdrop, our study offers empirical

[7] Sundaram and Yermack (2007) demonstrate that defined benefit pension plans are an important form of "inside debt". However, since the early 2000s, there has been a widespread shift in pension coverage from defined benefit pension plans to defined contribution plans in the U.S. (Choy et al. 2014), resulting in reduced inside debt positions. We argue that this shift may further emphasize the importance of DPM mechanisms. Our results are robust to including controls for the CEO's inside debt-to-equity ratio and other CEO characteristics.

[8] In this context, our study emphasizes the dynamic aspect of speculative monitoring. For example, short-term creditors engage in a vigilant form of engagement, opting to strategically withdraw by not renewing debt obligations when they encounter unfavorable news, rather than directly influencing firm management (Tirole, 2006). This can be seen as a prudent risk management strategy that allows creditors to protect their interests without the complexity of intervention.

evidence based on the arguments in John and John (1993) in a more complete manner.

2. BACKGROUND AND HYPOTHESES

2.1 Background

A common view is that shareholders possess an inherent call option within their investment, as proposed by Merton in 1974. This option allows shareholders to reap the benefits of the firm's value exceeding the face value of debt while creditors endure asset volatility. To bring risk-averse managers' priorities in line with their own, shareholders may create incentive structures that encourage pursuing riskier investments. Consequently, this may generate risk-shifting motivations for managers, who can benefit from high-risk projects despite potentially negative net present values (Jensen and Meckling, 1976).

Creditors, recognizing the risk-seeking tendencies of borrowers, attempt to curtail such behavior through vigilant monitoring and implementing loan covenants.[9] Notably, though compensation contracts serve as effective monitoring mechanisms, little research highlights the role of debt within managerial compensation policies. An exception lies in the work of John and John (1993), who contend that the combination should inform optimal compensation structures of all external claims issued by a firm rather than solely equity. Focusing only on aligning managerial incentives with shareholder interests can exacerbate risk-shifting issues between shareholders and creditors, leading to elevated agency costs of debt.

2.2 Hypotheses Development

To tackle the agency cost of debt, including debt performance metrics (DPMs) in executive compensation contracts can be a viable solution. Although debt contract covenants are commonly employed to align the interests of debtholders and managers, incomplete contracting theory highlights the challenges of delineating creditor rights for all potential contingencies. Debt covenants may reduce firm value by limiting corporate insiders' discretionary power to handle

[9] Creditors often engage in various practices to exert control and reduce the risk associated with their investments in firms (Hong et al. 2021). These methods include imposing stringent conditions on corporate undertakings, diligently seeking updates and raising inquiries about ventures with a high risk, exercising influence over managerial decisions via board representation, and brandishing the specter of loan recalls, leadership reshuffles, or even foreclosures to ensure compliance with their stipulations.

unforeseen circumstances.

While debt covenants can address some incentive problems, they may not resolve all issues, and renegotiation can be costly and limited by coordination and free-rider problems. Therefore, DPM contracting can provide an alternative way for lenders to monitor borrowers without strict restrictions. By specifying a debt-related target and its corresponding compensation reward, managers are incentivized to take positive actions, improving the borrower's credit quality. Interestingly, Christ et al. (2012) find that penalty contracts can engender greater distrust than reward contracts. Consequently, DPM contracts that offer rewards instead of penalties may encourage higher management efforts under contingencies not governed by the contract.

Using managerial compensation contracts to address the agency cost of debt benefits all lenders involved. In contrast, debt covenant contracts create conflicts of interest among different lenders, as loaned amounts and seniority of repayment differ. DPMs in compensation contracts align the interests of all lenders and offer a preferred way to address their concerns, especially when their interests are misaligned. To test our hypothesis that DPMs are used more frequently for firms with stringent lender monitoring, we state our first prediction as follows:

H1: *Firms with stringent lenders' monitoring are more likely to use DPMs in executive compensation contracts.*

From the borrowers' vantage point, DPMs empower them to pledge their developing creditworthiness in forthcoming periods. The specific contractual language specifies particular objectives, allowing borrowers to employ debt-related indicators to convey the extent of their expected credit quality enhancement. Consequently, after examining the structure of executive compensation contracts, potential creditors would logically deduce that managers are driven to harmonize their interests with those of the creditors. As residual claim holders, shareholders benefit from the diminished agency expenses of debt. Considering the moral hazard dilemma inherent in investment policy, which results in incomplete contracting, borrowers use executive compensation agreements as an unspoken contract to pre-commit creditworthiness, which is in line with the reasoning presented in John and John (1993).

Appendix A showcases various instances of DPM compensation agreements disclosed in proxy statements. For example, Trinity Industries, Inc. has allotted a 15% weight to "credit rating" in the performance evaluation of its 2010 stock program. By achieving a "BB+" (or "BBB-") rating,

the manager may secure 70% (or 200%) of the compensation target. This performance standard enables the firm to commit to attaining an "investment-grade" rating within the subsequent three-year period.

We hypothesize that companies exhibiting lower credit quality are more inclined to use DPMs. Firms with poorer credit quality often confront unforeseen contingencies and necessitate pre-commitments to enhance their creditworthiness, thereby reducing the expense of future borrowing. Simultaneously, their existing lender might enforce heightened monitoring due to escalating credit risks. Our second prediction is articulated as follows:

H2: *Firms with lower credit quality are more likely to use DPMs in executive compensation contracts.*

We posit that the pressure exerted by impending debt maturity significantly influences the inclusion of DPMs within a company's compensation structure. As debt maturity looms, lenders grow increasingly apprehensive about the borrower's capacity to repay, fueling concerns surrounding the firm's ongoing viability. The potential ramifications of these concerns include the possibility of inefficient liquidations (Diamond, 1991, 1993; Sharpe, 1991) or the forced sale of vital assets at distressingly low prices (Brunnermeier and Yogo, 2009).

Further, debt overhang theory suggests that the pressure exerted by maturing debt may cause shareholders or management to be compensated with stock options to internalize only a fraction of the potential benefits of investment, thereby leading to underinvestment.[10] While DPMs can occasionally contribute to underinvestment issues, these metrics generally offer greater control for shareholders. Additionally, DPMs may facilitate more favorable terms during debt renegotiation, such as extending the maturity date, which could ultimately alleviate underinvestment concerns.

A case in point is American Axle & Manufacturing Holdings, Inc., which established its 2010 threshold award level for net operating cash flow based on projections submitted to lenders during the amendment of their senior credit agreements and refinancing all senior debt maturities through 2014 (See Appendix A Example 6). Building upon these premises, we anticipate that firms experiencing debt maturity pressure are more inclined to incorporate DPMs into their compensation strategies. We articulate our prediction as follows:

[10] Debt overhang, formalized by Myers (1977), captures the insight that investment often leads to external benefits that accrue to the firm's debt claims.

H3: *Firms with higher debt maturity pressure are more likely to use DPMs in executive compensation contracts.*

When the firm expects high growth opportunities or high-risk projects are planned, the shareholders are eager to obtain debt financing because the lenders bear fixed income. In contrast, the shareholders obtain incremental call-option benefits from the projects (Harris and Raviv, 1991). Creditors, realizing the moral hazard of the shareholders, price this risk by insisting on high borrowing costs. With the concern of high costs associated with the new borrowing, shareholders have incentives to request DPMs inclusion, aiming to pledge the borrower's developing creditworthiness. After examining the structure of executive compensation contracts, potential creditors could infer the credit quality enhancement of the borrower in the forthcoming periods. Consequently, as residual claim holders, shareholders benefit from the lower agency debt costs. Building on these premises, we anticipate that DPMs are more likely to be present before new borrowing. We articulate our prediction as follows:

H4: *Firms with higher borrowing propensity are more likely to use DPMs in executive compensation contracts.*

In the intricate dance of compensation arrangements, the board and management collaborate to design the terms, with the board ultimately giving its stamp of approval as the shareholders' proxy. A fascinating aspect is the shareholders' reaction to employing debt-performance metrics (DPMs). One potential scenario is that shareholders, in response to DPM usage, may opt to incorporate more non-debt indicators within the compensation contracts as a countermeasure against the escalating agency costs of equity. Conversely, it is plausible that shareholders would only endorse the use of DPMs if they do not detrimentally impact their value - meaning that the agency cost of equity remains unaffected by DPMs, thus eliminating the need for adjustments. Although no formal hypothesis is posited for this conjecture, it remains a thought-provoking consideration.

3. DATA AND VARIABLES

3.1 Sample Construction

We collect DPMs from annual proxy statements. In August 2006, the SEC adopted sweeping

changes to its executive compensation disclosure rules that mandate that public companies disclose executive compensation information in their annual proxy statements. The revised regulations require a new "Compensation Discussion and Analysis" (CDA) section. The new CDA section must explain and analyze all material elements of the company's compensation goals, practices, and decisions for the CEO, CFO, three other highest-paid executive officers, and directors.[11] We download all proxy statements during the 2007-2020 proxy seasons through the EDGAR system and then identify DPM contracts using manually summarized regular expressions.[12] The next section provides more details about our methodology for identifying DPM contracts.

We require sample firms to have a valid Central Index Key (CIK, the EDGAR unique firm identifier). We remove all financial firms due to their unique regulatory status and leverage levels. To derive our full sample, we match the firms with DPM contracts to those listed in the U.S. major stock exchanges based on CIK and the fiscal year in the merged Compustat/CRSP database. Of the 5,690 unique firms, 1,066 (18.73%) have incorporated *DPMs* into their executive compensation contracts at least once from 2007 to 2020.

3.2 The Identification of DPM Contracts

We define the borrowers who have incorporated DPMs (debt-performance metrics) in their compensation designs in a given year if they: (1) plan to award the managers based on a specific debt-related ratio (including *Leverage ratio, Credit rating, Debt/EBITDA, Cash flow/Debt, Debt (net of cash), Debt level, Funds from operation/Debt, Cost of debt, Debt and interest coverage, Liquidity,* and *Debt/Earning*);[13] (2) determine their managers' compensation based on a debt-related target (including *Debt reduction, Debt financing, Debt payment, Covenant compliance, and Maintain debt*); (3) plan to award the managers based on a financial metric and indicate that the purpose of including this metric is debt-related. For example, Core Molding Technologies, Inc. indicates that "the 2020 annual incentive plan was transitioned from the historical profit-sharing plan to a pay-for-

[11] The new rules also require companies to disclose specific quantitative or qualitative performance targets used to determine bonus payouts for executives, unless such disclosure would cause competitive harm by revealing trade secrets or confidential commercial or financial information.
[12] Details on our summarized regular expressions can be requested.
[13] There are many mechanisms through which compensation policy can provide value-increasing incentives, including performance-based bonuses and salary revisions, stock options, and performance-based dismissal decisions. This study does not distinguish these different mechanisms.

performance plan that awarded improving "EBITDA" which would provide cash flows to stabilize and improve the business and refinance our credit facility." The purpose of including this "EBITDA" metric in the incentive plan is debt-related. Therefore, we identify this as a DPM contract. Appendix A lists more examples of firms adopting different DPMs in their compensation contracts.

We identify DPM contracts using regular expressions in Python. We first summarize debt performance metrics by referring to the Incentive Lab Database, which provides the performance metrics for S&P500 and a significant portion of S&P400. The debt performance metrics can have different expressions. For example, "debt to EBITDA" and "net debt to adjusted pro forma EBITDA" should be classified into the same category. Therefore, to better identify debt performance metrics, we do not use keyword search but construct regular expressions of the metrics. Then, we parse all proxy statements and extract three sentences (and 1,000 characters) before and after these debt performance metrics. Next, by reading around 1,000 filtered paragraphs, we manually identify about 150 DPM compensation contracts and summarize regular regressions for these contracts. Then, we identify all DPM contracts by using these summarized regular regressions. Finally, we manually read through and filtered this reduced set of paragraphs by doing several rounds of random checking and filtering to arrive at a final set of 3,127 firm-years with DPM contracts.

3.3 Summary Statistics

Figure 1 Panel A displays the time trend of the percentage of firms with DPM contracts during the fiscal year 2007-2020. The fiscal year 2007 is the first year in which the CDA section is mandated.[14] Before discussing changes in the percentage of firms with DPM contracts over time, we note that the average leverage ratio (debt/assets) increased by 50% between 2007 and 2020, while the percentage of firms with DPM contracts increased by 196% during the same periods, rising from 3.4% to 10%. Interestingly, we notice a significant increasing trend between 2007-2010 and 2017-2020, during which there were also significant fluctuations in supply-side lending strictness (as measured by the net percentage of banks tightening lending standards), as seen in

[14] The new CDA section must explain and analyze all material elements of the company's compensation goals, practices and decisions for the CEO, CFO, three other highest-paid executive officers, and the directors.

Figure 1 Panel B. Figure 1 Panel C displays the industry distribution (Fama & French 12 industries classification) of the percentage of firm-years with DPMs contracts during the fiscal year 2007-2020. DPMs are common across industries. About 31.4% of firm-years with DPM contracts are operating in "Other" and "Chemicals and Allied Products" Industries, while roughly 19% of firm-years in the "Wholesale, Retail, and Some Services" have incorporated DPMs during our sample period (the sample mean is 7% as shown in Table 2 Panel A).

[Insert Figure 1]

Figure 2 further depicts the DPM distribution among the sample firms when they have either syndicated loans, bonds, or both. We categorize the 5,690 unique firms into different groups based on whether the firms have outstanding loans or bonds during the sample period. It shows that among the 43% of unique firms that participate in the main debt markets, they include DPM in their managerial compensation contract, strengthening the case of DPM serving creditors' interest.

[Insert Figure 2]

Table 1 shows the frequency of different DPMs used by firms. The most frequently used DPM is "*Debt Reduction*"; about 33.6% of firm-years with DPM contracts incorporate the "*Debt Reduction*" target. Compared to the financial ratio, the debt-related targets are more frequently incorporated (i.e., *Debt Reduction, Debt financing, Debt payment*).[15] Among all the debt-related financial ratios, the most frequently used are "*Leverage ratio*" (i.e., debt to capital ratio or debt to assets ratio) and "*Credit rating.*" Other common financial ratios in credit agreements are also frequently used in compensation contracts, such as "*Debt/EBITDA*" and "*Cash flow/Debt.*"

[Insert Table 1]

In addition, Figure 3 compares the types of DPMs and covenants. It displays the average proportion of each type of DPMs (or loan covenants) out of the total in each firm-year. Following Christensen and Nikolaev (2012), we categorize covenants and DPMs into capital-based and performance-based.[16] We aggregate the outstanding covenants at the firm-year level. The

[15] The high frequency of the use of debt-related targets DPMs may be caused by our categorization method. For example, if a firm uses free cash flow as a performance measure and then indicates that the use of this measure is to reduce debt, then we count this measure as both the "*Debt reduction*" metric and the "*Cash flow/Debt*" metric.

[16] Specifically, we define capital-based covenants as those based on a function of variables such as net worth, leverage ratio (debt to asset or equity), loan-to-value, and current ratio. Performance-based covenants, on the other hand, are defined as those based on variables such as debt-to-cash flow and coverage ratio. Using the same logic, we categorize

proportion is calculated by dividing the average number of different types of DPMs (or covenants) in each firm-year by the average number of all types in each firm-year. The figure shows that DPMs typically concentrate on capital-based metrics such as debt or leverage levels, while debt covenants focus more on performance-based metrics such as debt-to-cash flow ratios. Note that, interestingly, in some cases, borrowers even select DPM metrics based on the covenants outlined in their debt contracts (see Appendix A Example 5).

[Insert Figure 3]

Table 2 Panel A presents summary statistics for the sample of firms listed in the U.S. major stock exchanges during the fiscal year 2007-2020 in the merged Compustat/CRSP database. We exclude those firms with missing values for *Debt/EBITDA, Leverage, Debt/Equity, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth,* and *FirmAge*. All variable definitions and data sources can be found in Appendix B. We winsorize all the continuous variables at the 1st and 99th percentiles to reduce the influence of outliers. 7% of the firm-years contain DPM contracts, while this percentage becomes 26.5% if we only look at those firms that have used DPM contracts during the whole sample period. The average number of DPMs used is 0.1 for a firm in one year.

[Insert Table 2]

Table 2 Panel B shows how the firm-level characteristics vary across firm-years with DPMs and firm-years without DPMs. In general, firm-years with DPM contracts have significantly lower credit ratings, higher probabilities of expected default, and higher leverage. These statistics support our second hypothesis that firms with lower credit quality have more incentives to construct executive compensation with DPMs, which we explore further in Section IV. Interestingly, these firm-years with DPM contracts usually have larger size, higher tangibility, higher operating cash flow, and higher ROA, but lower market-to-book ratio and lower sales growth. These statistics seem to suggest that, compared to young firms, mature firms are more likely to incorporate DPMs in their compensation designs. Moreover, firms that are covered by rating agencies and firms that have accessed the syndicated loan market are more likely to incorporate DPMs in their

DPMs into capital-based DPM (i.e., debt reduction, debt financing, debt payment, maintain debt, leverage ratio, debt (net of cash), debt level, liquidity) and performance-based DPM (i.e., debt/EBITDA, cash flow/debt, funds from operation/debt, debt/earning, debt and interest coverage).

compensation designs. These statistics seem to suggest that outside monitoring may trigger the use of DPMs.

4. EMPIRICAL FINDINGS

4.1 Credit Quality and DPM Contracting

We use three measures of credit quality to estimate the impact of a credit quality on the likelihood of observing a DPM compensation contract in a firm. First, for the full sample, following Nini et al. (2009), we use the borrower's debt-to-EBITDA ratio as a measure of credit quality. The motivation for using debt-to-EBITDA is that it is easy to measure, available for almost all borrowers, and is the basis for the most common financial covenants utilized by banks. Second, we proxy credit quality by using the expected default frequency (*EDF*) calculated based on Merton's (1974) model. We compute *EDF* using the procedure in Bharath and Shumway (2008). We use the median value of quarterly *EDF* in that fiscal year to measure the expected default frequency. Higher *EDF* indicates a higher default probability.[17] Last, we use the borrower's credit rating (*CreditRating*) in the previous year as a measure of credit quality. Larger *CreditRating* indicates better ratings. The drawback of the credit rating measure is that it is only available for rated firms, which comprise 29% of our sample.

[Insert Table 3]

Table 3 presents estimated coefficients from linear regressions that relate the probability of having DPMs (or the number of DPMs) to the measures of borrower credit quality. All regressions control for firm-specific characteristics (including *Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year-fixed effects, and firm (or industry) fixed effects. In all regressions, standard errors are clustered at the firm level. We use two dependent variables in our regressions: 1) *DPM* is an indicator variable that equals one if the firm has a DPM contract in the given year, i.e., when the firm incorporates debt performance metrics in their executive compensation designs; 2) *NumDPM* is the number of debt performance metrics a firm uses in a given year.

[17] Details on the computation of these values and STATA code refer to the appendix of Gomes, Grotteria, and Wachter (2019). The calculation method of *EDF* causes some missing values.

Almost in all specifications (except for columns (1) and (5) in Table 3 Panel B), there is a statistically significant increase in the likelihood of using DPMs and an increase in the number of used DPMs (*NumDPM*) when the value of *Debt-to-EBITDA* and *EDF* increases or when the value of *CreditRating* decreases. In the tests in Online Appendix, the main results are robust when we further control for CEO characteristics, including the CEO's inside debt-to-equity ratio, total compensation level, tenure years, and CEO duality; also, the results remain robust when we use the Logit model instead of OLS estimation. The results suggest that, even within a firm, credit quality is negatively associated with the presence of DPMs.

In Table 3 Panel B, we further use the *EDF* quantile indicator variables to explore the impact of credit quality on DPM. We define *EDF_High* as a dummy variable that indicates those firm-years with the value of expected default frequency in the highest quantile, and we define *EDF_Low* as a dummy variable that indicates those firm-years with the value of expected default frequency in the lowest quantile. In column (4), the results show that, compared with other firms (i.e., those with *EDF* value in the 2nd, 3rd, and 4th quantile), firms with *EDF* value in the highest quantile have a higher likelihood (i.e., 2.3% increase) to use DPMs. Given the mean likelihood of 7%, this effect represents a 33% increase in the likelihood evaluated relative to the mean. Compared with other firms, firms with *EDF* value in the lowest quantile have a lower likelihood (i.e., 3.1% decrease) to use DPMs, which represents a 44% decrease in the likelihood evaluated relative to the mean.

In Table 3 Panel C, we also use the credit rating category indicator to explore the impact of credit quality. We define "*BB rated or worse*" as a dummy variable that indicates those firm-years with speculative-grade ratings. We define "*A rated or better*" as a dummy variable that indicates those firm-years with credit ratings above A. The omitted group contains those firm-years with the lowest investment-grade ratings (BBB). In column (3), the results show that there is a statistically significant increase (i.e., 8% increase) in the likelihood of a firm using DPMs when moving from the BBB rated to a speculative-grade rating, which is around 51% increase of the mean in the rated sample. However, there is a statistically significant decrease (i.e., a 9.2% decrease) in the likelihood of a firm using DPMs when moving from the BBB rated to the higher investment-grade rating, which is around a 59% decrease of the mean in the rated sample. Furthermore, Morgan (2002) argues that differences of opinion between rating agencies will be both frequent and larger in

magnitude when more uncertainty exists regarding the ex-ante distribution of credit risk. In column (4), we include a dummy variable, "*RatingDisagree*", which equals 1 if split ratings exist for a firm in a given year. Our result shows that the likelihood of a firm using DPMs experiences a significant increase by 3.3% when there exist split ratings, which represent a 21% increase of the mean in the rated sample. This suggests that borrowers are more likely to use DPMs when more uncertainty exists regarding their credit risks.

Overall, we find that borrowers are more likely to use DPMs in response to increases in their credit risks, as measured by their debt-to-EBITDA, expected default frequency (based on Merton's (1974) model), and credit rating. This result suggests that aligning managerial behaviors with the interests of creditors becomes more relevant as the riskiness of the debt increases. It is also consistent with the model of John and John (1993), in which a negative relationship between pay-performance sensitivity and leverage is derived.

In Figure 4, we graphically relate the presence of DPMs to the level of market credit risk. Δ*DPM* is calculated as the difference between realized and predicted DPM probability, derived from the linear regressions that relate the probability of having DPMs to lagged firm-specific characteristics (including *Leverage, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*) and firm-fixed effects. Δ*NetDebt* is calculated as the difference between realized and predicted net debt issuance, derived from the linear regressions that relate the net debt issuance scaled by lagged assets to lagged firm-specific characteristics and firm-fixed effects. Our proxy for high market credit risk is a variable indicating Moody's Baa–Aaa credit spread was greater than or equal to the median value for the years from 2000 to 2020. The results show that when the market credit spread is high, firms are less likely to access debt financing while using DPMs more frequently in the compensation contracts, consistent with the notion that firms use DPM to mitigate creditors' concerns.

[Insert Figure 4]

4.2 Lender Monitoring and DPM Contracting

Our preliminary tests are consistent with our arguments but allow only limited causal

inferences. To facilitate causal inferences, our identification strategy relies on a lender-specific shock, defaults in a lender's corporate loan portfolio, as an exogenous shock to the lenders' monitoring incentives. We estimate the impact of stringent lender monitoring on the likelihood of observing a DPM compensation contract in a firm.

This choice is motivated by several recent papers that strongly suggest that defaults to lender loan portfolios affect lending behavior at the defaulted-upon banks. For example, Murfin (2012) shows that banks write tighter contracts than their peers after suffering recent payment defaults to their own loan portfolios. Christensen et al. (2022) show that lenders respond to recent payment defaults to their own portfolios by increasing the number and strictness of performance-based but not capital-based covenants in debt contracts. They argue that recent defaults can deplete capital and cause the lender to prefer heavier and timelier control over borrowers; further, recent defaults can also inform the lender's screening ability or its inability to control a borrower's moral hazard, thereby impacting its lending behavior. Following these arguments, we predict that lenders who experience recent payment defaults are likely to attach greater value to the monitoring role of DPMs.

Following Murfin (2012), we rely on the Capital IQ S&P credit ratings database to identify borrowers who experience default or selective default. This captures borrowers that have had a payment default on at least one obligation.[18] The default borrowers are matched back to DealScan, which provides the list of loans for each default borrower. After removing loans that were not outstanding at the time of default based on their reported origination and maturity dates, we obtain a record of all the defaults for a given loan arranger and the timing of those defaults.[19] We identify the current borrowers of the loan arranger who experienced recent payment defaults in their portfolio as the treatment group. We define the treatment time as the lender's first experience of defaults since 1993, and in our regressions, we only analyze the first treatment effects for a borrower, excluding companies without syndicated loans as well as defaulting companies. Analyses

[18] This count may miss defaults by small, unrated borrowers, but will capture visible defaults likely to sway loan officer behavior.

[19] We focus on loan arrangers (or managers) assigned during the general syndication (i.e., retail phase) because these lenders are significant syndication participants with large loan commitments (S&P market intelligence 2020, see: https://www.lcdcomps.com/d/pdf/LCD%20Loan%20Primer.pdf).

in Online Appendix reveal that our results are robust if we eliminate borrowers for which the first treatment falls before 2007 (i.e., the starting year of our sample period). If corporate defaults occur in the borrower's region or industry, there could potentially be an econometric issue due to their correlation with local and industry-specific economic factors. These factors influence borrower fundamentals and may be correlated with the use of DPM monitoring for reasons other than lender preferences. To mitigate this issue, we also follow Murfin (2012) and exclude payment defaults in the borrower's geographic region and industry.[20] We collect the default sample over the period 2007–2020.

We use a difference-in-difference research design. We examine the changes in the likelihood of using DPMs of treatment firms, from before their current lenders experienced recent payment default, relative to contemporaneous changes for a set of control firms that have the most similar characteristics as the treatment firms, but their current lenders do not experience recent payment defaults.

[Insert Table 4]

Table 4 presents estimated coefficients from linear regressions that relate the probability of having DPMs (or the number of DPMs) to the defaults in a lender's corporate loan portfolio. $Post_t \times Default_i$ is an indicator variable that equals one if at least one loan arranger of the borrower has experienced a payment default before the given year, and the borrower's loans arranged by this lender are outstanding at the time of default. All regressions control for firm-specific characteristics (including *Debt/EBITDA, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge)*, year-fixed effects, and firm-fixed effects. In all regressions, standard errors are clustered at firm level.

Table 4 Panel A reports the tests on the full sample of firms, excluding those without syndicated loans and defaulting borrowers. Table 4 Panel B further excludes the lenders' current borrowers who are in the same industries or geographic regions as the defaulting borrowers at the time of defaults. We use two dependent variables in our regressions: 1) *DPM* is an indicator variable that equals one if the firm has a DPM contract in the given year; 2) *NumDPM* is the number of debt performance metrics used in the given year by a firm. In Columns (1) and (2), we report results

[20] Within the United States and Canada, the geographic region of the borrower is state and province, respectively. All other domiciles are classified as one international region.

using a large, unmatched sample of control firms. In Columns (3) and (4), we conduct entropy-balanced matching with three moments. In Columns (5) and (6), we conduct propensity-score matching using nearest neighbor matching with replacement. In Columns (7) and (8), we conduct propensity-score matching using three-nearest neighbor matching with a caliper of 0.03. We conduct all matching based on *Rated, InvestmentGrade, Leverage, MtB, and Assets*.

In all specifications, the results show that after lenders experience recent payment defaults, their current other borrowers experience an increase in the likelihood to incorporate DPMs between 3.6% and 4.2% (depending on the specification), even when defaulting borrowers are in different industries and geographic regions from the current borrower. Given the mean likelihood of 10.5% in the sample of firms that have accessed the syndicated loan market, this effect represents a 34%-40% increase in the likelihood evaluated relative to the mean. These results provide evidence in support of hypothesis one, which is that firms with stringent lenders' monitoring are more likely to use DPMs in executive compensation contracts.

As with any difference-in-difference design, our approach assumes that the entire frequency distribution of DPM in the treated and untreated firms would move in parallel in the absence of the treatment. To evaluate the treatment effects of the pre- and post-treatment periods, we use a difference-in-difference event study design. We consider three leads and three lags around the treatment period. We examine the changes in the likelihood of using DPMs of treatment firms, within a six-year window around their current lender's experience of payment default, relative to contemporaneous changes for a set of control firms that have the most similar characteristics as the treatment firms, but their current lenders do not experience recent payment defaults during the sample period. In this test, we have a smaller sample size since we only consider a six-year window around the treatment event. Table 4 Panel C reports the DID event study results. In all specifications, the results show that after lenders experience recent payment defaults, their current other borrowers experience an increase in the likelihood to incorporate DPM, while we do not find treatment effects before the treatment event. In Figure 5, we further plot the event-study dynamics as shown in Table 4, Panel C, Column (1) (in orange with circle markers). Then, we also address recent econometric concerns with staggered DID designs by showing robustness to the use of two alternative estimators: Callaway and Sant'Anna (2021) (in red with cross markers), and the Stacked

DID estimator (in blue with diamond markers). Overall, our results are robust across alternative DID estimators, as suggested by Baker et al. (2022).

[Insert Figure 5]

4.3 Repayment Pressure and DPM Contracting

The important aspects of debt maturity are that imminent maturity increases potential costs stemming from repayment risk and refinancing risk. We hypothesize that debt principal repayment pressure plays an important role in spurring the presence of DPMs. To proxy for repayment pressure, prior work focuses on the fraction of a firm's total debt that is due in the next three years. Following Harford et al. (2014), we further exclude debt with less than a year to maturity when issued.[21] As such, we use the fraction of a firm's long-term debt due in the following years (including the current portion of this debt) as our main proxy for the debt repayment pressure. To better explore the impact of this pressure, we further obtain the distribution of debt maturity by using six indicator variables: *Due_1st_Year%*, *Due_2nd_Year%*, *Due_3rd_Year%*, *Due_4th_Year%*, *Due_5th_Year%,* and *Due_other_Year%*. These variables represent the proportion of long-term debt due in one year, in the 2nd year, in the 3rd year, in the 4th year, in the 5th year, and debts due in more than 5 years, respectively.

[Insert Table 5]

Table 5 presents estimated coefficients from linear regressions that relate the probability of having DPMs (or the number of DPMs) to the debt maturity pressure. All regressions control for firm-specific characteristics (including *Leverage*, *Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, and FirmAge*), year- and firm-fixed effects. In all regressions, standard errors are clustered at the firm level. We use two dependent variables in our regressions: 1) *DPM* is an indicator variable that equals one if the firm has a DPM contract in the given year; 2) *NumDPM* is the number of debt performance metrics used in the given year by a firm.

In all specifications, our results show that borrowers are more likely to use DPMs in response

[21] We do so because these debts are used to finance a firm's short-term assets and other short-term liquidity needs that are often seasonal in nature.

to the shortening debt maturity; this is especially true when more debts are maturing in 2 years or less. This result is robust when we control for firm-level characteristics, firm-fixed effects, and year-fixed effects. This suggests that, even within a firm, the time-series changes of maturity pressure could trigger the use of DPMs. In columns (2) and (3) of Panel A and Panel B, the results show that firms with a higher proportion of long-term debt due in the next two-year period experience a significant increase in the likelihood of using DPMs, that is, a 10% increase of the proportion of long-term debt due in next two years leads to an approximately 0.25% increase of the likelihood of using DPMs. However, the debt maturity pressure due in the 3rd, 4th, and 5th year does not significantly impact the likelihood of using DPMs.

4.4 Shareholders' Response to the Inclusion of DPMs: Non-debt Metrics

As compensation plans are approved by the board representing the shareholders, we further explore the shareholders' response to the use of DPMs. It is possible that, in response to the use of DPMs, the shareholders put more non-debt metrics in the compensation contracts to mitigate the increasing agency cost of equity. However, it is also possible that, if DPMs do not harm the value of shareholders (i.e., the agency cost of equity does not increase due to the *DPMs*), shareholders would approve the use of DPMs and thus have no need to make any adjustments.

We collect non-debt performance metrics (i.e., non-debt-related accounting metrics and stock price metrics) from the Incentive Lab Database, which provides the performance metrics for S&P500 and a significant portion of S&P400, thus leading to a smaller sample. Therefore, in the tests below, we only use a sample of firms that have records in the Incentive Lab Database. To measure the use of non-debt metrics, we count the number of non-debt performance metrics for each firm-year. We collect the sample over the period 2007-2020.

[Insert Table 6]

Table 6 Panel A compares how the number of non-debt metrics varies across firm-years with DPMs and firm-years without DPMs. The results show that firm-years with DPM contracts have significantly more non-debt metrics (i.e., 0.474) in the compensation design. The statistics support our prediction that in response to the use of DPMs, the shareholders put more non-debt metrics in the compensation contracts to mitigate the increasing agency cost of equity, something we explore further in Table 6 Panel B. This significant difference may come from the systematic

differences between firms that have different levels of debt. To mitigate this issue, we further present an analysis of a subsample of firms that have used DPMs during the sample period. Although the magnitude becomes smaller, the results still show that firm-years with DPM contracts have significantly more non-debt metrics in the compensation design.

Table 6 Panel B presents estimated coefficients from linear regressions that relate the number of non-debt metrics to the presence of DPMs and the number of DPMs *(NumDPM)*. All regressions control for firm-specific characteristics (including *Debt/EBITDA, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, and FirmAge*), year- and firm-fixed effects. In all regressions, standard errors are clustered at firm level. We use two independent variables in our regressions: 1) *DPM* is an indicator variable that equals one if the firm has a DPM contract in the given year; 2) *NumDPM* is the number of debt performance metrics used in the given year by a firm. The dependent variable is the *Number of Non-debt metrics*, which represents the number of non-debt metrics utilized by the firm in the same year. In columns (1) and (2), we conduct the estimation in the full sample, while in columns (3) and (4), we conduct the estimation in a subsample of firms that have used DPMs during the sample period. In columns (5) and (6), we further conduct the estimation using a matched sample. We conduct propensity-score matching using three-nearest neighbor matching with a caliper of 0.03 based on the firm's outstanding amount of syndicated loans scaled by its total assets in a given year.

In all specifications, there is a statistically significant increase in the number of non-debt metrics utilized by the firm when a DPM is imposed in the same year. The results suggest that, even within a firm, the number of non-debt metrics utilized by the firm is highly associated with the presence of DPMs in the same year. This estimation provides evidence that shareholders rebalance the executive incentives in the presence of DPMs, thereby tilting incentives away from the interests of creditors.

4.5 Debt Financing Needs and DPM Contracting

So far, we have explored the factors that affect the inclusion of DPM in managerial compensation contracts, focusing on the lenders' perspective. We now turn to the shareholders' angle in Table 7. Shareholders, relative to debtholders, are concerned more about obtaining the

upbeat potential from growth opportunities. In other words, when such financing needs arise, shareholders are eager to obtain debt financing with a lower cost of borrowing. It follows that shareholders are willing to include DPM in compensation contracts if such an arrangement facilitates loan financing and lowers the cost of borrowing. Table 7 checks whether DPMs are more likely to be included before the issuance of a new debt issuance and whether DPM inclusion is associated with a lower cost of debt.

[Insert Table 7]

Table 7 Panel A presents estimated coefficients from linear regressions that relate the probability of having DPMs (or the number of DPMs) to the following issuance of a new bond or new syndicated loan in the same year. Panel A contains the sample of firms that issued at least one new bond or new syndicated loan during the sample period. We find that after controlling for industry and year-fixed effects, the subsequent bond or loan issuance is positively associated with the probability of having DPMs. Economically, in column (1), we find that the likelihood of having DPMs experiences a significant increase by 81% or 47%, respectively. When we split the sample into firms with bonds or loans exclusively in columns (3) – (6), we find similar inferences.

We next turn to the consequence of DPM for the cost of borrowing. Table 7 Panel B presents the results with a sample of firms that issue at least two syndicated loans or two public bonds during the sample period. Our strategy here is to compare the cost of borrowing between the first and second borrowing for the same firm. In Panel B, the dependent variable (*Diff_LoanSpread* or *Diff_BondSpread*) is the difference in yield spread between the current loan and the previous loan (or between the current bond and the previous bond) for the same firm; the independent variable (*DPM*) is a dummy variable indicating if the firm incorporated at least one DPM after the issuance of the prior bond/loan but before the issuance of the current bond/loan. In columns (1) and (2), we observe that the inclusion of DPM in the compensation contract is associated with an approximately 15 basis points lower loan yield spread, respectively, compared to when the firm does not include DPM in the compensation contract before obtaining a new loan. In contrast, in columns (3) and (4), we find no effect on the bond yield spread. Alternative sample results in columns (5) and (6) confirm the findings of the main sample. The results are consistent with the expectations that bondholders have a better second market to diversify their risk than lenders. In

addition, loans often grant lenders access to private information about the firm operations, while bondholders usually do not have that. As such, the benefit of DPM on the yield spread only manifests among the loan lenders. Overall, Table 7 results clearly indicate that the shareholders desire the inclusion of DPM when debt financing benefits them.

4.6 Debt Overhang

Our arguments are inspired by John and John (1993), who model risk-shifting and CEO compensations. However, our results could also be consistent with debt overhang theory (Myers, 1977). Shareholders concerned with large levels of existing debt deterring future investment could include DPMs in the compensation contract. In this scenario, lowering the immediate debt costs is a secondary outcome. Our descriptive results point to this explanation because "debt reduction" is a significant component of DPMs (refer to Table 1). We replicate the estimations from Tables 3 and 5, but categorizing DPMs into "debt reduction" metrics and other metrics (See Online Appendix). We demonstrate that credit risks and debt maturity pressure can prompt borrowers to incorporate "debt-reduction" DPMs and/or other types of DPMs. However, we do not observe significant increases in "debt-reduction" DPMs when lenders change their perception of future default risk. Instead, we do observe such increases in other types of DPMs. This overall suggests shareholders, rather than lenders, are likely to use the managerial compensation mechanism to address debt overhang concerns.[22] Nevertheless, all results so far do not rule out the possibility of a risk-shifting explanation.

4.7 DPM Contracting and Risk-taking Behaviors

In our last set of results, we explore the association between the presence of DPMs and future risk-taking behaviors. Again, using Trinity Industries as an example, after incorporating "credit rating" DPMs for the performance period 2010-2012, the company maintained its target level of "BB+" and then achieved the investment-grade "BBB-" in May 2013, indicating a reduction in the company's credit risk following the introduction of DPMs. Empirically, following prior

[22] Another way to eliminate debt overhang problem is to renegotiate past debt contracts (Myers 1977). DPMs may facilitate more favorable terms during debt renegotiation, such as extending the maturity date, which could ultimately alleviate underinvestment concerns. A case in point is American Axle & Manufacturing Holdings, Inc., which established its 2010 threshold award level for net operating cash flow based on projections submitted to lenders during the amendment of their senior credit agreements and refinancing all senior debt maturities through 2014 (See Appendix A Example 6).

literature (e.g., Hong et al. (2021)), we use two proxies for risky investments. The first proxy is research and development investments (R&D) intensity. This proxy is motivated by Shi (2003), who shows that "for creditors, the R&D risk dominates their benefits." We scale R&D expenses by sales to obtain R&D intensity. The second proxy is selling, general, and administrative outlays (SG&A). This proxy (SG&A) is motivated by Choi and Richardson (2016), who show that operating leverage (ratio of SG&A to operating costs) is associated with higher asset volatility. We scale SG&A costs by operating expenses to obtain SG&A.

[Insert Table 8]

Table 8 presents estimated coefficients from linear regressions that relate future risky investments to the presence of DPMs and the number of DPMs *(NumDPM)*. All regressions control for firm-specific characteristics (including *Debt/EBITDA, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year- and industry-fixed effects. In all regressions, standard errors are clustered at the firm level. We use two independent variables in our regressions: 1) *DPM* is an indicator variable that equals one if the firm has a DPM contract in the given year; 2) *NumDPM* is the number of debt performance metrics used in the given year by a firm. The dependent variable is $RDIntensity_{t+1}$, $RDIntensity_{(t+1)-(t+3)}$, $SG\&A_{t+1}$, $SG\&A_{(t+1)-(t+3)}$, which represents R&D intensity in the next year, R&D intensity in the next three years, SG&A in the next year and SG&A in the next three years, respectively.

The results show that firms with a DPM contract experience significant decreases in their R&D intensity and SG&A, at least in the next three years. This result is robust to including firm-level control variables, industry-fixed effects, and year-fixed effects. These negative associations suggest that managers are less likely to take risky investments after the presence of DPMs. Alternatively, shareholders may have predicted the low growth opportunities and thus are more likely to approve the inclusion of DPMs in the previous years.

5. CONCLUSION

Based on novel data from the proxy statements, we provide empirical evidence of how and when firms *explicitly* incorporate debt-related performance metrics into executive compensation

across various types of firms. These metrics appear to help align managerial behaviors with the interests of creditors, and thus, the managers have incentives to change the operating characteristics of the firm to mitigate the risk-shifting problem between the shareholders and the creditors.

The results show that around 19% of the firms listed in the U.S. major stock exchanges have incorporated DPMs in their compensation designs at least once during the period 2007-2020, particularly after their creditors' monitoring incentives become stronger after their credit quality deteriorates, or when they are facing debt repayment pressure. Further, we find similar results when debt financing benefits the shareholders. We also demonstrate that, in response to the inclusion of DPMs, shareholders put more non-debt metrics in their incentive programs. In addition, we find evidence that firms with DPM contracts experience significant decreases in their R&D intensity and SG&A, at least in the next three years. Overall, our empirical results suggest that borrowers take the agency cost of debt into their executive compensation considerations, not only during contingencies but also at normal times. Our study also highlights the importance of debt-related factors in executive compensation beyond simple cash flow measures.

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Appendix A: Examples of DPM in compensation contracts

Example 1: Trinity Industries, Inc.
https://www.sec.gov/Archives/edgar/data/99780/000119312513135351/d505161ddef14a.htm
https://www.sec.gov/Archives/edgar/data/99780/000095012311031796/d80055def14a.htm

In March 2010, the HR Committee approved the establishment of four key metrics in determining equity grants for the performance periods 2010-2011 and 2010-2012. The metrics are (i) cumulative Company ROE, (ii) cumulative net income, (iii) cumulative revenue from acquisitions or organic growth, and (iv) **the Company's credit rating**. Each of these metrics cultivates management concentration on performance improvements linked to long-term stockholder value. Taken together, these metrics compel management to address growth and investment relative to risk and liquidity. The performance-based threshold level and target level performance goals for all named executive officers with respect to the four metrics are shown in Table 5.

Grant Periods	Return on Equity (30% Weight)			Net Income (30% Weight)			Revenue from Acquisition or Organic Growth (25% Weight)			Credit Rating (15% Weight)		
	Threshold	Target	Maximum	Threshold	Target	Maximum	Threshold	Target	Maximum	Threshold	Target	Maximum
2012	5%	8%	15%	$75 M	$125 M	$200 M	$150 M	$250 M	$400 M	BB	BB+	BBB-
2013	8%	12%	20%	$150 M	$200 M	$300 M	$250 M	$375 M	$600 M	BB	BB+	BBB-

Example 2: American Electric Power Company, Inc.
https://www.sec.gov/Archives/edgar/data/4904/000119312510056811/ddef14a.htm

For 2009, the HR Committee also added a credit rating deduction to the funding measure. The credit rating deduction would have reduced the overall score for executive officers by 10% at the HR Committee's discretion **if one of the major credit rating agencies reduced the rating** on the Company's senior unsecured debt during the year. The HR Committee added this feature in 2009 because it believed the Company needed to maintain good access to the financial markets during the difficult economic times.

Example 3: Cheniere Energy, Inc.
https://www.sec.gov/Archives/edgar/data/3570/000119312511057743/dpre14a.htm

2011 Long-Term Incentive Awards. On January 4, 2011, the Compensation Committee also determined that the Company had achieved significant **corporate debt reduction** and milestones related to the liquefaction project at the Sabine Pass LNG terminal during 2010 that deserved recognition and used its discretion to approve a pool of 2,000,000 shares of restricted stock of the Company to be granted to certain employees, including the Executive Officers (the "2011 Long-Term Incentive Awards"). The Compensation Committee determined that the 2011 Long-Term Incentive Awards were appropriate to compensate certain employees, including the Executive Officers, for corporate debt reduction and the elimination of significant interest expense resulting in the improvement of the Company's liquidity position …The specific corporate debt reduction and liquefaction project milestones are outlined below:

- Corporate Debt Reduction
  - — Pre-paid $64 million of convertible debt and corresponding interest savings
  - — Pre-paid $102 million of term loan debt and corresponding interest savings
  - — Reduced by $3 million costs related to corporate overhead and tax payments

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Example 4: Southwestern Energy Company
https://www.sec.gov/Archives/edgar/data/7332/000120677420001113/swn3648531-def14a.htm

For each NEO, the Compensation Committee also determined the size of the individual component of the annual cash incentive, which together with the formulaic component, comprises the total individual award levels. At target, the individual component would constitute 30% of each NEO's annual cash incentive. The bonus amounts that each NEO actually received reflect both the overall company results and each individual's contributions to the Company's strong operating and strategic performance in 2019. For 2019, the Compensation Committee assessed Mr. Way's individual performance at target. In assessing Mr. Way's performance, the Compensation Committee considered Mr. Way's significant contribution to achieving, among other things, the following:

● **Decreased debt** by repurchasing $62 million of outstanding long-term senior notes at a discount and retiring the remaining $52 million of senior notes due in 2020

● Realized year-end **net debt/EBITDA** was 2.3x

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Example 5: LoJack Corporation

https://www.sec.gov/Archives/edgar/data/355777/000119312510079077/ddef14a.htm

In February 2010, the Committee further refined its practices and replaced the operating income targets with EBITDA targets in order to recognize the importance of cash flow **in light of the Company's compliance covenants** under its new credit facility. These measures more appropriately reflect our enhanced focus on our cash position, drive shareholder value and are directly influenced by management's actions. This performance metric also more closely tracks how management and the Company's lenders measure Company performance.

Example 6: American Axle & Manufacturing Holdings, Inc.

https://www.sec.gov/Archives/edgar/data/1062231/000095012311027006/k50099ddef14a.htm

In support of the Company's 2010 strategic initiatives, the Committee approved the use of net operating cash flow as the sole performance metric to be used in determining 2010 annual incentives for the following reasons:

◆ Cash flow is a critical financial metric for AAM at this time **due to its impact on liquidity and debt reduction**.

◆ Increasing cash flow is key to **achieving credit rating upgrades**, which will have a favorable impact on the Company's **cost of future financing**; and

◆ The Committee believes increasing cash flow benefits AAM stakeholders.

The 2010 threshold award level for net operating cash flow was based on projections provided to AAM's lenders in 2009 in **obtaining amendments to our senior credit agreements** and refinancing substantially all senior debt maturities through 2014.

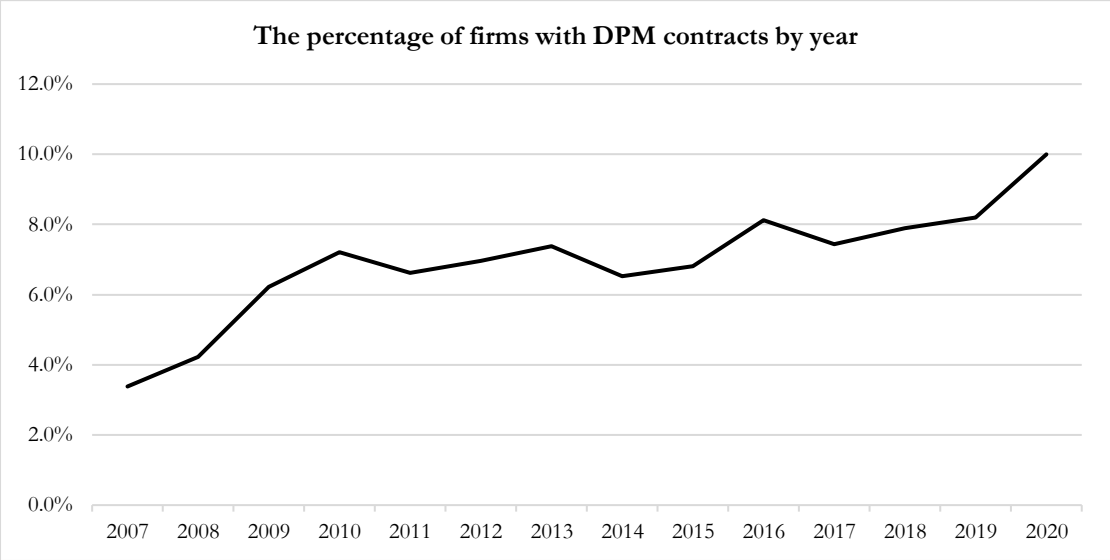
Appendix B: Variable Definition

Variables	Description	Source
Main Variables		
DPM	An indicator variable that equals one if the firm has a DPM contract in the given year, i.e., when the firm incorporates debt performance metrics in their executive compensation designs.	*EDGAR*
NumDPM	The number of debt performance metrics utilized by a firm in the given year.	*EDGAR*
Debt / EBITDA	Ratio of total debt to earnings before interest, taxes, depreciation, and amortization.	*Compustat/CRSP*
EDF	Expected default frequency (×1000), computed using the procedure in Bharath and Shumway (2008).	*CRSP* *Compustat*
Credit Rating	The numerical equivalent of S&P, Moody's, Fitch senior debt rating in the given fiscal year. It is set as equal to 24 for the highest senior debt rating, through 1 for the lowest senior debt rating. For firms not rated by S&P, we assign the Moody's senior debt rating; for firms not rated by either S&P or Moody's, we assign the Fitch senior debt rating.	*Capital IQ S&P Credit Ratings* *Mergent FISD*
Rating Disagree	Dummy equal to 1 if the firm is assigned different ratings by rating agencies in the given fiscal year.	*Capital IQ S&P Credit Ratings* *Mergent FISD*
Post × Default	An indicator variable that equals one if at least one loan arranger of the borrower has experienced a payment default before the given year, and the borrower's loans arranged by this lender are outstanding at the time of default.	*Capital IQ S&P Credit Ratings* *Dealscan*
Due_1st_Year%	The proportion of long-term debt due in one year.	*Compustat/CRSP*
Due_2nd_Year%	The proportion of long-term debt due in the 2nd year.	*Compustat/CRSP*
Due_3rd_Year%	The proportion of long-term debt due in the 3rd year.	*Compustat/CRSP*
Due_4th_Year%	The proportion of long-term debt due in the 4th year.	*Compustat/CRSP*
Due_5th_Year%	The proportion of long-term debt due in the 5th year.	*Compustat/CRSP*
Due_other_Year%	The proportion of long-term debt due in more than 5 years	*Compustat/CRSP*
Number of Non-debt metrics	The number of non-debt metrics (i.e., non-debt related accounting metrics or stock price metrics) utilized by the firm in the same year.	*Incentive Lab*
Issue_Loan	Dummy equal to 1 if the firm has a new loan issuance in the primary market in the year.	*Dealscan*
Issue_Bond	Dummy equal to 1 if the firm has a new bond issuance in the primary market in the year.	*Mergent FISD*
Diff_LoanSpread	Difference in loan yield spreads (i.e., all-in-spread-drawn) between the current loan and the previous one.	*Dealscan*
Diff_BondSpread	Difference in bond yield spreads (i.e., bond yield minus same-maturity treasury yield) between the current public bond and the previous one.	*Mergent FISD*
DPM_Included	Dummy equal to 1 if the firm incorporated at least one DPM after the issuance of the prior loan but before the issuance of the current loan.	*EDGAR*
RDIntensity	R&D expenses scaled by sales.	*Compustat/CRSP*

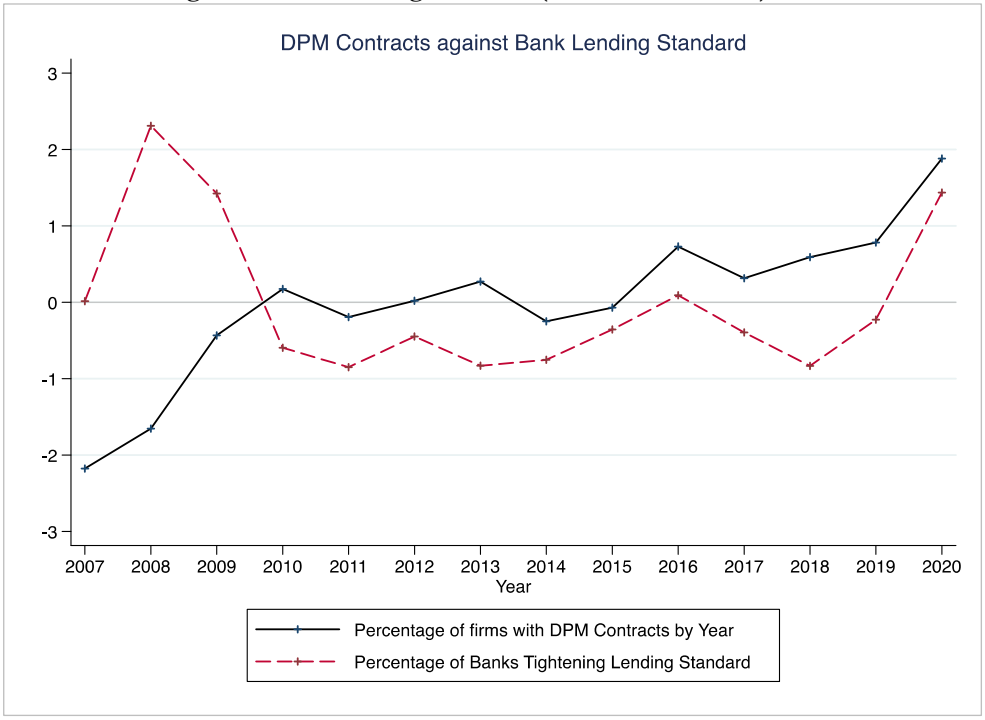
SG&A	SG&A costs scaled by operating expense.	*Compustat/CRSP*
Control Variables		
Debt / Equity	Ratio of total debt to shareholder equity (i.e., total assets-total liabilities-preferred stock)	*Compustat/CRSP*
Assets	Logged book value of total assets.	*Compustat/CRSP*
Tangibility	The ratio of net PP&E to total assets	*Compustat/CRSP*
OperatingCF	Ratio of operating income before depreciation to lagged total assets.	*Compustat/CRSP*
MtB	Ratio of Market Cap to Book Value of Equity, omitted for negative Book Equity	*Compustat/CRSP*
ROA	Ratio of earnings before interest and taxes to lagged total assets.	*Compustat/CRSP*
SalesGrowth	Calculated as sales minus previous year sales scaled by previous year sales.	*Compustat/CRSP*
FirmAge	The number of years since a company appears in CRSP.	*Compustat/CRSP*
Leverage	Ratio of total debt to total asset (book leverage).	*Compustat/CRSP*
InvestmentGrade	Dummy equal to one if the firm is rated at or above BBB- in the given fiscal year.	*Capital IQ S&P Credit Ratings* *Mergent FISD*
Rated	Dummy equal to 1 if borrower has a current credit rating.	*Capital IQ S&P Credit Ratings* *Mergent FISD*
Syndicated	Dummy equal to 1 if the firm has accessed the syndicated loan market.	*Dealscan*

Figure 1: DPM Characteristics
The figures present the fraction of 3,127 firm-years with DPM contracts over the period 2007-2020. Panel A plots the percentage of firms with DPMs sorted by fiscal year. Panel B presents the percentage of firms with DPM contracts against the net percentage of domestic banks tightening standards for C&I Loans to large and middle-market firms. Data on lending standards are collected from the Federal Reserve System's Senior Loan Officer Opinion Survey. Plots are standardized. Panel C plots the percentage of firm-year with DPMs across different industries.

Panel A: Percentage of Firms with DPM contracts by year



Panel B: DPM Contracts against Bank Lending Standard (Standardized Plots)



Panel C: Percentage of Firm-Years with DPM contracts by industry

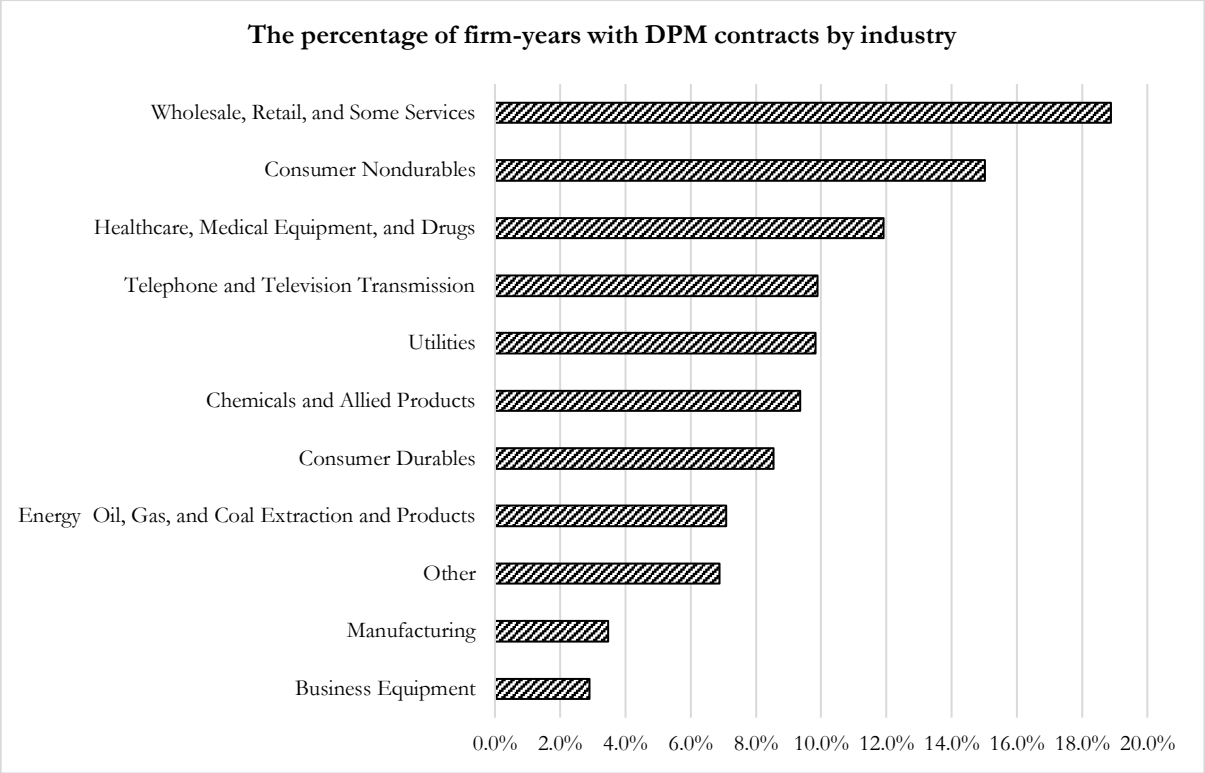


Figure 2: DPMs, Syndicated Loans and Bonds
The figure presents the percentage of unique firms using DPMs over the period 2007-2020 by different groups. We categorize the 5,690 unique firms into different groups based on whether the firms have outstanding loans or bonds during the sample period.

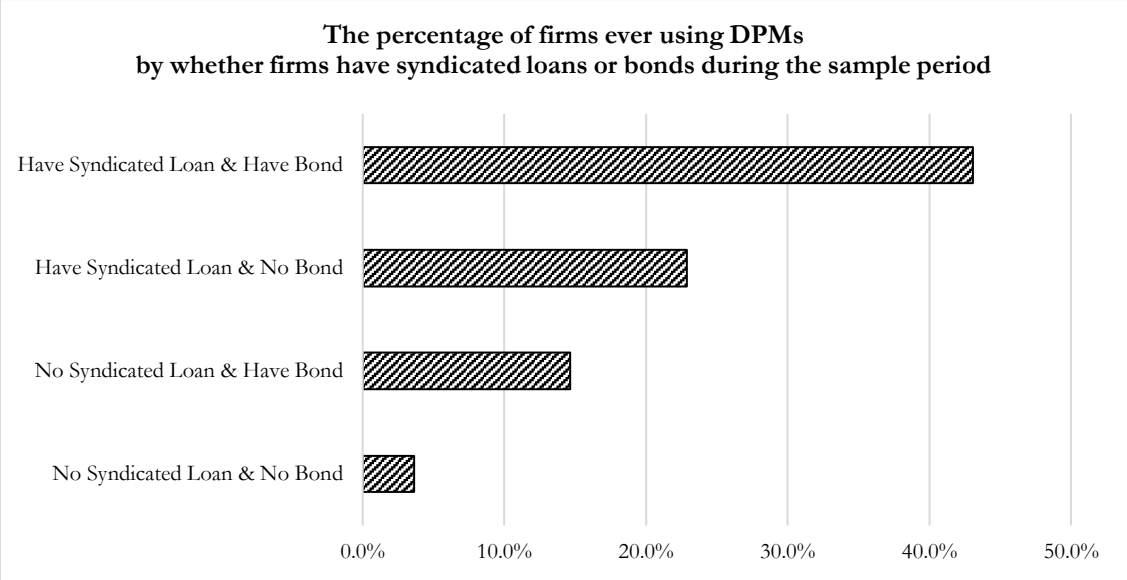


Figure 3: Comparing DPMs and Loan Covenants
The figure displays the average proportion of each type of DPMs (or loan covenants) out of the total in each firm-year. Following Christensen and Nikolaev (2012), we categorize covenants and DPMs into capital-based and performance-based. Specifically, we define capital-based covenants as those based on a function of variables such as net worth, leverage ratio (debt to asset or equity), loan-to-value, and current ratio. Performance-based covenants, on the other hand, are defined as those based on variables such as debt-to-cash flow and coverage ratio. Using the same logic, we categorize DPMs into capital-based DPM (i.e., debt reduction, debt financing, debt payment, maintain debt, leverage ratio, debt (net of cash), debt level, liquidity) and performance-based DPM (i.e., debt/EBITDA, cash flow/debt, funds from operation/debt, debt/earning, debt and interest coverage). We aggregate the outstanding covenants at the firm-year level. The proportion is calculated by dividing the average number of different types of DPMs (or covenants) in each firm-year by the average number of all types in each firm-year.

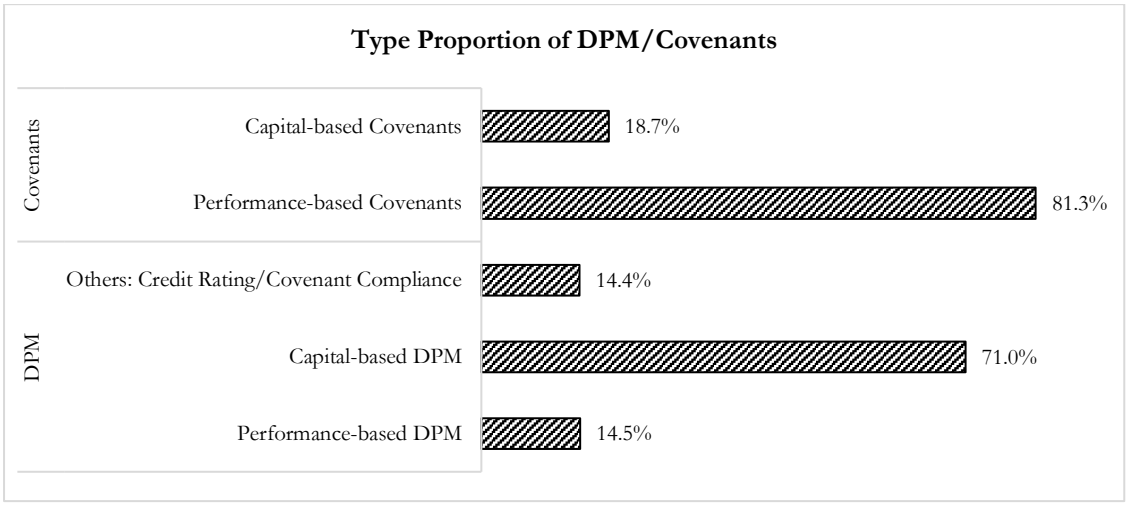


Figure 4: Credit Market Conditions, DPM, and Debt Issuance
This figure plots the association of the presence of DPMs, and net debt issuance with market credit risk. ΔDPM is calculated as the difference between realized and predicted DPM probability, derived from the linear regressions that relate the probability of having DPMs to lagged firm-specific characteristics (including *Leverage, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*) and firm-fixed effects. ΔNetDebt is calculated as the difference between realized and predicted net debt issuance, derived from the linear regressions that relate the net debt issuance scaled by lagged assets to lagged firm-specific characteristics and firm-fixed effects. Our proxy for high market credit risk is a variable indicating Moody's Baa–Aaa credit spread was greater than or equal to the median value for the years from 2000 to 2020.

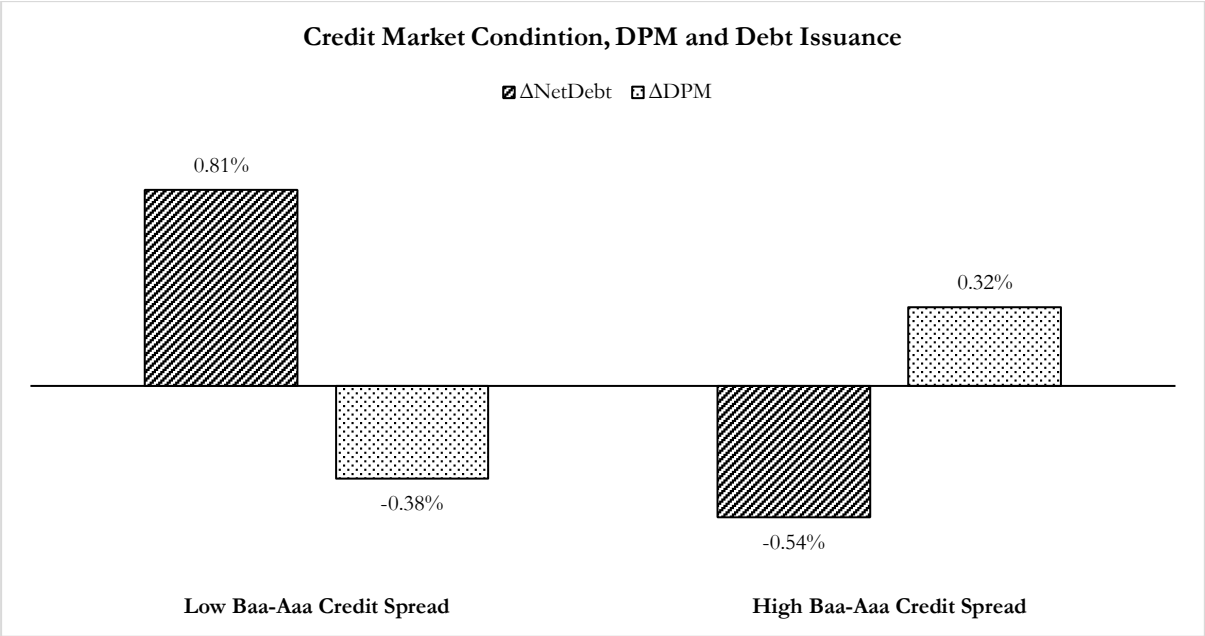


Figure 5: Event Study – Shocks to Lender's Monitoring Incentives
This figure plots the event-study dynamics of the probability of having DPMs around a lender-specific shock—defaults in a lender's corporate loan portfolio. On the horizontal axis, "0" represents the year when the default event occurs. We first plot the same estimator as shown in Table 4 Panel C Column (1) (in orange with circle markers). Then, we also address recent econometric concerns with staggered DID designs by showing robustness to the use of two alternative estimators: Callaway and Sant'Anna (2021) (in red with cross markers), and the Stacked DID estimator (in blue with diamond markers).

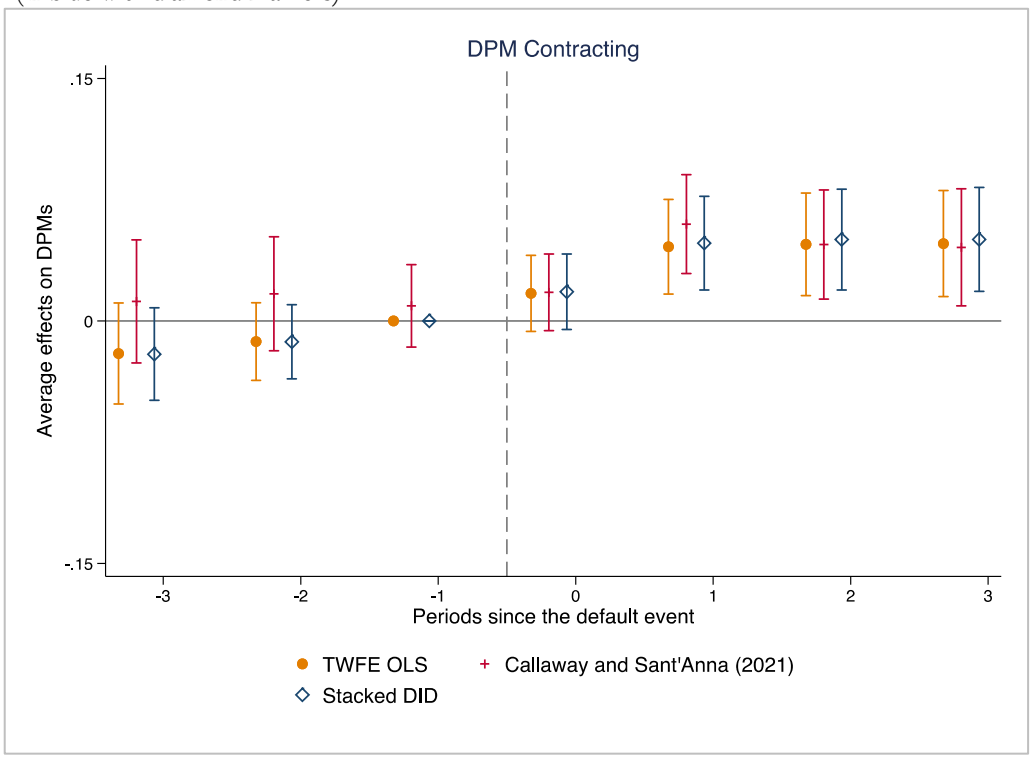


Table 1: Types of DPMs

This table presents the frequency of different DPMs used by firms. We collect the sample over the period 2007–2020. We define the borrowers have incorporated DPMs (debt performance metrics) in their compensation designs in a given year if they: (1) plan to award the managers based on a specific debt-related ratio (including *Leverage ratio, Credit rating, Debt/EBITDA, Cash flow/Debt, Debt (net of cash), Debt level, Funds from operation/Debt, Cost of debt, Debt and interest coverage, Liquidity and Debt/Earning*). (2) determine their managers' compensation based on a debt-related target (including *Debt reduction, Debt financing, Debt payment, Covenant compliance, and Maintain debt*). (3) plan to award the managers based on a financial metric and indicate that the purpose of including this metric is debt related (e.g., use "EBITDA" as a performance measure because it would provide cash flows to stabilize and improve the business and refinance the credit facility). The high frequency of the use of debt-related targets DPMs may be caused by our categorization method. For example, if a firm uses EBITDA as a performance measure and then indicates that the use of this measure is to refinance debt, then we count this measure as both the "*Debt financing*" metric and the "*Debt/EBITDA*" metric.

Number of DPM contracts			3,127
The Frequency of Metrics	**Debt Target**	Debt reduction	1,050
		Debt financing	598
		Debt payment	574
		Covenant compliance	134
		Maintain debt	40
	Debt to Balance Sheet	Leverage ratio	505
		Debt (net of cash)	112
		Debt level	77
	Credit Rating	Credit rating	471
	Debt to Cash Flow	Debt/EBITDA	328
		Cash flow/Debt	202
		Funds from operation/Debt	54
		Debt/Earning	12
	Liquidity	Liquidity	183
	Cost of debt	Cost of debt	18
	Coverage	Debt and interest coverage	18

Table 2: DPM Contracts and Firm Characteristics

Table 2 Panel A presents summary statistics for the sample of firms listed in the U.S major stock exchanges during the fiscal year 2007-2020 in the merged Compustat/CRSP database. We exclude those firms with missing values for *Debt/EBITDA, Leverage, Debt Equity, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*. *DPM* is an indicator variable that equals one if the firm has a DPM contract in the given year, i.e., when the firm incorporates debt performance metrics in its executive compensation designs. *NumDPM* is the number of debt performance metrics used in the given year by a firm. Table 2 Panel B compares firm characteristics between two groups: firm-years with DPM contracts and firm-years without DPM contracts. Larger *CreditRating* indicates better ratings. Higher *EDF* indicates higher default probability. All other variable definitions could be found in Appendix B. We winsorize all the continuous variables at the 1st and 99th percentiles to reduce the influence of outliers.

Panel A: Summary statistics

Variable	N	Mean	SD	Min	p25	p50	p75	Max
DPM	39,326	0.07	0.26	0.00	0.00	0.00	0.00	1.00
NumDPM	39,326	0.10	0.41	0.00	0.00	0.00	0.00	7.00
Debt/EBITDA	39,326	1.80	3.91	-15.64	0.00	1.15	2.97	21.41
Debt/Equity	39,326	0.84	1.65	0.00	0.03	0.36	0.92	11.83
Assets	39,326	6.75	2.10	2.12	5.23	6.70	8.19	11.72
Tangibility	39,326	0.26	0.25	0.00	0.07	0.17	0.40	0.91
OperatingCF	39,326	0.06	0.20	-1.26	0.05	0.10	0.15	0.39
MtB	39,326	3.61	4.95	0.27	1.30	2.16	3.83	36.10
ROA	39,326	0.02	0.20	-1.30	0.01	0.06	0.11	0.34
SalesGrowth	39,326	0.12	0.46	-0.80	-0.04	0.06	0.18	3.24
FirmAge	39,326	17.06	14.62	0.00	5.00	13.00	25.00	55.00
EDF	30,190	0.17	1.66	0.00	0.00	0.00	0.00	18.28
CreditRating	11,347	14.45	3.21	1.00	12.00	14.00	17.00	24.00

Panel B: Univariate Analysis

	Firm-year without *DPM* Contract		Firm-year with *DPM* Contract		Difference in Mean
	Mean	Median	Mean	Median	
Credit Rating	14.59	15.00	13.74	13.00	0.846***
EDF	0.16	0.00	0.30	0.00	-0.140***
Debt/EBITDA	1.67	0.99	3.38	3.12	-1.707***
Debt/Equity	0.78	0.32	1.63	0.96	-0.849***
Leverage	0.20	0.17	0.35	0.34	-0.148***
Assets	6.64	6.57	8.15	8.19	-1.504***
Tangibility	0.26	0.16	0.36	0.27	-0.099***
OperatingCF	0.06	0.10	0.10	0.10	-0.033***
MtB	3.65	2.19	3.17	1.87	0.475***
ROA	0.02	0.06	0.05	0.06	-0.030***
SalesGrowth	0.12	0.06	0.06	0.03	0.062***
FirmAge	16.58	13.00	23.11	19.00	-6.523***
Rated	0.26	0.00	0.62	1.00	-0.360***
Syndicated	0.61	1.00	0.92	1.00	-0.308***

Table 3: Credit Quality and DPM Contracting

This table presents estimated coefficients from linear regressions that relate the probability of having DPMs (or the number of DPMs) to the measures of borrower credit quality. We collect the sample over the period 2007–2020. Panel A contains the full sample, while Panel B only contains those firms with credit ratings. We use two dependent variables in our regressions: 1) *DPM* is an indicator variable that equals one if the firm has a DPM contract in the given year, i.e., when the firm incorporates debt performance metrics in their executive compensation designs. 2) *NumDPM* is the number of debt performance metrics used in the given year by a firm. All regressions control for lagged firm-specific characteristics (including *Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year fixed effects, and firm (or industry) fixed effects. In all regressions, standard errors are clustered for each firm. In Panel A, following Nini et al. (2009), we use the borrower's ratio of debt to EBITDA as a measure of credit quality. Higher *Debt/EBITDA* indicates lower credit quality. In Panel B and C, we also measured the firms' credit quality by their expected default frequency (×1000) computed using the procedure in Bharath and Shumway (2008) and credit rating. Higher *EDF* indicates higher default probability. Larger *CreditRating* indicates better ratings. We define *EDF_High* as a dummy variable that indicates those firm-years with the value of expected default frequency in the highest quantile, and we define *EDF_Low* as a dummy variable that indicates those firm-years with the value of expected default frequency in the lowest quantile. We define "*RatingDisagree*" as a dummy variable, which equals 1 if there exist split ratings for a firm in a given year. All variables are defined in Appendix B. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Proxy Credit Quality by Debt-to-EBITDA

	(1)	(2)	(3)	(4)	(5)	(6)
		DPM_t			$NumDPM_t$	
Debt/EBITDA $_{t-1}$	**0.007*** **	**0.004*** **	**0.002*** **	**0.012*** **	**0.007*** **	**0.004*** **
	(12.63)	**(8.65)**	**(4.61)**	**(11.90)**	**(8.38)**	**(4.80)**
Controls:						
Assets $_{t-1}$		0.017***	0.016***		0.026***	0.023***
		(11.73)	(3.92)		(11.28)	(3.53)
Tangibility $_{t-1}$		-0.020	0.002		-0.035	0.012
		(-1.44)	(0.09)		(-1.61)	(0.31)
OperatingCF $_{t-1}$		0.155**	0.297***		0.277**	0.432***
		(2.04)	(2.75)		(2.54)	(2.84)
MtB $_{t-1}$		-0.000	0.000		-0.001	-0.000
		(-0.62)	(0.14)		(-1.29)	(-0.58)
ROA $_{t-1}$		-0.216***	-0.335***		-0.370***	-0.483***
		(-2.88)	(-3.13)		(-3.42)	(-3.22)
SalesGrowth $_{t-1}$		-0.006***	0.000		-0.009***	0.001
		(-2.79)	(0.02)		(-2.74)	(0.26)
FirmAge $_{t-1}$		0.001***	-0.001		0.001***	-0.001
		(4.20)	(-0.73)		(3.53)	(-0.87)
Firm FE	No	No	Yes	No	No	Yes
Industry FE	No	Yes	No	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	39,326	39,326	38,856	39,326	39,326	38,856
Adj. R²	0.017	0.057	0.329	0.018	0.054	0.334

Panel B: Proxy Credit Quality by Expected Default Frequency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			DPM_t				$NumDPM_t$	
EDF_t	**0.000**		**0.003***		**0.003**		**0.008****	
	(0.02)		**(1.90)**		**(1.17)**		**(2.54)**	
EDF_High_t		**0.020****		**0.023*****		**0.040*****		**0.046*****
		(2.51)		**(2.74)**		**(2.76)**		**(3.04)**
EDF_Low_t		**-0.015****		**-0.031*****		**-0.023****		**-0.050*****
		(-2.07)		**(-4.38)**		**(-2.03)**		**(-4.45)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	Yes	Yes	No	No
Industry FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	29,729	29,729	30,190	30,190	29,729	29,729	30,190	30,190
Adj. R^2	0.317	0.318	0.062	0.066	0.324	0.325	0.059	0.064

Panel C: Proxy Credit Quality by Credit Rating

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			DPM_t				$NumDPM_t$	
$CreditRating_{t-1}$	**-0.022*****	**-0.021*****			**-0.043*****	**-0.040*****		
	(-4.63)	**(-7.37)**			**(-4.95)**	**(-7.49)**		
$A\ rated\ or\ better_{t-1}$			**-0.092*****				**-0.157*****	
			(-5.81)				**(-6.19)**	
$BB\ rated\ or\ worse_{t-1}$			**0.080*****				**0.154*****	
			(4.97)				**(5.59)**	
$RatingDisagree_{t-1}$				**0.033*****				**0.055*****
				(2.74)				**(2.64)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	No	Yes	No	No	No
Industry FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,185	11,347	11,347	11,347	11,185	11,347	11,347	11,347
Adj. R^2	0.335	0.051	0.053	0.038	0.349	0.057	0.057	0.041

Table 4: Shock to Lender's Monitoring Incentives and DPM Contracting

Using a lender-specific shock - defaults in a lender's corporate loan portfolio as a shock to the lenders' monitoring incentives, this table presents estimated coefficients from linear regressions that relate the probability of having DPMs (or the number of DPMs) to the lenders' monitoring incentives. We collect the defaults sample over the period 2007–2020 from Capital IQ S&P credit ratings database. We define the treatment time as the lender's first-time experiencing defaults since 1993, and we examine the first treatment effects for a borrower in our regressions. Panel A contains the full sample of firms, excluding those without syndicated loans and defaulting borrowers, Panel B further deletes the lenders' current borrowers who are in the same industries or geographic regions as the defaulting borrowers at the time of defaults. In Panel A and B, $Post_t \times Default_i$ is an indicator variable that equals one if at least one loan arranger of the borrower has experienced a payment default before the given year, and the borrower's loans arranged by this lender are outstanding at the time of default. In Panel C, to evaluate the treatment effects of the pre- and post-treatment periods, we use an event study specification within a six-year window around the treatment. $Default_{i,t}$ equals one if the borrower's current loan arranger experiences a payment default in its portfolio in the current year, zero otherwise. $Pre(-3)_t \times Default_i$, $Pre(-2)_t \times Default_i$, $Post(+1)_t \times Default_i$, $Post(+2)_t \times Default_i$, $Post(+3)_t \times Default_i$, are the 3-year lag, 2-year lag, 1-year lead, 2-year lead and 3-year lead around the default year, respectively. We use two dependent variables: 1) *DPM* is an indicator variable that equals one if the firm has a DPM contract in the given year. 2) *NumDPM* is the number of debt performance metrics used in the given year by a firm. All regressions control for lagged firm-specific characteristics (including *Debt/EBITDA*, *Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year-fixed effects and firm-fixed effects. Column (1) and (2) report results using a large unmatched sample of control firms. In Column (3) and (4), we conduct entropy-balanced matching with three moments. In Column (5) and (6), we conduct propensity-score matching using nearest neighbor matching with replacement. In Column (7) and (8), we conduct propensity-score matching using three-nearest neighbor matching with a caliper of 0.03. We conduct all matching based on *Rated, InvestmentGrade, Leverage, MtB, Assets*. All variables are defined in Appendix B. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Whole sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$
	Full Sample		Entropy Balance: three moments		PSM: nearest		PSM: three nearest	
$Post_t \times Default_i$	**0.042*** **	**0.052** **	**0.038*** **	**0.045** **	**0.040*** **	**0.042***	**0.041*** **	**0.050** **
	(3.11)	**(2.32)**	**(2.77)**	**(1.97)**	**(2.86)**	**(1.86)**	**(3.03)**	**(2.23)**
$Debt/EBITDA_{t-1}$	0.003***	0.005***	0.003***	0.005***	0.003***	0.006***	0.003***	0.005***
	(4.05)	(3.96)	(4.04)	(3.83)	(4.26)	(3.68)	(4.08)	(3.89)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	23,637	23,637	23,637	23,637	18,175	18,175	22,147	22,147
Adj. R^2	0.322	0.332	0.327	0.332	0.321	0.330	0.322	0.331

Panel B: Defaults from Different Region or SIC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$
	Full Sample		Entropy Balance: three moments		PSM: nearest		PSM: three nearest	
$Post_t \times Default_i$	**0.040*** **	**0.053** **	**0.036** **	**0.044***	**0.038** **	**0.040**	**0.038*** **	**0.047***
	(2.79)	**(2.14)**	**(2.44)**	**(1.74)**	**(2.55)**	**(1.58)**	**(2.59)**	**(1.91)**
$Debt/EBITDA_{t-1}$	0.003***	0.005***	0.003***	0.006***	0.004***	0.006***	0.003***	0.005***
	(3.98)	(3.87)	(4.06)	(3.75)	(4.49)	(3.55)	(4.01)	(3.47)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22,090	22,090	22,090	22,090	16,165	16,165	20,212	20,212
Adj. R^2	0.318	0.334	0.324	0.335	0.309	0.327	0.317	0.333

Panel C: Difference-in-Differences Event Study (with leads and lags)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$
	Full Sample		Entropy Balance: three moments		PSM: nearest		PSM: three nearest	
$Pre(-3)_t \times Default_i$	-0.020	-0.047*	-0.019	-0.042*	-0.018	-0.044*	-0.019	-0.046*
	(-1.27)	(-1.88)	(-1.18)	(-1.67)	(-1.13)	(-1.76)	(-1.19)	(-1.84)
$Pre(-2)_t \times Default_i$	-0.013	-0.011	-0.012	-0.008	-0.011	-0.008	-0.011	-0.009
	(-1.04)	(-0.53)	(-0.94)	(-0.38)	(-0.88)	(-0.39)	(-0.92)	(-0.46)
$Default_{i,t}$	0.017	-0.002	0.016	-0.003	0.017	-0.002	0.018	-0.001
	(1.42)	(-0.11)	(1.33)	(-0.15)	(1.39)	(-0.11)	(1.47)	(-0.05)
$Post(+1)_t \times Default_i$	0.046***	0.046**	0.043***	0.042*	0.046***	0.044*	0.046***	0.045**
	(3.07)	(2.02)	(2.83)	(1.83)	(3.00)	(1.87)	(3.06)	(1.98)
$Post(+2)_t \times Default_i$	0.047***	0.051**	0.043***	0.044*	0.045***	0.047*	0.047***	0.050*
	(2.92)	(1.99)	(2.61)	(1.67)	(2.73)	(1.78)	(2.91)	(1.94)
$Post(+3)_t \times Default_i$	0.048***	0.067**	0.041**	0.056**	0.046***	0.061**	0.048***	0.066**
	(2.86)	(2.48)	(2.40)	(2.03)	(2.65)	(2.22)	(2.84)	(2.45)
$Debt/EBITDA_{t-1}$	0.002**	0.003***	0.002***	0.004***	0.003***	0.005**	0.002**	0.004***
	(2.52)	(2.78)	(2.60)	(2.60)	(2.77)	(2.50)	(2.54)	(2.80)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,929	15,929	15,929	15,929	10,480	10,480	14,452	14,452
Adj. R^2	0.343	0.370	0.346	0.358	0.350	0.377	0.345	0.370

Table 5: Debt Maturity Pressure and DPM Contracting

This table presents estimated coefficients from linear regressions that relate the probability of having DPMs (or the number of DPMs) to debt maturity pressure. We collect the sample over the period 2007–2020. In Panel A, the dependent variable is *DPM*, which is an indicator variable that equals one if the firm has a DPM contract in the given year. In Panel B, the dependent variable is *NumDPM*, which is the number of debt performance metrics used in the given year by a firm. All regressions control for firm-specific characteristics (including *Leverage, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year fixed effects and firm fixed effects. We measure debt maturity by using six indicator variables: *Due_1st_Year%, Due_2nd_Year%, Due_3rd_Year%, Due_4th_Year%, Due_5th_Year%* and *Due_other_Year%*. These variables represent the proportion of long-term debt due in one year, in the 2nd year, in the 3rd year, in the 4th year, in the 5th year and debts due in more than 5 years, respectively. All variables are defined in Appendix B. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: The presence of DPMs

	(1)	(2)	(3)	(4)	(5)	(6)
				DPM_t		
Due_1st_Year % $_{t-1}$	**0.025*** **					
	(3.50)					
Due_2nd_Year % $_{t-1}$		**0.024*** **				
		(3.21)				
Due_3rd_Year % $_{t-1}$			0.011			
			(1.46)			
Due_4th_Year % $_{t-1}$				0.002		
				(0.24)		
Due_5th_Year % $_{t-1}$					-0.009	
					(-1.40)	
Due_Other_Year % $_{t-1}$						-0.030***
						(-3.76)
Leverage $_{t-1}$	0.172***	0.166***	0.163***	0.163***	0.164***	0.172***
	(6.60)	(6.47)	(6.38)	(6.36)	(6.40)	(6.67)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25,074	25,074	25,074	25,074	25,074	25,074
Adj. R^2	0.328	0.328	0.327	0.327	0.327	0.328

Panel B: The number of DPMs

	(1)	(2)	(3)	(4)	(5)	(6)
				$NumDPM_t$		
Due_1st_Year % $_{t-1}$	**0.039*** **					
	(3.84)					
Due_2nd_Year % $_{t-1}$		**0.034*** **				
		(3.14)				
Due_3rd_Year % $_{t-1}$			0.014			
			(1.36)			
Due_4th_Year % $_{t-1}$				0.016		
				(1.51)		
Due_5th_Year % $_{t-1}$					-0.015	
					(-1.60)	
Due_Other_Year % $_{t-1}$						-0.053***
						(-3.98)
Leverage $_{t-1}$	0.314***	0.305***	0.301***	0.300***	0.303***	0.317***
	(6.98)	(6.88)	(6.81)	(6.78)	(6.83)	(7.09)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25,074	25,074	25,074	25,074	25,074	25,074
Adj. R^2	0.328	0.328	0.328	0.328	0.328	0.328

Table 6: Shareholders' Response to the Inclusion of DPMs: Non-debt Metrics

Table 6 Panel A compares how the number of non-debt metrics varies across firm-years with DPMs and firm-years without DPMs. We collect non-debt performance metrics (i.e., non-debt related accounting metrics or stock price metrics) from Incentive Lab Database which provides the performance metrics for S&P500 and a significant portion of S&P400. Therefore, in the tables below, we use a sample of firms that have records in the Incentive Lab Database. Moreover, we also present an analysis of a subsample of firms that have used DPMs during the sample period. Table 6 Panel B presents estimated coefficients from linear regressions that relate the number of non-debt metrics to the presence of DPMs (*DPM*) and the number of DPMs (*NumDPM*). In Panel B Column (5) and (6), we also use a matched sample. We conduct propensity-score matching using three-nearest neighbor matching with a caliper of 0.03 based on the firm's outstanding amount of syndicated loans scaled by its total assets in a given year. All regressions control for firm-specific characteristics (including *Debt/EBITDA, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year fixed effects and firm fixed effects. In all regressions, standard errors are clustered for each firm. We use two independent variables in our regressions: 1) *DPM* is an indicator variable that equals one if the firm has a DPM contract in the given year, i.e., when the firm incorporates debt performance metrics in their executive compensation designs. 2) *NumDPM* is the number of debt performance metrics used in the given year by a firm. The dependent variable is *Number of Non-debt metrics*, which represents the number of non-debt metrics utilized by the firm in the same year. All variables are defined in Appendix B. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Univariate Analysis

Sample: Firm with records in the Incentive Lab Database

	Firm-year without *DPM* Contract			Firm-year with *DPM* Contract			Difference in Mean
	Sample	Mean	Median	Sample	Mean	Median	
Number of Non-debt metrics	11,193	2.73	3.00	1,644	3.21	3.00	**-0.474*****

Sub-Sample: DPM Firms
(i.e., firms that have used DPM in the sample period)

	Firm-year without *DPM* Contract			Firm-year with *DPM* Contract			Difference in Mean
	Sample	Mean	Median	Sample	Mean	Median	
Number of Non-debt metrics	4,357	2.94	3.00	1,644	3.21	3.00	**-0.262*****

Panel B: Regression on the number of non-debt metrics

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of Non-debt Metrics$_t$					
	Full Sample		Sub-Sample: DPM Firms		Matched sample: Loan outstanding	
DPM$_t$	**0.183*****		**0.176*****		**0.163*****	
	(3.77)		**(3.64)**		**(2.90)**	
NumDPM$_t$		**0.115*****		**0.113*****		**0.109*****
		(3.73)		**(3.67)**		**(3.27)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,778	12,778	5,997	5,997	4,682	4,682
Adj. R^2	0.587	0.587	0.523	0.523	0.553	0.553

Table 7: Borrowing Needs, DPM, and Cost of Borrowing

Panel A presents estimated coefficients from linear regressions that relate the probability of having DPMs (or the number of DPMs) to the following issuance of a new debt in the same year. Panel B shows the results of the cost of borrowing in response to DPM inclusion between the two consecutive borrowings for the same firm. We collect the sample over the period 2007–2020. In Panel A, Columns (1) and (2) contain the full sample, Columns (3) and (4) contain the sample of firms that issued at least one bond during the sample period, and Columns (5) and (6) contain the sample of firms that issued at least one syndicated loan during the sample period. Panel B contains the sample of firms that issued at least two syndicated loans or two bonds during the sample period, we further restrict our sample to those firms having both bond and loan issuances during the sample period. In panel B, we exclude convertible bonds, variable coupon bonds, and private placement bonds. All regressions control for lagged firm-specific characteristics (including *Leverage, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*) and industry fixed effects. In Panel B, we also control for Moody's Baa-Aaa Spread, loan-level or bond-level characteristics. In Panel A, standard errors are clustered for each firm. *DPM* is an indicator variable that equals one if the firm has a DPM contract in the given year, i.e., when the firm incorporates debt performance metrics in their executive compensation designs. *NumDPM* is the number of debt performance metrics used in the given year by a firm. In Panel A, the independent variable is *Issue_Loan* (or *Issue_Bond*), which is a dummy variable indicating if the firm has a new loan issuance (or bond issuance) in the year. In panel B, the dependent variable is *Diff_LoanSpread* (or *Diff_BondSpread*), which represents the yield spread difference between the current loan and the prior loan (or between the current bond and the prior bond). For firms issuing multiple bonds in the same year, we only keep the bond with a lower yield spread, resulting in a smaller sample size. The independent variable (*DPM_Included)* is a dummy variable indicating if the firm incorporated at least one DPM after the issuance of the prior loan but before the issuance of the current loan. All variables are defined in Appendix B. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: DPM and Debt Issuance

	(1)	(2)	(3)	(4)	(5)	(6)
	DPM$_t$	***NumDPM$_t$***	***DPM$_t$***	***NumDPM$_t$***	***DPM$_t$***	***NumDPM$_t$***
	Full Sample		Firms with Bond Issuances		Firms with Syndicated Loan Issuances	
Issue_Bond$_t$	**0.057*****	**0.087*****	**0.035*****	**0.046*****		
	(6.62)	**(5.79)**	**(4.28)**	**(3.20)**		
Issue_Loan$_t$	**0.033*****	**0.045*****			**0.018*****	**0.026*****
	(6.21)	**(5.23)**			**(3.34)**	**(2.92)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	39,326	39,326	13,247	13,247	22,675	22,675
Adj. R²	0.063	0.060	0.054	0.055	0.055	0.055

Panel B: DPM and Cost of Borrowing

	(1)	(2)	(3)	(4)	(5)	(6)
	Diff_LoanSpread		***Diff_BondSpread***		***Diff_LoanSpread***	***Diff_BondSpread***
	Loan Market		Bond Market		Subsample: Firms with Bonds & Loans Issuances	
DPM_Included	**-15.548*****	**-16.171*****	**-4.042**	**-2.442**	**-13.501****	**-6.845**
	(-2.79)	**(-3.11)**	**(-0.43)**	**(-0.26)**	**(-1.98)**	**(-0.71)**
Controls:						
ΔBaaAaaSpread	Yes	Yes	Yes	Yes	Yes	Yes
Debt Changes	No	Yes	No	Yes	No	No
Firm Changes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,870	2,870	1,445	1,445	1,716	1,352
Adj. R²	0.187	0.292	0.100	0.108	0.201	0.102

Table 8: DPM Contracting and Risk-taking Behaviors

The tables present estimated coefficients from linear regressions that relate future risky investments to the presence of DPMs (*DPM*) and the number of DPMs *(NumDPM)*. We use two proxies for risky investments. The first proxy is research and development investments (R&D) intensity. We scale R&D expenses by sales to obtain R&D intensity. The second proxy is selling, general, and administrative outlays (SG&A). We scale SG&A costs by operating expenses to obtain SG&A. We collect the sample over the period 2007–2020. All regressions control for firm-specific characteristics (including *Debt/EBITDA, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year fixed effects and industry fixed effects. In all regressions, standard errors are clustered for each firm. We use two independent variables in our regressions: 1) *DPM* is an indicator variable that equals one if the firm has a DPM contract in the given year, i.e., when the firm incorporates debt performance metrics in their executive compensation designs. 2) *NumDPM* is the number of debt performance metrics used in the given year by a firm. In our regressions, the dependent variable is $RDIntensity_{t+1}$, $RDIntensity_{(t+1)-(t+3)}$, $SG\&A_{t+1}$, $SG\&A_{(t+1)-(t+3)}$, which represents R&D intensity in the next year, R&D intensity in the next three years, SG&A in the next year and SG&A in the next three years, respectively. All variables are defined in Appendix B. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: The presence of DPMs

	(1)	(2)	(3)	(4)
	$RDIntensity_{t+1}$	$RDIntensity_{(t+1)-(t+3)}$	$SG\&A_{t+1}$	$SG\&A_{(t+1)-(t+3)}$
DPM_t	**-0.117*** **	**-0.111*** **	**-0.034*** **	**-0.031*** **
	(-4.00)	**(-5.40)**	**(-5.52)**	**(-4.52)**
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	37,144	28,664	33,433	25,623
Adj. R^2	0.223	0.244	0.446	0.422

Panel B: The number of DPMs

	(1)	(2)	(3)	(4)
	$RDIntensity_{t+1}$	$RDIntensity_{(t+1)-(t+3)}$	$SG\&A_{t+1}$	$SG\&A_{(t+1)-(t+3)}$
$NumDPM_t$	**-0.064*** **	**-0.062*** **	**-0.021*** **	**-0.022*** **
	(-4.44)	**(-5.37)**	**(-6.07)**	**(-5.37)**
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	37,144	28,664	33,433	25,623
Adj. R^2	0.224	0.245	0.446	0.423

Online Appendix I

Table IA.1: Credit Quality and Cash-Flow Related Metrics

This table presents tests that relate the probability of having cash flow-based metrics (CFM) to the measures of borrower credit quality. We collect CFMs over the period 2007–2020 from the Incentive Lab Database, which provides the performance metrics for S&P500 and a significant portion of S&P400. We categorize contracts with CFMs into DPMs and non-DPMs according to our definition. The dependent variable *CFM* is a dummy variable that takes a value of 1 if cash-flow-based metrics are present. The dependent variables *DPM_CFM* and *NonDPM_CFM* are dummy variables that take a value of 1 if a contract with cash-flow-based metrics is present as DPM or non-DPM contract, respectively. We use similar specifications as in Table 3. We control for firm-specific characteristics (including *Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year-fixed effects, and firm-fixed effects. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Proxy Credit Quality by Debt-to-EBITDA

	(1)	(2)	(3)
	NonDPM_CFM$_t$	***DPM_CFM$_t$***	***CFM$_t$***
Debt/EBITDA $_{t-1}$	**0.002**	**0.004*****	**0.006*****
	(1.15)	**(3.37)**	**(3.76)**
Assets $_{t-1}$	0.013	-0.002	0.011
	(0.86)	(-0.23)	(0.72)
Tangibility $_{t-1}$	-0.021	-0.069	-0.090
	(-0.20)	(-1.31)	(-0.87)
OperatingCF $_{t-1}$	-0.079	0.547*	0.468
	(-0.17)	(1.94)	(0.87)
MtB $_{t-1}$	-0.001	-0.001	-0.002
	(-0.63)	(-1.63)	(-1.54)
ROA $_{t-1}$	-0.069	-0.665**	-0.734
	(-0.15)	(-2.41)	(-1.39)
SalesGrowth $_{t-1}$	-0.011	0.003	-0.009
	(-0.91)	(0.32)	(-0.75)
FirmAge $_{t-1}$	-0.003	0.000	-0.003
	(-1.22)	(0.09)	(-1.20)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	12,778	12,778	12,778
Adj. R^2	0.470	0.269	0.584

Panel B: Proxy Credit Quality by Expected Default Frequency

	(1)	(2)	(3)	(4)	(5)	(6)
	NonDPM_CFMs$_t$		***DPM_CFMs$_t$***		***CFMs$_t$***	
EDF$_t$	**-0.001**		**-0.001**		**-0.002**	
	(-0.42)		**(-0.27)**		**(-0.71)**	
EDF_High$_t$		**-0.008**		**0.028**		**0.020**
		(-0.33)		**(1.41)**		**(0.84)**
EDF_Low$_t$		**-0.017**		**-0.036****		**-0.053*****
		(-0.94)		**(-2.57)**		**(-3.28)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11,423	11,423	11,423	11,423	11,423	11,423
Adj. R^2	0.454	0.454	0.262	0.265	0.573	0.574

Panel C: Proxy Credit Quality by Credit Rating

	(1)	(2)	(3)	(4)	(5)	(6)
	NonDPM_CFMs$_t$		***DPM_CFMs$_t$***		***CFMs$_t$***	
CreditRating$_{t-1}$	**-0.008**		**-0.021*****		**-0.029*****	
	(-1.12)		**(-3.84)**		**(-4.25)**	
A rated or better$_{t-1}$		**-0.006**		**-0.063*****		**-0.069****
		(-0.17)		**(-3.35)**		**(-2.15)**
BB rated or worse$_{t-1}$		**0.043**		**0.031**		**0.075****
		(1.36)		**(1.47)**		**(2.39)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7,211	7,211	7,211	7,211	7,211	7,211
Adj. R^2	0.462	0.462	0.277	0.275	0.576	0.575

Table IA.2: Credit Quality and DPM Contracting (Add CEO-Level Controls)

This table presents robustness tests that relate the probability of having DPMs (or the number of DPMs) to the measures of borrower credit quality. We collect the sample over the period 2007–2020. The dependent variable in our regressions is *DPM*, an indicator variable that equals one if the firm has a DPM contract in the given year, i.e., when the firm incorporates debt performance metrics in their executive compensation designs. We use similar specifications as in Table 3 but further control for lagged CEO-level characteristics. We collect these variables from ExecuComp database, resulting in a smaller sample size. CEO's *Inside Debt/Equity* equals the value of inside debt (pension + deferred compensation) divided by the value of inside equity (stock + options). CEO's *TotalCompensation* is the total compensation-as reported in SEC filing. CEO's *Tenure* is the number of years since an executive became CEO. CEO's *Duality* is a dummy variable taking a value of 1 if the CEO is chairman of the board, and 0 otherwise. We control for firm-specific characteristics (including *Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year fixed effects and firm (or industry) fixed effects. All variables are defined in Appendix B. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					DPM_t			
EDF_t	**-0.000**		**0.008****					
	(-0.08)		**(2.41)**					
EDF_High_t		**0.037****		**0.059*****				
		(2.38)		**(3.41)**				
EDF_Low_t		**-0.023***		**-0.051*****				
		(-1.91)		**(-4.08)**				
$CreditRating_{t-1}$					**-0.028*****	**-0.023*****		
					(-4.82)	**(-6.48)**		
$A\ rated\ or\ better_{t-1}$							**-0.085*****	
							(-4.53)	
$BB\ rated\ or\ worse_{t-1}$							**0.089*****	
							(4.66)	
$RatingDisagree_{t-1}$								**0.023***
								(1.70)
Inside Debt/Equity$_{t-1}$	0.009	0.008	0.023***	0.024***	0.004	0.021*	0.019*	0.017
	(1.24)	(1.11)	(2.71)	(2.73)	(0.45)	(1.90)	(1.73)	(1.49)
TotalCompensation$_{t-1}$	0.011**	0.013***	0.023***	0.024***	0.012	0.039***	0.039***	0.041***
	(2.22)	(2.60)	(4.32)	(4.65)	(1.33)	(4.26)	(4.39)	(4.37)
Tenure$_{t-1}$	-0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000
	(-0.53)	(-0.48)	(-0.77)	(-0.59)	(0.28)	(0.15)	(-0.09)	(-0.03)
Duality$_{t-1}$	-0.000	0.000	0.006	0.007	0.010	0.021	0.021	0.015
	(-0.03)	(0.00)	(0.67)	(0.80)	(0.58)	(1.41)	(1.45)	(0.98)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	Yes	No	No	No
Industry FE	No	No	Yes	Yes	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16,067	16,067	16,148	16,148	7,854	7,943	7,943	7,943
Adj. R^2	0.304	0.306	0.064	0.073	0.308	0.076	0.076	0.062

Table IA.3: Credit Quality and DPM Contracting (Logit Model)

This table presents robustness tests that relate the probability of having DPMs (or the number of DPMs) to the measures of borrower credit quality by using the Logit model. We collect the sample over the period 2007–2020. The dependent variable in our regressions is *DPM*, an indicator variable that equals one if the firm has a DPM contract in the given year, i.e., when the firm incorporates debt performance metrics in their executive compensation designs. We use similar specifications as in Table 3, but estimate them using a Logit model rather than OLS. We control for firm-specific characteristics (including *Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*) and also CEO-level characteristics, year fixed effects and firm (or industry) fixed effects. All variables are defined in Appendix B. z-statistics are in parentheses. Standard errors are Huber-White sandwich estimator. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					DPM$_t$			
EDF$_t$	**-0.009**		**0.042****					
	(-0.40)		**(2.05)**					
EDF_High$_t$		**0.293****		**0.368*****				
		(1.99)		**(5.04)**				
EDF_Low$_t$		**-0.272***		**-0.521*****				
		(-1.95)		**(-4.20)**				
CreditRating$_{t-1}$					**-0.266*****	**-0.177*****		
					(-5.33)	**(-4.71)**		
A rated or better$_{t-1}$							**-0.749*****	
							(-4.53)	
BB rated or worse$_{t-1}$							**0.664*****	
							(4.91)	
RatingDisagree$_{t-1}$								**0.142**
								(1.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	Yes	No	No	No
Industry FE	No	No	Yes	Yes	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,211	7,211	16,148	16,148	4,391	7,943	7,943	7,943
Pseudo. R^2	0.047	0.052	0.044	0.055	0.059	0.057	0.057	0.038

Table IA.4: Lender's monitoring incentives and DPM Contracting (Narrow Treatment Group)
Using a lender-specific shock - defaults in a lender's corporate loan portfolio as a shock to the lenders' monitoring incentives, this table presents estimated coefficients from linear regressions that relate the probability of having DPMs (or the number of DPMs) to the lenders' monitoring incentives. We collect the defaults sample over the period 2007–2020 from Capital IQ S&P credit ratings database. Table IA.4 uses the same specification as in Table 4 Panel B but eliminates borrowers for which the first treatment falls before 2007 (i.e., the starting year of our sample period). In all columns in Table IA.4, we use the full sample of firms that have accessed the syndicated loan market. All regressions control for firm-specific characteristics (including *Debt/EBITDA*, *Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*) and year fixed effects. In all regressions, standard errors are clustered for each firm. We conduct all matching based on *Rated, InvestmentGrade, Leverage, MtB, Assets*. All variables are defined in Appendix B. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$	DPM_t	$Num\ DPM_t$
	Full Sample		Entropy Balance: three moments		PSM: nearest		PSM: three nearest	
$Post_t \times Default_i$	**0.045*** **	**0.065*** **	**0.042*** **	**0.053** **	**0.044*** **	**0.050** **	**0.045*** **	**0.061** **
	(3.14)	**(2.71)**	**(2.86)**	**(2.16)**	**(2.99)**	**(2.02)**	**(3.12)**	**(2.53)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	17,595	17,595	17,595	17,595	9,945	9,945	14,121	14,121
Adj. R^2	0.297	0.312	0.305	0.321	0.299	0.320	0.292	0.305

Table IA.5: Credit Quality and Types of DPMs

This table presents estimated coefficients from linear regressions that relate the probability of having different types of DPMs to the measures of borrower credit quality. We collect the sample over the period 2007–2020. Panel A contains the full sample, while Panel B only contains those firms with credit ratings. We categorize DPMs into "debt reduction" metrics and other metrics. *DPM* is an indicator variable that equals one if the firm has a certain type DPM contract in the given year, i.e., when the firm incorporates debt performance metrics in their executive compensation designs. All regressions control for lagged firm-specific characteristics (including *Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year fixed effects and firm (or industry) fixed effects. In all regressions, standard errors are clustered for each firm. We measured the firms' credit quality by their expected default frequency (×1000) computed using the procedure in Bharath and Shumway (2008) and credit rating. Higher *EDF* indicates higher default probability. Larger *CreditRating* indicates better ratings. We define *EDF_High* as a dummy variable which indicates those firm-years with the value of expected default frequency in the highest quantile, and we define *EDF_Low* as a dummy variable which indicates those firm-years with the value of expected default frequency in the lowest quantile. We define "*RatingDisagree*" as a dummy variable, which equals to 1 if there exist split ratings for a firm in a given year. All variables are defined in Appendix B. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Expected Default Frequency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					DPM_t			
	Type: Debt Reduction				Other Types			
EDF_t	**0.002****		**0.003*****		**-0.000**		**0.001**	
	(1.98)		**(2.88)**		**(-0.27)**		**(0.91)**	
EDF_High_t		**0.016*****		**0.021*****		**0.012**		**0.014***
		(2.81)		**(3.65)**		**(1.62)**		**(1.78)**
EDF_Low_t		**-0.005**		**-0.014*****		**-0.014****		**-0.027*****
		(-0.95)		**(-3.07)**		**(-2.12)**		**(-4.05)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	Yes	Yes	No	No
Industry FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	29,729	29,729	30,190	30,190	29,729	29,729	30,190	30,190
Adj. R²	0.251	0.252	0.024	0.028	0.292	0.293	0.058	0.061

Panel B: Credit Rating

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				DPM_t				
	Type: Debt Reduction				Other Types			
$CreditRating_{t-1}$	**-0.013*****	**-0.011*****			**-0.016*****	**-0.017*****		
	(-3.96)	**(-6.36)**			**(-3.45)**	**(-6.26)**		
$A\ rated\ or\ better_{t-1}$			**-0.031*****				**-0.078*****	
			(-4.44)				**(-5.09)**	
$BB\ rated\ or\ worse_{t-1}$			**0.047*****				**0.065*****	
			(4.55)				**(4.23)**	
$RatingDisagree_{t-1}$				**0.018****				**0.022****
				(2.40)				**(1.97)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	No	Yes	No	No	No
Industry FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,185	11,347	11,347	11,347	11,185	11,347	11,347	11,347
Adj. R²	0.262	0.036	0.034	0.026	0.324	0.045	0.047	0.035

Table IA.6: Debt Maturity Pressure and Types of DPMs

This table presents estimated coefficients from linear regressions that relate the probability of having different types of DPMs to the measures of debt maturity pressure. We collect the sample over the period 2007–2020. In Panel A, the dependent variable is *DPM (Debt Reduction)*, which is an indicator variable that equals one if the firm has a "debt reduction" DPM contract in the given year. In Panel B, the dependent variable is *DPM (Other Types)*, which is an indicator variable that equals one if the firm has other types of DPM contract in the given year. All regressions control for firm-specific characteristics (including *Leverage, Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year fixed effects and firm fixed effects. In all regressions, standard errors are clustered for each firm. We measure debt maturity by using six indicator variables: *Due_1st_Year%, Due_2nd_Year%, Due_3rd_Year%, Due_4th_Year%, Due_5th_Year%* and *Due_other_Year%*. These variables represent the proportion of long-term debt due in one year, in the 2nd year, in the 3rd year, in the 4th year, in the 5th year and debts due in more than 5 years, respectively. All variables are defined in Appendix B. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: "Debt Reduction" DPMs

	(1)	(2)	(3)	(4)	(5)	(6)
			DPM_t			
			Type: Debt Reduction			
Due_1st_Year % $_{t-1}$	**0.012*****					
	(3.21)					
Due_2nd_Year % $_{t-1}$		**0.018*****				
		(4.08)				
Due_3rd_Year % $_{t-1}$			0.001			
			(0.16)			
Due_4th_Year % $_{t-1}$				0.005		
				(1.19)		
Due_5th_Year % $_{t-1}$					-0.006	
					(-1.40)	
Due_Other_Year % $_{t-1}$						-0.018***
						(-3.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25,074	25,074	25,074	25,074	25,074	25,074
Adj. R^2	0.246	0.246	0.246	0.246	0.246	0.246

Panel B: Other Types of DPMs

	(1)	(2)	(3)	(4)	(5)	(6)
			DPM_t			
			Type: Other Types			
Due_1st_Year % $_{t-1}$	**0.018*****					
	(2.69)					
Due_2nd_Year % $_{t-1}$		**0.011***				
		(1.67)				
Due_3rd_Year % $_{t-1}$			0.009			
			(1.37)			
Due_4th_Year % $_{t-1}$				0.001		
				(0.15)		
Due_5th_Year % $_{t-1}$					-0.005	
					(-0.87)	
Due_Other_Year % $_{t-1}$						-0.019**
						(-2.53)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25,074	25,074	25,074	25,074	25,074	25,074
Adj. R^2	0.303	0.303	0.303	0.303	0.303	0.304

Table IA.7: Shock to Lender's Monitoring Incentives and Types of DPMs

We use a similar specification as in Table 4 Panel B. We categorize DPMs into "debt reduction" metrics and other metrics. DPM is an indicator variable that equals one if the firm has a certain type DPM contract in the given year. Panel A presents the results for "Debt Reduction" DPMs, while Panel B presents the results for other types DPMs. All regressions control for lagged firm-specific characteristics (including *Debt/EBITDA*, *Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), year fixed effects and firm fixed effects. In all regressions, standard errors are clustered for each firm. In Column (1), we report results using a large unmatched sample of control firms. In Column (2), we conduct entropy-balanced matching with three moments. In Column (3), we conduct propensity-score matching using nearest neighbor matching with replacement. In Column (4), we conduct propensity-score matching using three-nearest neighbor matching with a caliper of 0.03. We conduct all matching based on *Rated, InvestmentGrade, Leverage, MtB, Assets*. All variables are defined in Appendix B. t-statistics are in parentheses. Standard errors are Huber-White sandwich estimator clustered at the firm level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: "Debt Reduction" DPMs

	(1)	(2)	(3)	(4)
		DPM_t		
		Type: Debt Reduction		
	Full Sample	Entropy Balance: three moments	PSM: nearest	PSM: three nearest
$Post_t \times Default_i$	**0.014**	**0.010**	**0.008**	**0.011**
	(1.49)	**(1.07)**	**(0.81)**	**(1.21)**
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	22,090	22,090	16,165	20,212
Adj. R²	0.257	0.260	0.243	0.251

Panel B: Other Types of DPMs

	(1)	(2)	(3)	(4)
		DPM_t		
		Type: Other Types		
	Full Sample	Entropy Balance: three moments	PSM: nearest	PSM: three nearest
$Post_t \times Default_i$	**0.035****	**0.031****	**0.034****	**0.033****
	(2.53)	**(2.19)**	**(2.42)**	**(2.39)**
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	22,090	22,090	16,165	20,212
Adj. R²	0.299	0.308	0.294	0.302

Chapter 2: The Impact of Information Exchange Technology on Syndicated Lending

ABSTRACT

This paper examines how digital platforms that improve information exchange between syndication arrangers and participant lenders affect syndicated lending. I use novel data on the adoption of centralized digital platforms, which support document sharing and interaction among syndicate members during both formation and post-origination stages. Platform adoption has increased steadily since the early 2000s, with early adopters more likely to be arrangers previously involved in information-intensive deals. Exploiting staggered adoption, I find that platform use is followed by an increase in the arranger's syndicated lending volume, particularly to more leveraged borrowers. Syndicates become broader, with more geographically dispersed and first-time participants, and arrangers retain smaller loan shares. These patterns are consistent with reduced structuring and communication costs for arrangers and lower information processing frictions for participants. Default rates remain unchanged. The findings suggest that reducing communication and processing frictions enables arrangers to scale financial intermediation without worsening loan performance. The results highlight that digital platforms transform private debt markets by improving how information is processed, without necessarily adding new information.

Keywords: Syndicated Lending, Information Exchange, Technology, Arranger-Participants

JEL Codes: G14, G21, D82, O33, M40

1. INTRODUCTION

Syndicated loans represent an important source of corporate financing, with global annual issuance totaling 4.7 trillion U.S. dollars in 2022, more than double the level recorded in 2009. Despite increased focus from policymakers and researchers on how technology transforms markets for equities (e.g., Gao et al., 2020; Goldstein et al., 2023), bonds (e.g., O'Hara et al., 2021), and bilateral loans (e.g., Fuster et al., 2019; Liberti et al., 2022; Jansen et al., 2024), technological developments in syndicated loans remain largely unexplored. Practitioners have frequently noted the slow adoption of FinTech solutions in this market.[23] Unlike publicly traded bonds and equities, syndicated loans rely heavily on private communication, involve fewer participants, and emphasize relationship strength (Campbell, 2013). Thus, technology affects syndicated lending differently than other asset classes. This study investigates how information technology shapes syndicated loan outcomes, exploiting a major innovation that improved the information sharing channel between arrangers and participant lenders. It highlights that communication and processing costs, though often overlooked, play a significant role in shaping lending outcomes in the syndicated loan market.

A syndicated loan involves multiple lenders jointly providing funds to a borrowing firm under a common agreement. The lead arranger negotiates loan terms with the borrower and guarantees part of the loan, and then seeks additional "participant" lenders to fund the remainder, adjusting terms based on participants' feedback. The arranger manages due diligence, syndication, and documentation, and subsequently oversees ongoing loan monitoring, making them more informed than participant lenders. In the presence of information asymmetry, participant lenders cannot directly observe borrower fundamentals or arranger incentives and must base their lending decisions on imperfect and noisy signals. This creates agency frictions that may deter participation. Arrangers, in turn, bear part of the risk associated with insufficient demand from participants, known as "pipeline risk" (Bruche et al., 2020).

[23] According to a recent *Bloomberg* article (Poh, 2023), "Bankers complain that technology adoption for syndicated loans has been slow compared with other markets such as bonds or equities because there's no standardization." A *McKinsey* report (2024) similarly emphasizes that syndicated loans require extensive communication and collaboration among all stakeholders, yet the supporting technology remains limited in effectiveness. For further details, see Bloomberg 2023 and McKinsey 2024.

A well-established literature documents that information asymmetry between arrangers and participant lenders influences the structure of syndicated loans (e.g., Sufi, 2007). Building on this insight, this paper examines the adoption of centralized digital platforms (hereafter, "platforms"), a form of information exchange technology that enables arrangers to distribute offering materials, share borrower updates, and coordinate communication with participants in a centralized setting, during both syndicate formation and post-origination stages. Although the underlying borrower information set does not necessarily change, these platforms reduce frictions in the transmission and processing of information among syndicate members. I study how this shift affects the behavior of arrangers and the structure of loan syndicates. Specifically, I ask: (1) How has information exchange in syndicated lending evolved over time? and (2) How has the adoption of this technology affected arrangers' syndication strategies, participation dynamics, and loan-level outcomes?

The empirical setting focuses on the adoption of early-stage information exchange platforms that began to emerge in the syndicated loan market in the late 1990s.[24] Prior to their adoption, while basic electronic communication tools were already in use, the distribution and coordination of deal materials remained highly manual and fragmented. Unlike mandatory disclosure systems such as EDGAR, these platforms were voluntarily adopted by arrangers to facilitate loan syndication and post-origination coordination. Examples include Debtdomain in Europe and Asia, as well as IntraLinks and SyndTrak in the United States.[25] As noted in Campbell (2013), at that time, arrangers and participants were already accustomed to documentation being transmitted electronically, so the adoption of these systems seemed a natural progression. These platforms reduce structuring and communication costs for arrangers and lower information processing frictions for participants by (1) storing deal documents in categorized, searchable formats; (2) standardizing internal knowledge within arranger teams; (3) simplifying the communication of

[24] Although this study focuses on early-stage platform adoption, it speaks to broader questions about how information exchange technology is reshaping syndicated lending, especially in light of recent initiatives like *Versana* that integrate real-time data and institutional workflows.

[25] Among them, IntraLinks is the primary platform in the U.S. syndicated loan market. In 1997, IntraLinks first introduced electronic information distribution for the loan syndication process using Lotus Notes groupware; and then expanded its service to loan monitoring in 1998. In 2001, IntraLinks further improved functionality and enabled external access through the global Internet. Further details are provided in Section 2.2.

materials to participants; and (4) enabling timely updates and the simultaneous processing of multiple deals. More details can be found in Section 2.2.

To answer the research questions, I construct a novel dataset that identifies potential platform adoption at the loan-deal level for U.S. domestic public companies between 1993 and 2021. Specifically, I identify platform adoption by reviewing loan contracts for disclosure clauses that designate "IntraLinks or similar platform" as the channel for sharing information with participant lenders.[26] For example, in the agreement shown in Appendix A, Example 1, the lead arranger is authorized to distribute materials via the IntraLinks website. I classify such loans as potentially using a platform. Among repeat arranger–borrower pairs, approximately 30% include a platform clause in one loan but not in another. This within-pair variation suggests that the clause reflects actual usage rather than boilerplate. Following an arranger's first observed platform use, the clause appears in 69% of subsequent loans on average (median: 100%), suggesting persistent adoption rather than one-off variation. Through this process, I identify three platforms consistent with industry practice: IntraLinks, SyndTrak, and Debtdomain. Figure 1 shows an upward trend in the adoption of platforms since 2000, reaching nearly 80% by 2012, consistent with external industry estimates.[27] Before 2009, IntraLinks dominated the market, while after that, SyndTrak began expanding its business, a shift that coincided with its strategic alliance agreement with Markit, a global financial information services company.[28]

This study builds on the theory of costly information processing, emphasizing that agents face costs in becoming aware of, acquiring, and integrating information (e.g., Grossman and Stiglitz, 1980; Blankespoor et al., 2020). In the context of syndicated lending, participant lenders face frictions arising from asymmetric information about borrower quality and arranger incentives, as well as from the cost of processing the materials needed to assess those risks. Lenders must decide whether, and to what extent, to engage with the information provided by the arranger. This decision reflects a trade-off between the expected benefit of processing, relative to the alternative

[26] Since arrangers bear legal responsibility for information delivery, contracts typically specify formal dissemination methods, such as a platform, fax, email, or company website.
[27] According to *Syndicated Lending: Practice and Documentation Annotated Edition* (sixth edition), "third-party deal sites have become the norm for syndicated loans in both the Americas and EMEA, with 78% and 89% respectively choosing to use a specialist platform."
[28] For more details, you can read the article: https://www.americanbanker.com/news/markit-dtcc-set-agreement.

of not processing, and the cost of processing the relevant materials. When the expected benefit is low relative to the cost, lenders may base participation decisions on simplified signals, such as easily observable financial metrics or prior beliefs formed through past interactions, with minimal processing effort. Digital platforms reduce processing costs along three dimensions: they lower awareness costs by notifying participants of new deal materials and centralizing materials in a shared environment; they reduce acquisition costs by offering a standardized channel for retrieving key documents; and they mitigate integration costs by structuring communications in a way that enhances clarity, comparability, and decision relevance. As information processing costs decline, participants are more likely to allocate effort toward information processing and to participate in deals that would otherwise lie at the margin of their participation decisions. This shift may result in more credit flowing to deals previously screened out based on simplified signals. These effects are most salient for information-intensive deals or those with limited participant prior exposure, where the trade-off between processing costs and expected benefits is most binding.

On the arranger side, the decision to originate a loan reflects a trade-off between the expected revenue from deal origination and the combined impact of borrower credit risk, pipeline risk, and transaction costs. As participant processing costs decline, more information is processed, and marginal deals attract broader participation, reducing the arranger's exposure to pipeline risk. Platforms also lower transaction costs by improving internal coordination and standardizing communication with participants. As this trade-off becomes more favorable, arrangers are more likely to originate deals, especially those that would previously have been screened out based on simplified signals. These effects are particularly salient for information-intensive deals or those requiring participation from lenders with limited prior exposure, where the risk of undersubscription is high and transaction costs are significant.

Even if platforms reduce processing costs, their impact depends on whether participants adjust their processing behavior. If simplified signals or prior beliefs are viewed as sufficient, the benefit of further processing may be low, especially for public borrowers. For sophisticated participants with established internal systems, the marginal cost savings from platform use may also be limited. For example, Goldstein et al. (2023) find no evidence that EDGAR inclusion affects firms' debt financing. Legal frictions also reduce incentives. With limited legal recourse

against arrangers (Down et al., 2024), participants may discount unverifiable information and rely on audited financials or credit ratings, which have traditionally guided their assessments. Finally, even if awareness and acquisition costs fall, integration costs may remain high enough to deter processing. These frictions make the effect of platform adoption on lending outcomes an empirical question.

In the first part of the paper, I explore why arrangers initially adopt platforms, or why the loans they arrange use platforms.[29] As platform adoption is voluntary, arrangers weigh expected benefits against fixed adoption costs, such as those related to operational adjustments. Consistent with the theoretical framework, I find that early adopters are arrangers who managed more loans with higher ex-ante information frictions in previous years. I assume these arrangers operate in lending sectors that require more costly information production, due to either high information intensity or limited ex-ante deal-specific knowledge among participants, and therefore benefit more from platform adoption. I proxy ex-ante information frictions within a syndicate using ex-post contracting outcomes of previous loans: the average geographic diversity of participants, the percentage of non-relationship participants, and the contract complexity for the loans they arranged over the past three years.[30] Next, I examine whether deals with negative signals on simplified performance metrics are more likely to be run on the platform. I focus on the debt-to-EBITDA ratio, a commonly used credit metric among lenders.[31] Consistent with the prediction, I find that more leveraged loans are significantly more likely to adopt the platform at origination. Finally, I show that arrangers who initially delay adoption for some loans eventually adopt the platform as more potential participants, especially those with prior lending relationships, join the platform. This pattern suggests that adoption is partly driven by participant demand.

[29] While platform use is observed at the deal level, the adoption decision reflects a broader shift in the arranger's practices. I therefore define treatment at the arranger level, using the first observed platform clause as the timing of adoption.

[30] In Table IA.1 of Online Appendix II, I verify the association between my measure of contract complexity (i.e., the length of contract) and other potential indicators of contracting complexity. The estimation shows that this measure is positively associated with the borrower's leverage level, participant geographic diversity, and participant non-relationship lending after controlling for arranger, year, and borrower industry fixed effects. It is also positively associated with loan amount, maturity, and credit spread, which together suggest that it is an appropriate measure for indicating contracting complexity.

[31] Debt-to-EBITDA is one of the most frequently cited credit metrics in offering materials, a standard basis for financial covenants, and is available for nearly all borrowers.

In the second part of the paper, I examine arrangers' syndication behaviors following initial platform adoption. As participant processing costs decrease and more information is processed, combined with lower transaction costs for arrangers, I expect arrangers to originate more deals, especially those that would previously have been screened out based on simplified signals, such as a high debt-to-EBITDA ratio. I examine their arranging activity surrounding initial platform adoption. Controlling for arranger and year fixed effects, I find a significant increase in both the number of new issues and total syndicated loan volume following adoption, for both new and existing borrowers. Event study estimates reveal no differential pre-trends and show that the increase emerges sharply at adoption and persists over time. The effects are concentrated in the top debt-to-EBITDA quartile, consistent with reduced reliance on simplified screening. Results are robust to controls for arrangers' liquidity and capital positions and hold under stacked difference-in-differences specifications.

Next, I examine the syndicate structure of successfully financed loans to support the argument that lower processing costs increase participants' willingness to process information and engage in marginal deals. Controlling for arranger, year, and borrower industry fixed effects, and accounting for borrower and loan characteristics, I find that syndicates become broader, with more geographically dispersed and first-time participants, and arrangers retain smaller loan shares. These loans typically have longer contracts, which serve as a proxy for information intensity. In addition, loan officers participating in platform-financed deals tend to engage in more loans during the same period. Overall, the results suggest platform adoption mitigates information frictions between arrangers and participants.

Lastly, I examine whether increased leveraged lending and broader participation following platform adoption are associated with weaker loan performance, proxied by covenant violations and payment defaults. While leveraged lending increases, I find no corresponding rise in real defaults, suggesting that arrangers scale intermediation without worsening loan performance. Notably, after 2004, IntraLinks separated public and private information posting, and some lenders can choose to remain on the public side. Amiraslani et al. (2023) document that the emergence of "public-side" lending facilitates broader lender participation by mitigating concerns about the

leakage of borrowers' private information into the public.[32] To further isolate its impact and obtain a clean effect of information exchange, I restrict the sample period to before 2003 or control for the presence of public lenders in my regressions. All main results remain robust.

Much of the literature in accounting and finance on technology focuses on its impact on the public market, showing that modern technology reduces information processing costs for public investors (e.g., Gao et al., 2020; Goldstein et al., 2023). In contrast, private markets have adopted technology more slowly and received less attention from both industry and academia. These markets rely on private communication, manual processes, and interdealer transactions, resulting in persistent frictions across multiple stages. This paper exploits the syndicated lending setting and focuses specifically on information exchange among syndicate members in the syndication and agency stages. It shows that platform-enabled improvements in communication and information processing enable arrangers to scale financial intermediation without worsening loan performance, particularly for information-intensive transactions. This study complements Fuster et al. (2019), who show that technology enables FinTech lenders in the mortgage market to process loans more quickly without increasing default risk, reducing frictions in bilateral borrower-lender relationships. In contrast, this paper examines how platform technology reduces frictions between arrangers and participants in a multi-lender setting, emphasizing the arranger's role in coordinating information and facilitating financial intermediation.

This study also relates to recent work on information-sharing technologies in credit markets, such as Liberti et al. (2022), who examine the adoption of a commercial credit bureau where lenders both access and contribute borrower-level information. However, this paper focuses on platforms that do not necessarily alter the underlying information set, but improve the transmission and processing of existing deal-specific information among syndicate members. The results highlight that digital platforms transform private debt markets by improving how information is processed, without necessarily adding new information. In addition, this study contributes to the syndicated loan literature. Sufi (2007) shows that information asymmetry between arrangers and participants affects syndicate structure, with arrangers retaining a larger share to signal a commitment to

[32] Using the same term-searching algorithms as in Amiraslani et al. (2023), I document that around 47% of platform-adopted loans indicate the potential use of the "public-side" function.

monitoring. Bruche et al. (2020) challenge this view, arguing that arrangers face a demand discovery problem and retain a larger fraction of "cold" or less desirable deals, which can tie up bank capital and constrain future activity. While Bruche et al. (2020) highlight that arrangers retain more in response to demand uncertainty and pipeline risk, my findings suggest that platform adoption mitigates these frictions by facilitating broader lender participation. As a result, arrangers retain smaller shares on average and engage in more arranging activity.

2. INSTITUTIONAL BACKGROUND

2.1 Loan Syndication Process

A syndicated loan involves two or more lenders jointly providing funds to a borrowing firm under common terms and conditions, but not necessarily in equal amounts, governed by a common agreement. The lead arranger, who establishes the relationship with the borrower, negotiates the contract terms with the borrower and guarantees a portion of the loan at a price range. The lead arranger then turns to "participant" lenders (i.e., relative value investors) that fund the rest; the lead may adjust the initial terms based on incremental information it acquires from potential participants. Arrangers are expected to play a key role in due diligence, book-running, and documentation during the syndication stage, followed by monitoring the loans in the agency stage.

Information exchange between arrangers and participants covers the entire lifecycle of a syndicated loan.[33] Specifically, during the syndication stage, mandated lead arrangers send invitation letters to potential participants and then distribute information memorandums (IM). IM outlines details of the transaction timetable, preliminary loan term sheets (e.g., amount, maturity, facility type, and discount to par), and a business and financial overview of the borrower, with attached financial reports. The information in IM is generally regarded as confidential. Examples of IM and term sheets can be found in Online Appendix I. After reviewing the IM, potential participants may notify the lead arranger of their willingness or unwillingness to participate in the loan; they may

[33] Ken Katz, product manager at Misys Banking Systems (now FIS Loan IQ), states, "Information is the lifeblood of the loan syndication market. The faster we can move information to the appropriate participants, the more responsive this market will be to its customers."

request additional information about the borrower from the arranger or may simply propose to take some portion of the loan under the terms it proposes to the arranger. With the right amount of participating demand, the deal is successfully closed. If it is under- or oversubscribed, the arranger may "flex" by adjusting terms. Potential participants are then given time to decide whether to invest under the new terms. This process can repeat through multiple rounds before the deal closes (Bruche et al., 2020). Extensive communications are necessary for engaging in and tracking such transactions. An example of communication between the arranger and potential participants can be found in Online Appendix I. In the agency stage, arrangers monitor the loan's performance, ensure compliance with terms, manage payments, and coordinate all renegotiations. Information exchange during this stage includes the borrower's quarterly or monthly financial disclosure, covenant compliance reports, amendment and waiver requests, financial projections, acquisition or disposition plans, and any other information requested by participant lenders. An example of information required in the agency stage can be found in Online Appendix I.

2.2 Information Exchange Technology

This study focuses on technology solutions designed to improve information exchange among syndicate members. Unlike bonds and equities, syndicated loans depend on fewer participants and the strength of relationships. It is a personal, relationship-driven market where individuals often know each other, and deals are traditionally distributed through telephone conversations or e-mails (Campbell, 2013). The impact of technology on syndicated lending has, therefore, been different from that on other asset classes. Back in the 1980s and 1990s, while basic communication technologies were already in use, the distribution and coordination of deal materials remained highly manual and fragmented. Using copiers and delivery services, facsimile machines, or e-mail takes time and may put confidentiality at risk (Ellen Byron, WSJ 2002).[34] Since the late 1990s, several information exchange solutions emerged and quietly changed how syndicated loans were closed and managed, such as Debtdomain in Europe and Asia, and IntraLinks and SyndTrak in the US. Campbell (2013) notes that arrangers and investors were already accustomed to electronic document transmission, making the adoption of systems like

[34] See https://www.wsj.com/articles/SB10112220714518913 20

IntraLinks a natural progression. Among these solutions, IntraLinks became the dominant platform in the U.S. syndicated loan market.

"***Save time, maintain control, and track activity with ease.*** *Everyone has constant access to the latest documentation, so you can spend less time on mailings, deliveries, and general administration and stop worrying about the security of emailed communications."*

----- *IntraLinks Website (2006)*

In 1997, IntraLinks, a New York-based startup, launched the "IntraLoan 1.0" service, a secure platform where syndicating participants could access loan documentation in digital form in the syndication process. Through the platform, arrangers send invitation letters to potential participants and post information memorandums in a central location. Potential participants can read, download, and filter the documents in a central location, and send back comments to the arrangers. The arrangers then offer feedback, revise the documents, and track the progress of the deal as it evolves. In January 1998, IntraLinks further added a new service to IntraLoan, allowing arrangers to monitor loan activity throughout the life of a transaction and distribute financials, amendments, and compliance information to participants.[35]

However, IntraLoan 1.0 required all participants to use Lotus Notes groupware as its interface, meaning that each participant needed to be running this software to connect to the system. In April 2001, IntraLinks launched an upgraded version with improved functionality and more reliable access via the global communications network. Authorized participants could now connect directly through an internet browser. In the deal room, information can be categorized into sections such as legal documents, status reports, or transaction information. E-mail notifications ensure that such communications and reports become effective once posted. The screen indicates whether the document is a draft or the original, along with the document's title and author. The platform also offers convenient access to real-time market data and news (LPC), research reports (S&P), and SEC filings (EDGAR). In addition, arrangers and participants interact through the Q&A section. Appendix C illustrates the features of IntraLoan.[36]

[35] Borrowers can even post or fax information directly to the platforms. All of which helps ensure that participants get the critical information they need.

[36] More details on technology updates can be found in Online Appendix I.

All other online solutions follow a similar model as IntraLinks.[37] As shown in Figure 2, in the U.S. syndicated loan market, IntraLinks dominated before 2009. Afterward, SyndTrak Online, a product released by FIS Commercial Loan Servicing (formerly ACBS), a leading loan management system (i.e., back-office system), began expanding its business.[38] In the EMEA syndicate loan market, Debtdomain was introduced in 2001, initially serving as an online marketplace for secondary trading. Due to insufficient liquidity in the secondary market, Debtdomain added a primary syndication platform in 2002. According to Sean Tai, the founder of Debtdomain, "Historically the technology was reserved for larger and more complex deals, but it is now increasingly used in all loans. Smaller syndications, club, and even bilateral deals are now regularly launched on Debtdomain."

3. HYPOTHESES DEVELOPMENT

In the presence of information asymmetries, agency conflicts exist between syndication arrangers and participants (e.g., Ball et al., 2008; Ivashina, 2009). The lead arranger possesses private information about the borrower, gathered through a prior lending relationship or due diligence conducted before the syndication process. The adverse selection problem occurs during the syndication stage. Potential participants may anticipate that the arranger has incentives to syndicate lower-quality loans to extract private benefits, such as building a relationship with the borrower or earning underwriting fees. Therefore, delivered information cannot be credibly communicated to potential participants, leading to a "lemons" problem. The moral hazard problem occurs during the agency stage, where participants delegate monitoring tasks to the arranger but cannot observe his efforts. As a result, participants may anticipate less-than-optimal effort from the lead arranger, given that the lead arranger does not have exposure to the entire loan. Therefore, with information

[37] The cost of platform usage is somewhat trivial. Taking IntraLinks as an example, the company charges each loan syndication for business-critical communication, based on the number of users who are granted access to the secure online environment that they establish for the syndication. As outlined in the loan contracts, borrowers are responsible to pay or reimburse costs and expenses incurred in connection with Intralinks. An example of this is provided in one loan contract I collected: "Within ten (10) days of the Agent's request after the setup of the borrower's IntraLinks account, borrowers shall pay the Agent a 5,000 dollars IntraLinks setup fee."

[38] Another leading loan management system is Finastra's Loan IQ (known as Misys at the time), which entered into a strategic alliance with IntraLinks in 2006.

asymmetry, participants cannot directly control the actions of arrangers and borrowers and must weigh their lending decisions against the associated risks based on imperfect and noisy signals. This creates agency frictions that may deter participation.

The lead arrangers, as such, have to bear part of the risk associated with a shortage in participating demand. Bruche et al. (2020) refer to the risk that arrangers assume as "pipeline risk". When an arranger mandates, it makes a promise to the borrower about not only the terms but also the amount that will be raised.[39] When the demand is low, the arranger has to choose to retain shares in the loan. This is potentially costly as increased exposure to a single borrower restricts the diversification of the lead arranger's loan portfolio. In extreme cases, the deal may even fail. Bruche et al. (2020) empirically find that the overall "low-demand" loans arranged by a lead arranger in a quarter are negatively related to the bank's subsequent arranging activity and lending. They interpret the results as indicating that "low-demand" loans erode an arranger's regulatory capital, making it less capable and/or willing to engage in future arranging activities.

This study builds on the theory of costly information processing, emphasizing that agents face costs in becoming aware of, acquiring, and integrating information (e.g., Grossman and Stiglitz, 1980; Blankespoor et al., 2020). In the context of syndicated lending, participant lenders face frictions arising from asymmetric information about borrower quality and arranger incentives, as well as from the cost of processing the materials needed to assess those agency risks. Lenders must decide whether, and to what extent, to engage with the information provided by the arranger. This decision reflects a trade-off between the expected benefit of processing, relative to the alternative of not processing, and the cost of processing the relevant materials. When the expected benefit is low relative to the cost, lenders may base participation decisions on simplified signals, such as easily observable financial metrics or prior beliefs formed through past interactions, with minimal processing effort.

[39] Syndicated loans can be arranged through either an "underwritten" deal or a "best-efforts" deal. In an underwritten deal, the arranger guarantees loan terms to the borrower. For example, in terms of the loan amount, if the required sum cannot be raised at the guaranteed terms from the market, the arranger would have to supply the rest. In a best-efforts deal, the arranger would make no such guarantees. Arranger fees for underwritten deals (with flex provisions) tend to be in the range of 2%–3% of face value, whereas fees for best-efforts deals are around 0.25% (Bruche et al. 2020).

Digital platforms reduce processing costs along several dimensions: First, they lower awareness costs by notifying participants of new deal materials and centralizing materials in a shared environment, especially when multiple materials arrive simultaneously; they also reduce acquisition costs by offering a standardized channel for retrieving key documents. In the syndication stage, the offering materials usually consist of hundreds of pages and sometimes require additional information from arrangers, thus requiring intense information processing. The same idea applies to the agency stage, where participants need to make efforts to monitor by reviewing the materials provided by arrangers and borrowers. This concept aligns with the idea presented by Sran et al. (2024), who argue that centralizing information—allowing market participants to access multiple disclosures from a single source—helps reduce investors' information processing costs. Second, platforms mitigate integration costs by structuring communications to enhance clarity, comparability, and decision relevance. Beyond centralized disclosure, they offer features like document filtering, unread document flags, favorite document flags, and full-text search, all of which reduce participants' processing costs. More importantly, the Q&A function can further aid participants in processing complex information, which Blankespoor et al. (2020) categorize as reducing integration costs.

As information processing costs decline, participants are more likely to allocate effort toward information processing and to participate in deals that would otherwise lie at the margin of their participation decisions. This shift may result in more credit flowing to deals previously screened out based on simplified signals. These effects are most salient for information-intensive deals or those with limited participant prior exposure, where the trade-off between processing costs and expected benefits is most binding.

On the arranger side, the decision to originate a loan reflects a trade-off between the expected revenue from deal origination and the combined impact of borrower credit risk, pipeline risk, and transaction costs. As participant processing costs decline, more information is processed, and marginal deals attract broader participation, reducing the arranger's exposure to pipeline risk. Platforms also lower transaction costs. With the platform, arrangers can access the communication records of market participants with just a few clicks and easily identify potential participants for deals. The platform also helps improve internal communication by standardizing team knowledge.

In the syndication process, arrangers can quickly connect with each potential participant, provide document updates, and manage complex question-and-answer transactions. After syndication is complete, arrangers can post updated financials to the deal room, saving the team hours of copying, faxing, and mailing. Moreover, such a platform can establish and manage multiple syndicated loan offerings at the same time. As this trade-off becomes more favorable, arrangers are more likely to originate deals, especially those that would previously have been screened out based on simplified signals. These effects are particularly salient for information-intensive deals or those requiring participation from lenders with limited prior exposure, where the risk of undersubscription is high and transaction costs are significant.

Even if platforms reduce processing costs, their impact depends on whether participants adjust their processing behavior. If simplified signals or prior beliefs are viewed as sufficient, the benefit of further processing may be low, especially for public borrowers. For sophisticated participants with established internal systems, the marginal cost savings from platform use may also be limited. For example, Goldstein et al. (2023) find no evidence that EDGAR inclusion affects firms' debt financing. Legal frictions also reduce incentives. With limited legal recourse against arrangers (Down et al., 2024), participants may discount unverifiable information and rely on audited financials or credit ratings, which have traditionally guided their assessments. Finally, even if awareness and acquisition costs fall, integration costs may remain high enough to deter processing. These frictions make the effect of platform adoption on lending outcomes an empirical question.

4. DATA AND STATISTICS

4.1 Filtering Loan Contracts in SEC Filings

I identify loan contracts from SEC filings of all publicly traded firms (domestic firms traded on NYSE, AMEX, or NASDAQ) filed from 1993 to 2021. The SEC mandates disclosure of material agreements either as an exhibit to Form 8-K or the company's next periodic report, and syndicated loan contracts fall under this category. I searched for 8-K, 10-Q, and 10-K filings that contain an attached Exhibit 10, which relates to "material agreements". Following Nini et al. (2009),

I identify loan contract documents by employing terms-searching at the beginning part of each "material agreement" exhibit.[40] To ensure the disclosure of complete contracts, I only retain those loan filings with signature pages and constrain the file size to exceed a threshold. I also exclude "amendment" or "restatement" of loan contracts. Next, I match loan contracts in SEC filings with the corresponding records in the DealScan database. In detail, I obtain the Compustat identifier "gvkey" for both the filers of loan contracts in EDGAR and borrowers in the DealScan database. I match these two datasets based on the common identifier "gvkey". Afterward, for each "gvkey", I match loan contracts to corresponding DealScan records, ensuring that the reporting dates of loan contracts fall within a 90-day window centered around the "tranche active date" specified in the DealScan records (Bushman et al. 2021). This results in a final sample of 9,657 loan contracts filed from 1993 through 2021, consisting of 13,601 loan facilities.

4.2 Data Collection of "Platform" Adoption

I identify "platform" adoption by checking the presence of an "IntraLinks or similar platform" disclosure clause in the loan contracts. For example, in the loan contract provided in Appendix A, Example 1, the agreement specifies that required information may be shared by the lead arranger with participants via the IntraLinks website. I categorize this loan as potentially using a "platform". Three platforms—IntraLinks, SyndTrak, and DebtDomain—have been identified through the process. In some cases, a loan contract may list multiple platforms in its terms, as shown in Appendix A, Example 4. In addition, I also classify the presence of an "intranet website", even if the platform brand is not indicated, as the potential use of a "platform", as shown in Appendix A, Example 5, comprises only around 6% of my sample. I argue that legal liability for information delivery would result in contracts specifying the information dissemination channel, such as a platform, fax, email, or company website. The variation in contract language within the same arranger and borrowers further supports this argument. I acknowledge that this measure of "platform" adoption only reflects the potential adoption but does not accurately capture the actual usage.

[40] Terms include: "credit agreement", "loan agreement", "credit facility", "loan and security agreement", "loan & security agreement", "revolving credit", "financing and security agreement", "financing & security agreement", "credit and guarantee agreement", and "credit & guarantee agreement".

4.3 Construction of Loan-Level Variables

To measure the level of ex-ante information friction within a syndicate, I use two key concepts commonly used in the lending literature: distant lending (e.g., Agarwal et al., 2010) and relationship lending (e.g., Bharath et al., 2011). I assume that participants are more likely to hold private information about arrangers and borrowers who are geographically close or with whom they have established relationships, thus facing fewer information frictions. As such, I construct three measures of ex-ante information frictions within a syndicate: a) *Participants GeoDiversity,* which is the distribution of lending amounts across states within a syndicate, capturing the geographical dispersion of syndicate members. b) *%Non-Relation Participants (for borrower),* which is the percentage of participants without lending experience with the borrower in the past five years; c) *%Non-Relation Participants (for arranger)*, which is the percentage of participants without lending experience with the arranger in the past five years. To construct *Participants GeoDiversity,* I proceed in three steps. First, I decompose the loan facility into loan portions provided by each lender.[41] Second, I aggregate the lending amount at the lending state level.[42] Third, I construct *Participants GeoDiversity* as an inverted Herfindahl index using lending shares S_j by lending state *j*, as follows:

$$Participants\ GeoDiversity = 1 - \sum_{j=1}^{J} S_j^2$$

Next, I construct a simple measure "*Contract Complexity*", which is the loan contract length (standardized across the entire contract universe). This measure captures the complexity of contracting and the intensive information processing required to address ex-ante frictions and ongoing monitoring. In Table IA.1 of Online Appendix II, I estimate the association between my measure of *Contract Complexity* and other potential indicators of contracting complexity. The estimation shows that this measure is positively associated with the borrower's leverage level, *Participants GeoDiversity, %Non-Relation Participants (for borrower),* and *%Non-Relation Participants (for*

[41] Following Doerr et al. (2021), whenever DealScan provides information on the lending shares of each lender, I use this information to split loan volume accordingly. In cases in which lending shares are missing, I distribute the loan volume pro-rata among all lenders (including both arrangers and participants).

[42] To identify the lender's location, I use the Compustat-DealScan link table provided by Schwert (2018). The sample includes U.S. dollar-denominated loans from DealScan with start dates on or before December 31, 2019. This variable only covers data up to 2019.

arranger), after controlling for arranger, year, and borrower industry fixed effects. It is also positively associated with loan amount, maturity, and credit spread, which together suggests that it is an appropriate indicator of contracting complexity.

I use the *Debt-to-EBITDA* ratio as a proxy for simplified signals, which capture perceived credit risk of a borrower with minimal processing effort, for three main reasons: 1) it is the most common credit measure included in the summary statistics of offering materials; 2) it is one of the most frequently used financial covenants; and 3) it is easy to measure and available for almost all borrowers. Consequently, it is less costly for (potential) participants to process, and higher ratios are more likely to be perceived as risky with minimal processing effort.

4.4 Construction of Arranger-Level Variables

To capture the ex-ante information frictions of loans previously arranged by an arranger, I follow the same logic as in section 4.3. Specifically, I define one measure for outstanding loan portfolios and three measures for newly issued loans over the past three years.

Lagged Outstanding-Participants GeoDiversity, which captures the distribution of outstanding lending amounts across states in an arranger's arranging portfolio in the previous year. To construct this measure, I follow several steps. First, I build the arranger's outstanding loan portfolio based on the loans' active and maturity dates. Second, I break down each loan facility into portions provided by each lender. Third, I aggregate the outstanding amounts at the participating state level for each arranger in a given year. Finally, I construct *Outstanding-Participants GeoDiversity* as an inverted Herfindahl index, based on state-level lending shares for each arranger in a given year.

Avg Participating GeoDiversity, which is the average value of *Participants GeoDiversity* for loans arranged by the arranger during the previous three years; *Avg %Non-Relation Participants (for borrower),* which is the average value of *%Non-Relation Participants (for borrower)* for loans arranged by the arranger during the previous three years; *Avg %Non-Relation Participants (for arranger),* which is the average value of *%Non-Relation Participants (for arranger)* for loans arranged by the arranger during the previous three years; *Avg Contracting Complexity,* which is the average value of *Contract Complexity* for loans arranged by the arranger during the previous three years; *Avg Borrower Reporting Complexity*, refers to the three-year average size of 10-K filings (standardized in the Compustat universe) for

borrowers whose loans were arranged by the arranger during the previous three years.

In addition, I construct a measure to capture the average workload of loan officers for each arranger in a given year, *Avg Loan Deal Arranged per Officer*, which represents the average number of loan deals arranged by each officer in the previous year. Following Herpfer (2021), I parse loan officer names from the signature pages of each loan contract.[43]

4.5 Descriptive Statistics

Figure 1 describes the time trends of platform adoptions in loan deals. Panel A aggregates all platforms and describes an upward trend in the adoption of platforms since 2000, approaching 80% in 2012. This number resembles the figures indicated in the industry.[44] Until recently, more than 90% of newly issued loans have listed "platforms" in their loan contracts. Panel B shows the trend by different platforms. Before 2009, IntraLinks dominated the market, while after that, SyndTrak began expanding its business, a shift that coincided with its strategic alliance agreement with Markit, a global financial information services company. Debtdomain, on the other hand, represented a smaller share of the US market. To rule out the possibility that the variation is driven by new market entrants, I further exclude arrangers who entered the market after 1997, the year IntraLinks was established, and still observe the same time-series pattern.

[Insert Figure 1]

Figure 2 presents the percentage of platform adoption across various loan facility types (as reported in DealScan). Overall, term loans and revolving credits show comparable platform adoption rates, while loan types with shorter maturities, such as 354-day facilities, exhibit lower adoption rates. Note that "platform" clauses are reported only at the deal level. Using facility-level observations would inflate significance levels due to the lack of independence (Murfin, 2012). Therefore, I conduct further comparisons at the deal level in Section 5.1 Table 1.

[Insert Figure 2]

Figure 3 describes the initial adoption by different lead arrangers over time. I define a lead

[43] The resulting dataset contains machine-readable information on both the institutions and individuals involved in each contract and the data are of high quality. Further manual checks may be done in the future version.
[44] According to "*Syndicated Lending: Practice and Documentation Annotated Edition* (sixth edition)", "third-party deal sites have become the norm for syndicated loans in both the Americas and EMEA with 78% and 89% respectively choosing to use a specialist platform".

arranger as the one assigned the highest title within a syndicate (Chakraborty et al., 2018).[45] To track the time-series adoption pattern, I restrict the sample to arrangers who entered the market before 1997, when the first version of IntraLinks was created. I take care to address the potential confounding effects of banking M&A during this period. In dealing with bank M&A, I aggregate all acquired subsidiaries under the ultimate parent if the M&A occurred before 1997. If the M&A happened after 1997, I treat the subsidiaries as independent institutions (e.g., Barclays is reported as the parent company of Lehman Brothers Inc. in DealScan, but I treat Lehman Brothers Inc. as an independent institution). In cases where DealScan continues to report lending activity separately (e.g., LaSalle Bank continues to appear in DealScan after its acquisition by ABN Amro), I follow DealScan and treat the institutions separately. Some arrangers ceased lending due to mergers during my sample period. To rule out the possibility that non-adoption was driven by bank mergers, I further restrict the sample to arrangers that continued operations independently at least until 2008, the year when most banks adopted the platform.[46] Figure 3 shows that around 90% of active arrangers adopted the platform in clusters before 2008, with clear peaks in 2002 after a new version of IntraLinks was released. Late adopters were typically non-active arrangers. During my sample period, only three arrangers did not adopt the platform: two became non-active, and one was merged after 2008.

[Insert Figure 3]

5. EMPIRICAL FINDINGS

5.1 Compare Loan Contracts with and without Platform Adoption Clauses

I simply start my analysis by comparing loans that have been successfully financed with and without "platform" clauses at the loan facility level and deal level.[47] As I noted earlier, I expect that a centralized information exchange platform can reduce the information processing costs of

[45] See Online Appendix of Chakraborty et al. (2018).
[46] I conduct all arranger-year level analyses using this sample selection, and this choice does not affect the main empirical conclusions in the study.
[47] Note that "platform" clauses are reported only at the deal level. Using facility-level observations would inflate significance levels due to the lack of independence (Murfin, 2012). Therefore, I report characteristics at both levels separately.

participants. As these costs decline, participants are more likely to allocate effort toward information processing and to participate in deals that would otherwise lie at the margin of their participation decisions. Therefore, I expect that "platform"-financed loans involve greater contracting complexity and attract participants with higher ex-ante information frictions, where the trade-off between processing costs and expected benefits is most critical.

Table 1, Panel A, presents loan-level characteristics for facilities and deals with and without "platform" clauses from 2000 (the first adoption year in my sample) to 2021. I exclude all loans borrowed by financial companies. Variable definitions are provided in Appendix C. Consistent with my prediction, loan faculties with "platform" clauses have significantly higher *Participants GeoDiversity* and *%Non-Relation Participants (for borrower)*, potentially suggesting that platforms help mitigate ex-ante information frictions. These loans also exhibit greater contract complexity, reflected in longer contract lengths, and typically involve more participants and larger loan amounts. However, as some variables of interest may exhibit time-series or arranger-level patterns, I do not draw definitive conclusions in this section. I address these concerns with more rigorous fixed effects in a later section.

[Insert Table 1]

After 2004, IntraLinks separated public and private information posting, and some lenders chose to remain on the public side. Amiraslani et al. (2023) document that the emergence of "public-side" lending facilitates broader lender participation by mitigating concerns about the leakage of borrowers' private information into the public. Using the same term-searching algorithms as in Amiraslani et al. (2023), I document that around 47% of "platform" loans indicate the potential use of the "public-side" function. To isolate its impact, I further compare data from 2000 to 2003, before the technological updates. Overall, the results are consistent with Table 1 Panel A.

Table 2 presents summary statistics at the arranger-facility and arranger-year levels from 1993 to 2021. The sample excludes loans borrowed by financial companies. For the arranger-facility sample, I drop loans with missing borrower-level characteristics. For the arranger-year sample, I restrict arrangers to those that entered the market before 1997 and remained active until at least 2008. For each arranger, the sample starts when it begins lending and ends either when it stops

lending or, at the latest, in 2021. Variable definitions are in Appendix C.

[Insert Table 2]

5.2 Determinants of Platform Adoption

Next, I explore why arrangers initially adopt platforms. As platform adoption is voluntary, arrangers weigh expected benefits against fixed adoption costs, such as those related to operational adjustments. I expect that early adopters are arrangers who managed more loans with higher ex-ante information frictions in previous years. I assume these arrangers operate in lending sectors that require more costly information production, due to either high information intensity or limited ex-ante deal-specific knowledge among participants, and therefore benefit more from platform adoption. While platform use is observed at the deal level, the adoption decision reflects a broader shift in the arranger's practices. I therefore define treatment at the arranger level, using the first observed platform clause as the timing of adoption.

Table 3, Panel A, examines how the information exchange demands of previously arranged loans predict the timing of initial platform adoption by arrangers. The sample includes arrangers that entered the market before 1997 and remained active until at least 2008. For each arranger, the sample ends when it adopts. I construct several measures to capture the ex-ante information frictions of loans previously arranged by an arranger, as described in section 4.4. The dependent variable is the number of years remaining before the arranger initially adopts the platform, and all columns use a Weibull accelerated failure time model, with standard errors clustered at the arranger level. The results show that arrangers with higher ex-ante information frictions in previously arranged loans—proxied by participating geographic diversity of loan portfolios, the percentage of non-relationship participants, and average contracting complexity—accelerate platform adoption. Specifically, a one-standard-deviation increase in geographic diversity of outstanding participants accelerates platform adoption by approximately 4 months, while similar increases in average contract complexity and the percentage of non-relationship participants each accelerate adoption by roughly 2 months. Additionally, loan officers with heavier workloads, measured by the average number of loans arranged per officer in the previous year, also adopt platforms earlier. These findings are consistent with my predictions.

[Insert Table 3]

Next, I examine whether deals with negative signals on simplified performance metrics are more likely to be run on the platform. I focus on the Debt-to-EBITDA ratio, a widely used credit metric among lenders. Table 3, Panel B, estimates the likelihood of platform adoption for individual loan contracts based on borrower and loan characteristics. The sample begins in 2000, the first year of observed platform adoption, and excludes loans from financial companies or those with missing borrower-level characteristics. All columns use a logit model, with loan facility as the unit of observation. I control for year fixed effects and borrower-industry fixed effects, with standard errors clustered at the borrower-industry level. Consistent with the prediction, the results show that more leveraged borrowers, as proxied by their lagged Debt-to-EBITDA ratios, are more likely to adopt the platform in their loan facilities. These findings are robust to the inclusion of other loan contract terms.

Finally, I show that arrangers who initially delay platform adoption for some loans eventually adopt as more potential participants, especially those with prior lending relationships, join the platform, suggesting that adoption is partly driven by participant demand. Table 3, Panel C, uses the same specification as Panel B but additionally tests the impact of potential participant usage experience. The results show that an increase in the number of potential participants joining the platform significantly raises the likelihood of platform adoption in a loan. I define potential participants as those who have extended loans in the previous five years (*# Participants in Market*) and those who participated in the arranger's syndications in the previous five years *(# Relation Participants (for arrangers)*). All variable definitions and data sources are provided in Appendix C.

5.3 Arranging Activities Around Initial Platform Adoption by Arrangers

The previous section documents that arrangers or loans requiring more costly information processing by participants are more likely to adopt the platform in the first place.[48] Given this, a natural consequence of platform adoption is a shift in arrangers' syndication behaviors after their initial adoption. As participant processing costs decrease and more information is processed,

[48] Importantly, the average potential platform adoption rate among loan facilities arranged by the lead arranger after initial adoption is 69%, with a median of 100%.

combined with lower transaction costs for arrangers, I expect arrangers to originate more deals, especially those that would previously have been screened out based on simplified signals, such as a high debt-to-EBITDA ratio.

Table 4, Panel A estimates new loan issuances around initial platform adoption by arrangers. The sample includes arrangers active before 1997 and still operating at least until 2008, with observations ending either when the arranger exits the market or in 2021. Financial company borrowers are excluded. All columns use TWFE models with year and arranger fixed effects, and the unit of observation is arranger-year. The dependent variables are the inverse hyperbolic sine of the number of loans (columns 1 and 2) and the natural logarithm of loan amount (columns 3 and 4). T-statistics are calculated using arranger- and year-clustered standard errors. Variable definitions and data sources are provided in Appendix C. Columns 1 and 3 show that arrangers issued more new loans and arranged larger loan volume after initial platform adoption. Results are robust to controls for arrangers' liquidity and capital positions, including arranger's total assets, asset-to-equity ratio, and tier-1 capital ratio.

[Insert Table 4 and Figure 4]

Table 4, Panel B separately estimates new loan issuances for first-time and repeat borrowing around the initial platform adoption by arrangers. First-time borrowing refers to the first syndication transaction between the arranger and the borrower. The results suggest that following initial platform adoption, the arranger issued more new deals and larger amounts, both for first-time borrowers and for those with previous arranging history. To rule out the possibility that large loan maturities coincide with initial platform adoption, Panel C estimates the cumulative outstanding loans under management around the time of initial platform adoption by arrangers. The results suggest that following initial platform adoption, the arranger indeed manages a significantly larger amount of outstanding loans. Figure 4 presents event study estimates using similar specifications as in Table 4. The sample spans from -5 to -1 (five years before adoption) and 1 to 5+ (five years after adoption and beyond), capturing both pre-trends and long-term effects. The results indicate no differential pre-trends, with a sharp increase at adoption that persists over time. Overall, I document that following the initial platform adoption, arrangers facilitate more syndicated lending volumes.

Table 5 estimates leveraged loan issuances around the initial platform adoption by arrangers. Panel A uses the same sample selection criteria and specifications as Table 4 Panel C. The results indicate that, following initial platform adoption, arrangers manage significantly larger volumes for more leveraged borrowers—specifically, those in the top debt-to-EBITDA quartile by year and industry within the Compustat universe, consistent with my expectations. In addition, the percentage of leveraged loans in arrangers' overall outstanding portfolio also increases, reflecting a broader shift toward loan management. Figure 5 presents the corresponding TWFE event study dynamics, capturing both pre-trends and long-term effects. The results indicate no differential pre-trends, with a sharp increase at adoption that persists over time. This finding is robust to controls for arrangers' liquidity and capital positions, including total assets, asset-to-equity ratio, and tier-1 capital ratio.

[Insert Table 5 and Figure 5]

In Table 5, Panel B, I further analyze the phenomenon of more leveraged lending at the loan facility level. The dependent variable is the debt-to-EBITDA quartile by year and industry in the Compustat universe. This analysis includes additional controls for borrower-level and arranger-loan facility-level characteristics, as well as borrower-industry fixed effects or borrower-fixed effects. Standard errors are clustered at the arranger, year, and borrower-industry levels. The results indicate that, following initial platform adoption, arrangers are more likely to finance more leveraged borrowers, even when using similar loan contract designs.

Table 6 tests the robustness of the conclusions from Tables 4 and 5 using a stacked approach, rather than a TWFE model. This approach only considers not-yet adopters as the control group, comparing them to early adopters. The sample begins when the arranger starts lending and ends either when the arranger ceases lending or, at the latest, in 2003, ensuring that at least 40% of arrangers had not yet adopted. In Panels A and B, the sample is a panel of arranger-cohort-year observations, where each cohort includes all arrangers treated in the same year and those that have not yet adopted. In Panel C, the observation is at the arranger-loan facility-cohort-year level. Across all panels, standard errors are clustered at the arranger×cohort level. Overall, the results confirm that arrangers finance more leveraged borrowers after their initial platform adoption, consistent

with earlier findings. This pre-2004 sample selection also helps isolate the impact of public-side lenders, as noted in Amiraslani et al. (2023).

[Insert Table 6]

5.4 Platform Adoption and Syndicate Structure

I have now confirmed that initial platform adoption predicts an increase in syndicated lending volume by arrangers, particularly for more leveraged loans. This finding is consistent with the argument that platform adoption reduces participants' information processing costs. As these costs decline, participants are more likely to allocate effort toward processing borrower information and participate in deals that would otherwise lie at the margin of their participation decisions. In the next section, I formally shift focus to the syndicate structure of successfully financed loans. I expect that platform-financed loans can involve greater contracting complexity and attract participants with higher ex-ante information frictions, where the trade-off between processing costs and expected benefits is most critical.

Table 7 estimates the syndicate structure as a function of the platform adoption. All columns use a TWFE model with year and arranger fixed effects. I restrict the sample to arrangers who entered the market before 1997 and continued operations at least until 2008. The sample begins when the arranger starts lending and ends either when the arranger ceases lending or, at the latest, in 2021. I drop all loans borrowed by financial companies. In all panels, the unit of observation is the arranger-loan facility; and the independent variable is whether the loan adopts the platform. After controlling for arranger fixed effects, year fixed effects, and borrower industry or borrower fixed effects, my results indicate the following: 1) "platform"-financed loans have more geographic diversity among participants, even when controlling for the borrower and loan-level characteristics; 2) "platform"-financed loans have more non-relationship participants, defined as those without lending experience with the borrower in the past five years, even when controlling for the borrower and loan-level characteristics; 3) "platform"-financed loans have more non-relationship participants lacking prior experience with the arranger, even for similar borrowers but not necessarily identical loan terms; 4) "platform" financed loans, for the similar borrower, on average, have lower lead share retained by arrangers.

[Insert Table 7]

Table 8 estimates loan contracting outcomes as a function of platform adoption, using the same specifications as in Table 7. After controlling for arranger fixed effects, year fixed effects, and borrower industry or borrower fixed effects, the results indicate the following: 1) "platform"-financed loans exhibit greater contracting complexity, as measured by the standardized value of contract length; 2) loan officers (including both arrangers and participants) involved in "platform"-financed loans tend to manage more loans, on average, during the same period.

[Insert Table 8]

In summary, the results indicate that platform-financed loans are associated with broader syndicates, characterized by more geographically dispersed and first-time participants, as well as smaller arranger shares, consistent with my prediction. These loans also tend to have longer contracts, serving as a proxy for information intensity. Additionally, loan officers involved in platform-financed deals participate in more loans during the same period. Overall, this evidence suggests that platform adoption reduces information frictions between arrangers and participants. To further isolate the impact of public-side lenders, as noted by Amiraslani et al. (2023), I control for the presence of a public-side lender clause in the regressions. The results remain robust, as shown in Table IA.2 of Online Appendix II.

5.5 Platform Adoption and Negative Events

Lastly, I examine whether increased leveraged lending and broader participation following platform adoption are associated with weaker loan performance, proxied by covenant violations and payment defaults. Table 9 estimates the association between platform adoption and the incidence of negative events. In Panel A, the dependent variable indicates whether the borrower reports a financial covenant violation during the loan facility's outstanding period. The covenant violation dataset, collected by Nini et al. (2012), covers the period from the second quarter of 1997 to the fourth quarter of 2008. Accordingly, I restrict my sample to facilities that originated during this period. In Panel B, the dependent variable indicates whether the borrower defaulted during the loan facility's outstanding period. I only examine the universe of rated borrowers using data provided by S&P rating agencies. The results show that although platform adoption does increase

leveraged lending, it does not lead to a higher incidence of borrower defaults.

[Insert Table 9]

6. CONCLUSION

In conclusion, my empirical findings suggest that digital platforms that improve information exchange between arrangers and participants reshape syndicated lending dynamics. Platform adoption has increased steadily since the early 2000s, with early adopters more likely to be arrangers previously involved in information-intensive deals. Exploiting staggered adoption, I find that platform use is followed by an increase in the arranger's syndicated lending volume, particularly to more leveraged borrowers. Syndicates become broader, with more geographically dispersed and first-time participants, and arrangers retain smaller loan shares. Default rates remain unchanged. The findings suggest that reducing communication and processing frictions enables arrangers to scale financial intermediation without worsening loan performance. The results highlight that digital platforms transform private debt markets by improving how information is processed, without necessarily adding new information.

While much of the literature focuses on technology's impact in public markets (e.g., Gao et al., 2020; Goldstein et al., 2023), private markets have been slower to adopt technology, relying on private communication, manual processes, and interdealer transactions, resulting in persistent frictions across multiple stages. This paper shows that platform-enabled improvements in information exchange reduce frictions in multi-lender syndication, allowing arrangers to scale financial intermediation without worsening loan performance. This study complements Fuster et al. (2019), who show that technology enables FinTech lenders in the mortgage market to process loans more quickly without increasing default risk, reducing frictions in bilateral borrower-lender relationships. Unlike the bilateral settings in Liberti et al. (2022), this paper focuses on platforms that improve the processing of existing deal-specific information within syndicates, without necessarily adding new information. This study also contributes to the syndicated loan literature, extending Sufi (2007) and Bruche et al. (2020) by showing that platform adoption reduces demand uncertainty, allowing arrangers to retain smaller shares and engage in more arranging activity.

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Appendix A: Examples of "Information Exchange Platform" Clauses

Example 1:

https://www.sec.gov/Archives/edgar/data/37912/000119312505085328/dex10.htm

From the date hereof and for so long as any Term Loan remains outstanding, the Borrower agrees to:

Subject to the next succeeding sentence, information delivered pursuant to this Section 5.01 to the Administrative Agent **may be made available by the Administrative Agent to the Lenders by posting such information on the Intralinks website** on the Internet at http://www.intralinks.com. Information delivered pursuant to this Section 5.01 may also be delivered by electronic communication pursuant to procedures approved by the Administrative Agent pursuant to Section 10.01 hereto. Information required to be delivered pursuant to this Section 5.01 (to the extent not made available as set forth above) shall be deemed to have been delivered to the Administrative Agent on the date on which the Borrower provides written notice to the Administrative Agent that such information has been posted on the Borrower's website on the Internet at http://www.delta.com (to the extent such information has been posted or is available as described in such notice). Information required to be delivered pursuant to this Section 5.01 shall be in a format which is suitable for transmission.

Example 2:

https://www.sec.gov/Archives/edgar/data/49071/000004907101500045/dayagt.txt

The Company will and will cause each of its Subsidiaries to maintain a standard modern system of accounting in which full, true and correct entries will be made of all dealings or transactions in relation to its business and affairs in accordance with GAAP consistently applied, and will furnish **(or make available via the IntraLinks website)** the following to the Agent and each Bank (if not provided via Intralinks, in duplicate if so requested):

(a) Annual Statements. (b) Quarterly Statements. (c) ERISA Reports.

Example 3:

https://www.sec.gov/Archives/edgar/data/1441236/000156459019027499/clw-ex101_6.htm

Documents required to be delivered pursuant to this Section 8.01 may be delivered electronically and if so delivered, shall be deemed to have been delivered on the date (i) on which the Company posts such documents, or provides a link thereto, on the Company's website or (ii) **on which such documents are posted on the Company's behalf on IntraLinks or another relevant website, if any, to which each Bank and the Administrative Agent have access (whether a commercial, third-party website or whether sponsored by the Administrative Agent).** Notwithstanding anything contained herein, in every instance the Company (i) shall be required to provide paper copies of the certificates required under this Section 8.01 to the Administrative Agent and (ii) shall notify any Bank when documents required to be delivered pursuant to this Section 8.01 have been delivered electronically to the extent that such Bank has requested so to be notified. Except for such certificates, the Administrative Agent shall have no obligation to request the delivery or to maintain copies of the documents referred to above, and in any event shall have no responsibility to monitor compliance by the Company with any such request for delivery, and each Bank shall be solely responsible for requesting delivery to it or maintaining its copies of such documents.

Example 4:

https://www.sec.gov/Archives/edgar/data/720005/000072000515000055/exhibit101rjfcreditagreeme.htm

The Borrower hereby acknowledges that (a) the Administrative Agent and/or the Arrangers may, but shall not be obligated to, make available to the Lenders materials and/or information provided by or on behalf of the Borrower hereunder (collectively, "Borrower Materials") by **posting the Borrower Materials on IntraLinks, Syndtrak, ClearPar or a substantially similar electronic transmission system** (the "Platform") and (b) certain of the Lenders (each a "Public Lender") may have personnel who do not wish to receive material non-public information with respect to the Borrower or its Affiliates, or the respective securities of any of the foregoing, and who may be engaged in investment and other market-related activities with respect to such Persons' securities.

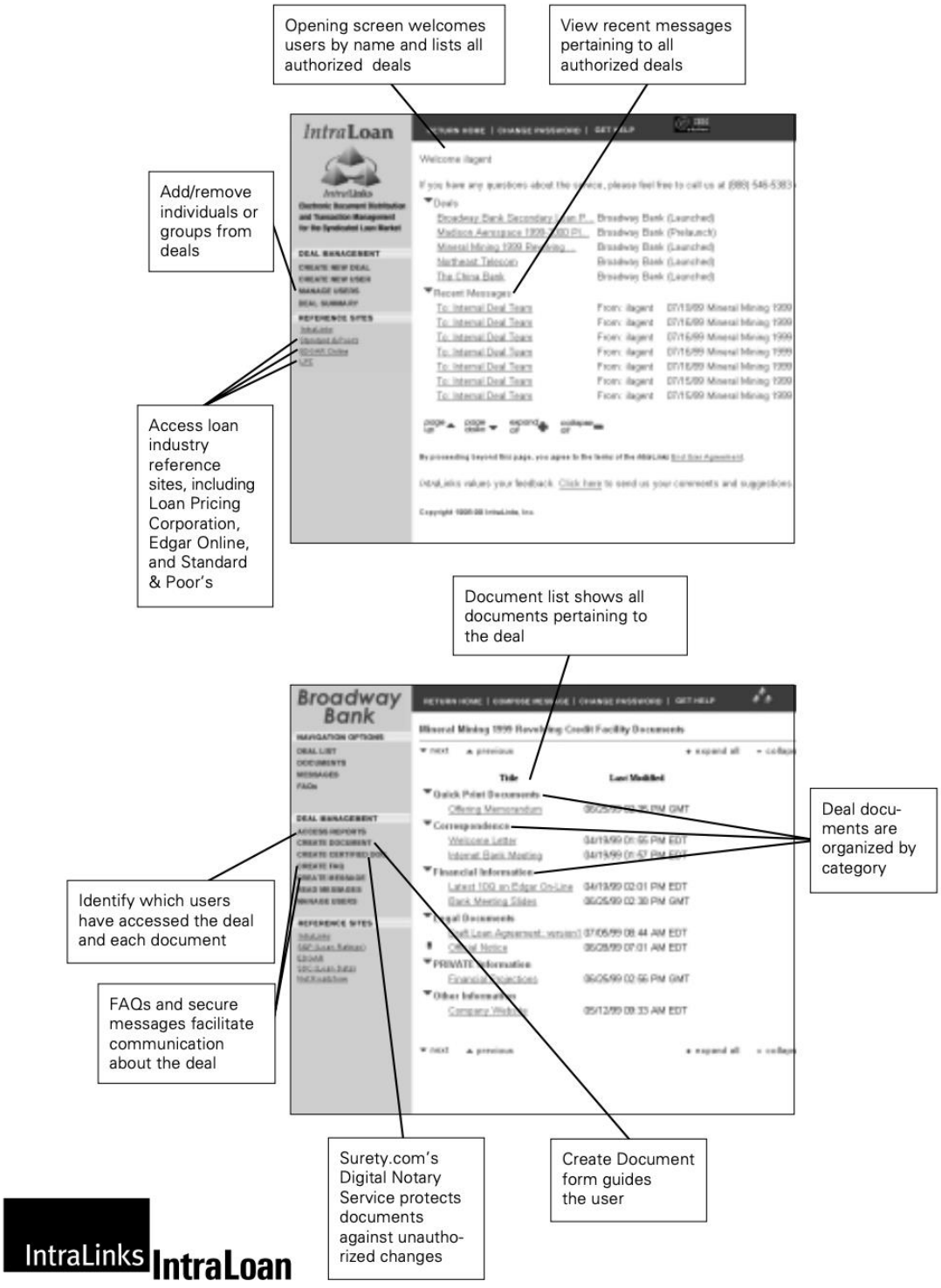
Example 5:

https://www.sec.gov/Archives/edgar/data/1350381/000162828019008771/inwk-ablloanandsecurityagr.htm

Documents required to be delivered pursuant to Section 10.1.2(a) or (b) or Section 10.1.2(g) or (h) (to the extent any such documents are included in materials otherwise filed with the SEC) may be delivered electronically and if so delivered, shall be deemed to have been delivered on the date (i) on which the Borrower Agent posts such documents, or provides a link thereto on the Borrower's website on the Internet at the website address listed on the signature pages hereto; or (ii) **on which such documents are posted on the Borrower Agent's behalf on an Internet or intranet website, if any, to which each Lender and the Agent have access (whether a commercial, third-party website or whether sponsored by the Agent);** ……

Appendix B: The Features of Information Exchange Platform

The figures are sourced from IntraLinks SEC Form S-1 filings dated July 1999 (CIK0001024623).



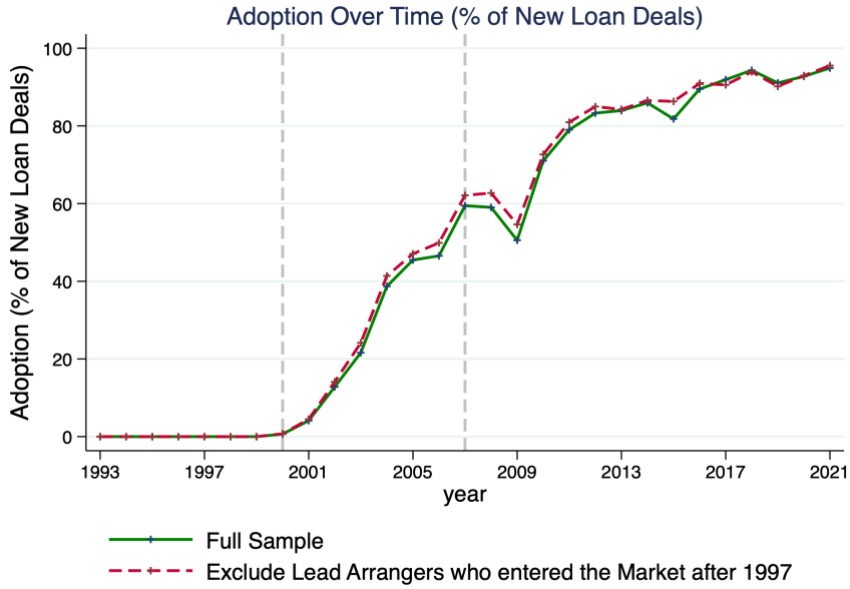
Appendix C: Variable Definition

Variables	Description	Source
Facility-Level Variables		
Participants GeoDiversity	An inverted Herfindahl index captures the distribution of lending amounts across states within a syndicate, where a higher value indicates greater geographic diversity in lending.	*Compustat/DealScan*
# Participants	Number of participants within a syndicate.	*DealScan*
% Non-Relation Participants (for borrower)	The percentage of participants who don't have lending experience with the borrower in the past five years.	*DealScan*
% Non-Relation Participants (for arranger)	The percentage of participants who don't have lending experience with the arranger in the past five years.	*DealScan*
% Foreign Participants (for arranger)	The percentage of participants who are operating in a foreign country.	*DealScan*
LnAmount	Logged value of facility amount (million US dollar)	*DealScan*
Spread (bp)	All-in spread drawn above LIBOR	*DealScan*
LnSpread	Logged value of All-in spread drawn above LIBOR	*DealScan*
Maturity (in years)	Loan maturity (in years)	*DealScan*
PerformancePricing	A dummy variable equal to 1 if performance pricing exists	*DealScan*
Secured	A dummy variable equal to 1 if the loan is secured by collaterals	*DealScan*
Lead Retained Share	The lending share (%) retained by the lead arrangers	*DealScan*
Refinancing	A dummy variable equal to 1 if the loan is used to refinance prior loans.	*DealScan*
Revolver/Line	A dummy variable equal to 1 indicates the loan is a Revolver/Line	*DealScan*
# Participants in Market Joined Platform	Number of participants who lent money in the market in the previous five years joined the platform	*DealScan/SEC filings*
# Relation Participants Joined Platform (for borrowers)	Number of participants who lent money to the borrower in the previous five years joined the platform	*DealScan/SEC filings*
# Relation Participants Joined Platform (for arrangers)	Number of participants who participated in the arranger's lending in the previous five years joined the platform	*DealScan/SEC filings*
# Participants in Market	Number of participants who lent money in the market in the previous five years	*DealScan*
# Relation Participants (for borrowers)	Number of participants who lent money to the borrower in the previous five years	*DealScan*
# Relation Participants (for arrangers)	Number of participants who participated in the arranger's lending in the previous five years	*DealScan*
Deal-Level Variables		
# Arrangers	Number of arrangers who have the highest title	*DealScan*
Contract Complexity	Standardized value of the length of loan contract	*SEC filings*
# Facilities	Number of facilities in a deal (contract)	*DealScan*
LnDealAmount	Logged value of deal amount (million US dollar)	*DealScan*
# Covenants	Number of covenants in a deal (contract)	*DealScan*
RelationshipBanking	A dummy variable equal to 1 if the borrower had a syndication relationship with the arranger in the past five years	*DealScan*
Ind_PublicLender	A dummy variable equal to 1 indicates the presence of public-side lenders, as studied in Amiraslani et al. (2023)	*SEC filings*
Adoption	A dummy variable equal to 1 indicates the presence of platform adoption clause	*SEC filings*
Arranger-Level Variables		
Time to Initial Adoption	Number of years remaining before the arranger initially adopts the platform	*SEC filings*
Lagged Outstanding-Participants GeoDiversity	An inverted Herfindahl index captures the distribution of outstanding lending amounts across states in an arranger's arranging	*Compustat/DealScan*

	portfolio in the previous year, where a higher value indicates greater geographic diversity in lending.	
Avg Participating GeoDiversity	Average value of *Participants GeoDiversity* for loans arranged by the arranger during the previous three years	*Compustat/DealScan*
Avg %Non-Relation Participants (for borrower)	Average value of *%Non-Relation Participants (for borrower)* for loans arranged by the arranger during the previous three years	*DealScan*
Avg %Non-Relation Participants (for arranger)	Average value of *%Non-Relation Participants (for arranger)* for loans arranged by the arranger during the previous three years	*DealScan*
Avg Contracting Complexity	Average value of *Contract Complexity* for loans arranged by the arranger during the previous three years	*SEC filings*
Avg Borrower Reporting Complexity	Three-year average file size of 10-K filings (standardized in the Compustat universe) for borrowers whose loans were arranged by the arranger during the previous three years	*WRDS SEC Analytics Suite*
Avg Loan Deal Arranged per Officer	Average number of loan deals arranged by each officer in the previous year	*SEC filings/DealScan*
# Arranging Loan Officers	Number of loan officers arranging loans in the previous year.	*SEC filings/DealScan*
# Lagged Loan Deal Arranged	Number of loan deals arranged in the previous year	*DealScan*
# Lagged Leveraged Deal Arranged	Number of loan deals with a high debt-to-EBITDA ratio arranged in the previous year, where high debt-to-EBITDA is defined as being in the top quartile by year and industry within the Compustat universe	*DealScan*
# Newly Issued Loans	Inverse hyperbolic sine of the number of newly issued loans in a given year	*DealScan*
LnAmount (Newly Issued Loans)	Logarithm of the newly issued aggregated loan amount in a given year	*DealScan*
# Loans Outstanding	Inverse hyperbolic sine of the number of loans outstanding in a given year	*DealScan*
LnAmount (Loans Outstanding)	Logarithm of the aggregated loan outstanding amount in a given year	*DealScan*
% Amount Outstanding with high Debt/EBITDA (Quartile 4)	Proportion of the outstanding loan amount with a debt-to-EBITDA ratio in the top quartile, calculated by year and industry within the Compustat universe.	*Compustat/DealScan*
LnAssets	Logarithm of the total assets of the arranger in a given year	*Compustat*
Assets-to-Equity	Ratio of total assets to equity of the arranger in a given year	*Compustat*
Tier 1 Capital ratio	Tier 1 capital ratio of the arranger in a given year	*Compustat*
Borrower-Level Variables		
Debt/EBITDA	Ratio of total debt to EBITDA	*Compustat/CRSP*
Debt/EBITDA quartile	Categorizes firms into quartiles based on their debt-to-EBITDA ratio by year and industry within the Compustat universe	*Compustat/CRSP*
Assets	Logged book value of total assets.	*Compustat/CRSP*
Tangibility	The ratio of net PP&E to total assets	*Compustat/CRSP*
OperatingCF	Ratio of operating income before depreciation to lagged total assets.	*Compustat/CRSP*
MtB	Ratio of Market Cap to Book Value of Equity, omitted for negative Book Equity	*Compustat/CRSP*
ROA	Ratio of earnings before interest and taxes to lagged total assets.	*Compustat/CRSP*
SalesGrowth	Calculated as sales minus previous year sales scaled by average sales.	*Compustat/CRSP*
FirmAge	The number of years since a company appears in CRSP.	*Compustat/CRSP*

Figure 1: Time Trends of Platform Adoption Clauses in Loan Deals
The figures present the time trends of "platform" technology adoptions in loan deals. Panel A aggregates all "platforms" (including IntraLinks, SyndTrak, DebtDomain, and other intranet websites), and Panel B shows the trend by different "platforms".

Panel A: All Technology Platforms



Panel B: By Different Technology Platforms

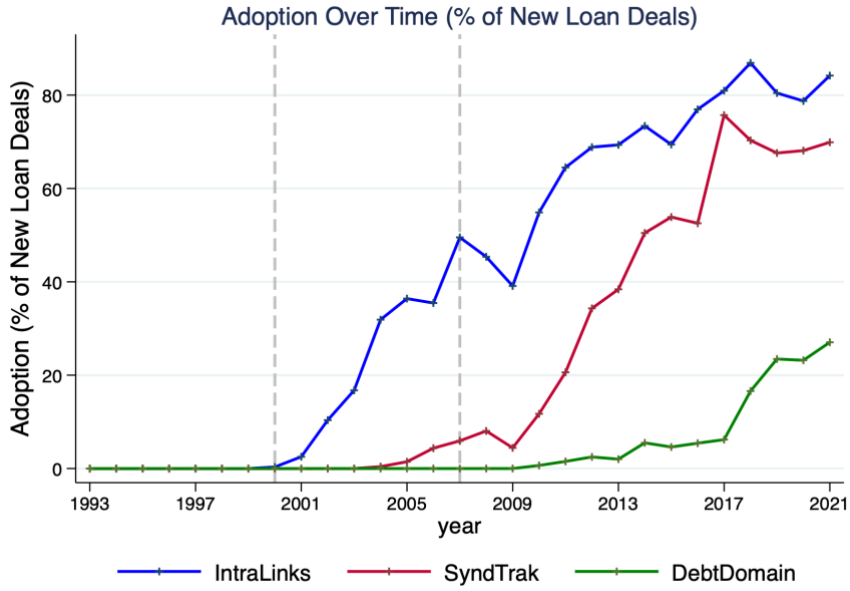


Figure 2: Platform Adoption Clauses by Loan Facility Types (as Reported in DealScan)
The figure presents the percentage of "platform" adoption across various loan facility types.

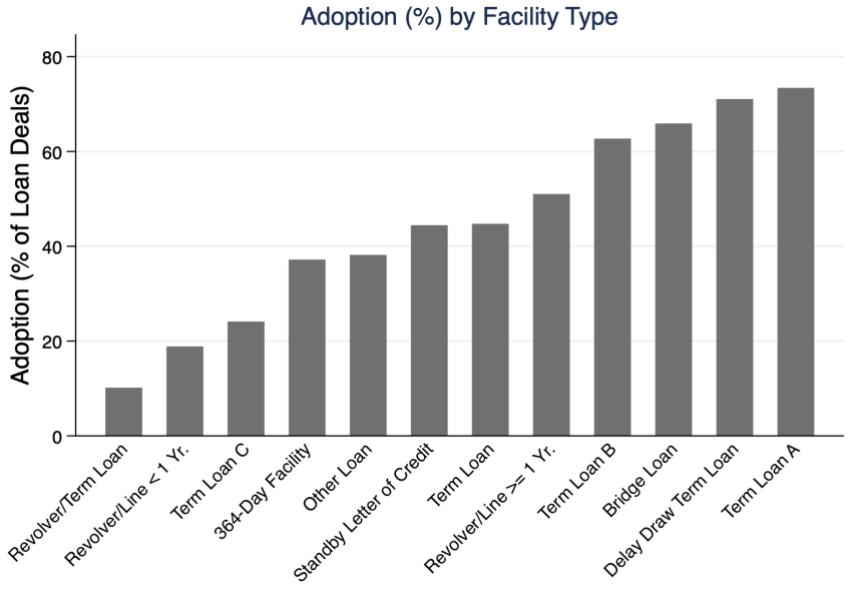


Figure 3: Trends in Lead Arrangers' First Platform Adoption Clause
The figure presents the number and percentage of lead arrangers' initial "platform" adoptions over time, collected from loan contracts in SEC filings. I restrict arrangers to those who entered the market before 1997 and continued their operations at least until 2008.

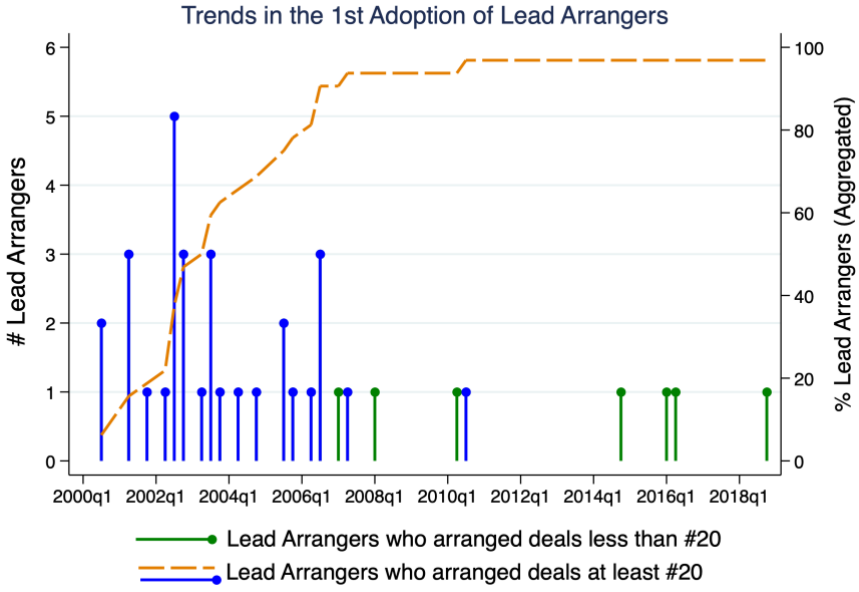
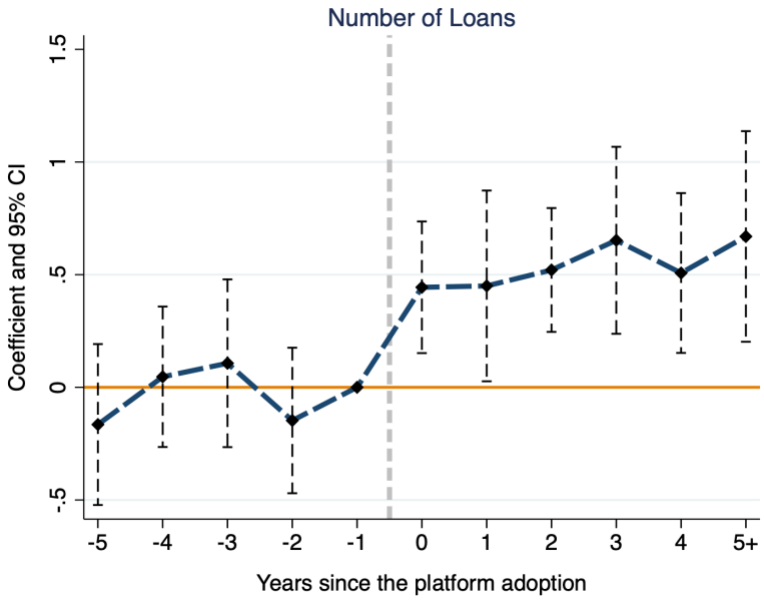
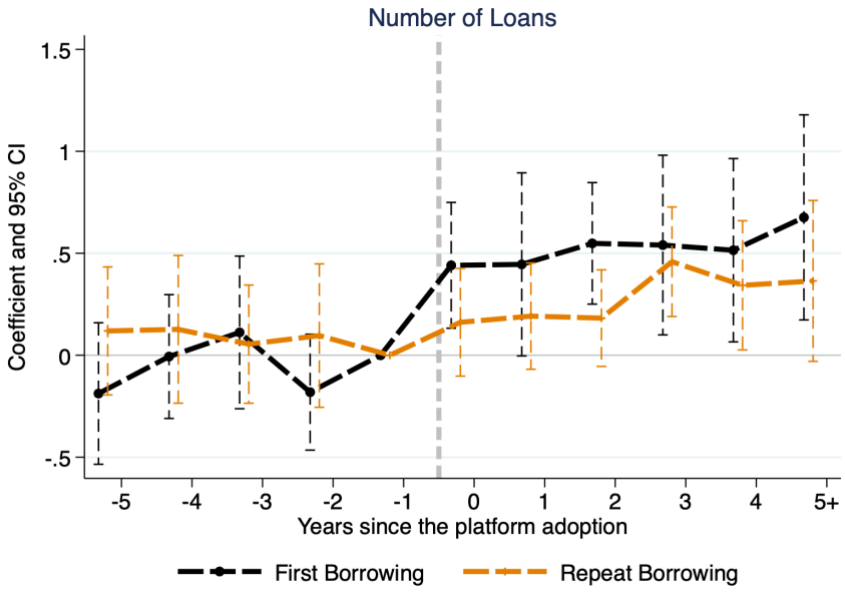


Figure 4: Loans Under Management Around Platform Adoption
The figure presents the estimated coefficients from regressions at the arranger-year level for each year relative to the initial platform adoption by arrangers. Panel A estimates the inverse hyperbolic sine of the number of new loan issuances around the time of initial adoption. Panel B separately estimates new loan issuances for first-time and repeat borrowing, with first-time borrowing defined as the first syndication between the arranger and borrower. Panel C estimates cumulative outstanding loans under management. The same sample selection criteria and specifications as in Table 4 are applied. The year (0) denotes the adoption year. The year preceding adoption (-1) is the excluded category, reported as zero in the figures.

Panel A: Newly Issued Loan Deals



Panel B: Newly Issued Loan Deals (First Borrowing or Repeat Borrowing)



Panel C: Cumulative Outstanding Loan Amount (million US dollars)

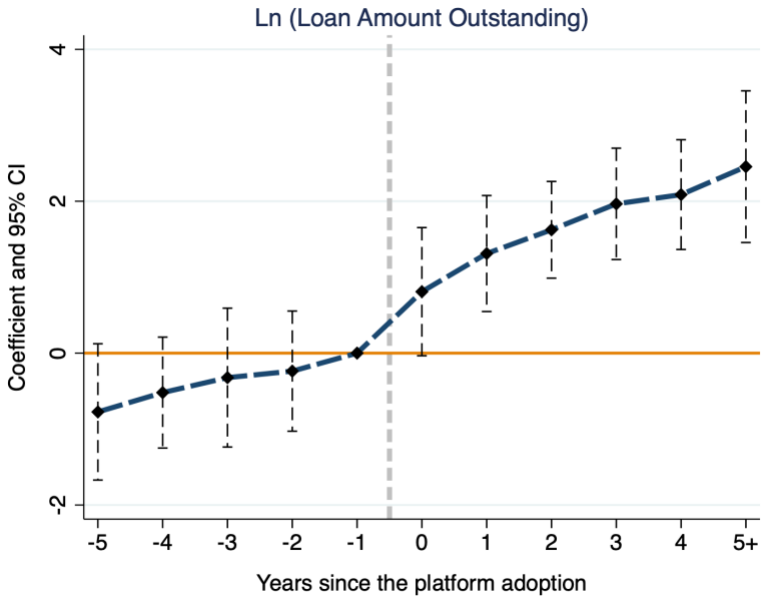
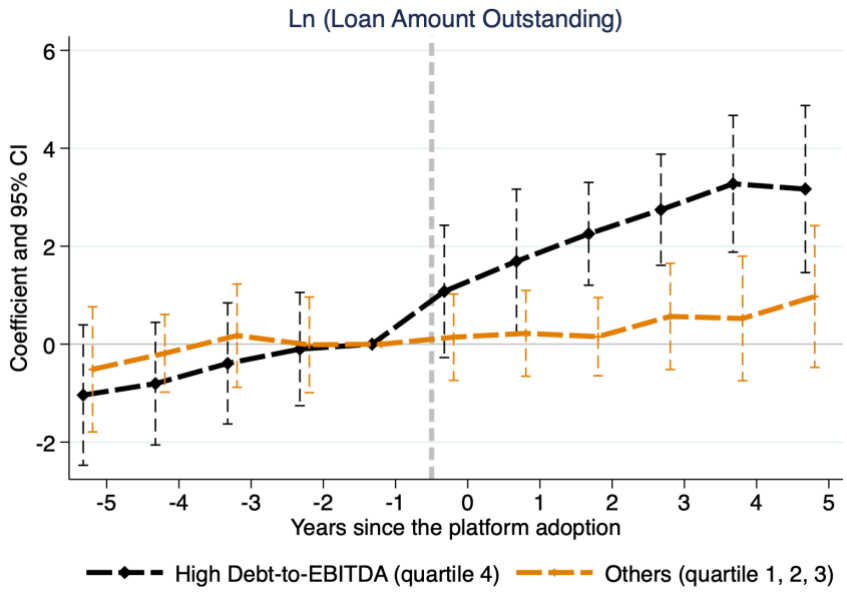


Figure 5: High Debt-to-EBITDA Loans Around Platform Adoption
The figure presents the estimated coefficients from regressions at the arranger-year level for each year relative to the initial platform adoption by arrangers. In Panel A, the dependent variable is the logarithm of the loan amount outstanding. In Panel B, the dependent variable is the proportion of the loan amount with a debt-to-EBITDA ratio in the top quartile by year and industry in the Compustat universe. The same sample selection criteria and specifications as in Table 5 are applied. The year (0) denotes the adoption year. The year preceding adoption (-1) is the excluded category, reported as zero in the figures.

Panel A: Loan Amount with High Debt-to-EBITDA ratio



Panel B: Proportion of Loan Amount with High Debt-to-EBITDA ratio

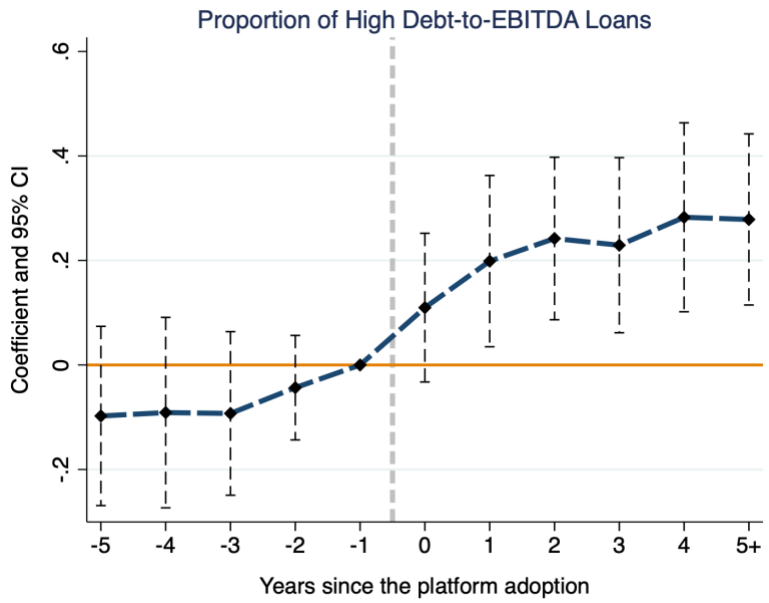


Table 1: Compare Loan Contracts with and without Platform Adoption Clauses

Panel A shows the raw data on how loan-level characteristics vary across loan facilities or deals with the "Platform Adoption Clause" and without this clause from 2000 (the first adoption year in my sample) to 2021. Panel B shows the comparison from 2000 to 2003, before the first technological updates. The unit of observation is at the arranger-facility or arranger-deal level. I define a lead arranger as the one assigned the highest title within a syndicate (Chakraborty et al. 2018). I drop all loans borrowed by financial companies. All variable definitions and data sources can be found in Appendix C. *, * *, and *** denote significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: Sample Period (2000-2021)

	Loans with Platform Adoption Clause			Loans without Platform Adoption Clause			Difference in Mean
	Sample	Mean	Median	Sample	Mean	Median	
				Facility-Level			
Participants GeoDiveristy	5,388	0.59	0.67	3,439	0.45	0.56	0.142***
# Participants	5,800	8.81	7.00	3,481	6.49	4.00	2.311***
%Non-Relation Participants (for borrower)	5,800	0.63	0.67	3,481	0.52	0.62	0.103***
%Non-Relation Participants (for arranger)	5,800	0.16	0.06	3,481	0.20	0.06	-0.036***
% Foreign Participants	5,800	0.24	0.25	3,481	0.17	0.00	0.072***
LnAmount	5,800	5.82	5.86	3,481	4.76	4.84	1.057***
Spread (bp)	5,323	226.96	175.00	3,170	228.97	200.00	-2.01
Maturity (in years)	5,707	4.36	5.00	3,402	3.81	4.00	0.558***
Secured	5,800	0.48	0.00	3,481	0.60	1.00	-0.119***
PerformancePricing	5,800	0.50	1.00	3,481	0.53	1.00	-0.022**
Lead Retained Share	1,711	23.47	14.35	1,035	33.21	21.52	-9.741***
				Deal-Level			
#Arrangers	3,931	1.18	1.00	2,512	1.16	1.00	0.02
Contract Complexity	3,931	0.42	0.19	2,512	-0.46	-0.49	0.885***
# Facilities	3,931	1.47	1.00	2,512	1.38	1.00	0.087***
Have Revolver/Line	3,931	0.70	1.00	2,512	0.71	1.00	-0.01
Have Term Loan A	3,931	0.13	0.00	2,512	0.05	0.00	0.075***
Have Term Loan B+	3,931	0.16	0.00	2,512	0.12	0.00	0.043***
LnDealAmount	3,930	6.28	6.24	2,512	5.11	5.08	1.171***
# Covenants	3,931	0.62	1.00	2,512	0.73	1.00	-0.110***
Purpose: M&A	3,931	0.24	0.00	2,512	0.16	0.00	0.081***
Purpose: Backup	3,931	0.02	0.00	2,512	0.04	0.00	-0.028***
Purpose: Working Capital	3,931	0.15	0.00	2,512	0.27	0.00	-0.121***
Purpose: Refinancing	3,931	0.04	0.00	2,512	0.09	0.00	-0.052***
Purpose: General Purpose	3,931	0.50	0.00	2,512	0.38	0.00	0.122***
RelationBanking	3,931	0.29	0.00	2,512	0.22	0.00	0.077***
Ind_PublicLender	3,931	0.47	0.00	2,512	0.01	0.00	0.467***

Panel B: Sample Period (2000-2003)

	Loans with Platform Adoption Clause			Loans without Platform Adoption Clause			Difference in Mean
	Sample	Mean	Median	Sample	Mean	Median	
			Facility-Level				
Participants GeoDiveristy	193	0.59	0.71	1,412	0.44	0.50	0.144***
# Participants	193	8.64	7.00	1,412	6.43	3.00	2.207***
%Non-Relation Participants (for borrower)	193	0.71	0.80	1,412	0.54	0.67	0.178***
%Non-Relation Participants (for arranger)	193	0.27	0.20	1,412	0.24	0.14	0.02
% Foreign Participants	193	0.17	0.11	1,412	0.16	0.00	0.01
LnAmount	193	5.05	5.11	1,412	4.33	4.55	0.727***
Spread (bp)	186	217.78	175.00	1,319	237.38	225.00	-19.61
Maturity (in years)	190	3.46	3.00	1,379	3.41	3.00	0.05
Secured	193	0.49	0.00	1,412	0.65	1.00	-0.161***
PerformancePricing	193	0.71	1.00	1,412	0.56	1.00	0.154***
Lead Retained Share	75	28.05	17.65	454	33.54	23.66	-5.49
			Deal-Level				
#Arrangers	139	1.07	1.00	983	1.04	1.00	0.03
Contract Complexity	139	-0.08	-0.17	983	-0.49	-0.51	0.415***
# Facilities	139	1.39	1.00	983	1.43	1.00	-0.04
Have Revolver/Line	139	0.72	1.00	983	0.70	1.00	0.02
Have Term Loan A	139	0.04	0.00	983	0.06	0.00	-0.02
Have Term Loan B+	139	0.14	0.00	983	0.12	0.00	0.02
LnDealAmount	139	5.43	5.53	983	4.70	4.84	0.734***
# Covenants	139	0.86	1.00	983	0.82	1.00	0.04
Purpose: M&A	139	0.17	0.00	983	0.14	0.00	0.03
Purpose: Backup	139	0.11	0.00	983	0.08	0.00	0.03
Purpose: Working Capital	139	0.37	0.00	983	0.27	0.00	0.105**
Purpose: Refinancing	139	0.07	0.00	983	0.19	0.00	-0.115***
Purpose: General Purpose	139	0.24	0.00	983	0.25	0.00	-0
RelationBanking	139	0.24	0.00	983	0.15	0.00	0.094***
Ind_PublicLender	139	0	0.00	983	0	0.00	0

Table 2: Summary Statistics

The table presents summary statistics of the main variables for the sample at the arranger-facility or arranger-year level during the years 1993-2021. The sample begins when the arranger starts lending and ends either when the arranger ceases lending or, at the latest, in 2021. I drop all loans borrowed by financial companies. For the arranger-facility sample, I exclude those loans with missing values for borrower-level characteristics. For the arranger-year sample, I restrict arrangers to those who entered the market before 1997 and continued operations at least until 2008. All variable definitions can be found in Appendix C. Note that # *Newly Issued Loans* and # *Loans Outstanding* are values after the inverse hyperbolic sine transformation.

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Arranger-facility sample								
Participants GeoDiveristy	9,215	0.53	0.29	-0.00	0.44	0.63	0.75	1.00
# Participants	9,635	8.23	8.66	0.00	2.00	6.00	12.00	95.00
% Non-Relation Participants (for borrower)	9,635	0.59	0.32	0.00	0.40	0.67	0.86	0.99
% Non-Relation Participants (for arranger)	9,635	0.19	0.25	0.00	0.00	0.07	0.33	0.99
% Foreign Participants	9,635	0.22	0.22	0.00	0.00	0.20	0.40	0.94
Contract Complexity	9,635	0.10	0.97	-1.57	-0.50	-0.07	0.52	7.06
LnAmount	9,635	5.32	1.61	0.22	4.33	5.44	6.40	10.80
Spread (bp)	8,870	208.16	149.10	-95.00	112.50	175.00	275.00	1,325.00
Maturity (in years)	9,410	4.11	1.91	0.00	3.00	5.00	5.00	20.50
Secured	9,635	0.51	0.50	0.00	0.00	1.00	1.00	1.00
PerformancePricing	9,635	0.54	0.50	0.00	0.00	1.00	1.00	1.00
Lead Retained Share	3,113	26.63	24.81	0.00	9.75	16.67	33.33	100.00
Debt/EBITDA	9,635	3.05	4.82	-25.54	1.08	2.54	4.41	25.82
Debt/EBITDA quartile	9,635	3.04	1.00	1.00	2.00	3.00	4.00	4.00
Assets	9,635	7.53	1.84	3.32	6.22	7.53	8.90	11.43
Tangibility	9,635	0.31	0.24	0.01	0.11	0.23	0.46	0.90
OperatingCF	9,635	0.12	0.09	-0.29	0.08	0.11	0.16	0.36
MtB	9,635	3.74	6.56	0.31	1.38	2.17	3.55	54.77
ROA	9,635	0.07	0.09	-0.38	0.04	0.07	0.11	0.31
SalesGrowth	9,635	0.12	0.26	-0.70	0.00	0.09	0.21	1.15
FirmAge	9,635	19.20	15.40	0.00	6.00	15.00	30.00	58.00
RelationBanking	9,635	0.24	0.43	0.00	0.00	0.00	0.00	1.00
Arranger-year sample								
# Newly Issued Loans	954	1.48	1.34	0.00	0.00	1.44	2.31	5.58
LnAmount (Newly Issued Loans)	954	5.07	3.65	0.00	0.00	5.89	7.75	12.12
# Loans Outstanding	1,009	2.71	1.58	0.00	1.44	2.64	3.64	6.82
LnAmount (Loans Outstanding)	1,009	7.33	2.99	0.00	5.79	7.84	9.08	13.26
% Amount Outstanding with high Debt/EBITDA (Quartile 4)	925	0.44	0.31	0.00	0.17	0.42	0.67	1.00

Table 3: Determinants of Platform Adoption

Panel A estimates the time to initial platform adoption as a function of arranger characteristics. The dependent variable is the number of years remaining before the arranger initially adopts. I restrict arrangers to those who entered the market before 1997 and continued operations at least until 2008. The sample begins in 1997 and ends when the arranger adopts. All columns use a Weibull accelerated failure time model. The unit of observation is arranger-year. The coefficients are *Z*-statistics calculated with standard errors clustered at the arranger level. Panel B estimates the likelihood of adopting the platform in a specific loan contract as a function of borrower and loan characteristics. The sample begins in the first year of adoption, 2000. I drop all loans borrowed by financial companies. I exclude those loans with missing values for borrower-level characteristics. All columns use a logit model. The unit of observation is the loan facility. The coefficients are *Z*-statistics calculated with standard errors clustered at the borrower industry level. Panel C uses the same specification as Panel B but further estimates the likelihood of adoption based on the adoption records of potential participants. All variable definitions and data sources can be found in Appendix C. *, * *, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Arranger-Level Determinants of Time to Initial Platform Adoption

	(1)	(2)	(3)	(4)	(5)
			Time to Initial Adoption		
Information Exchange Demand:					
Lagged Outstanding-Participants GeoDiversity	**-1.037*** (-4.52)**				
(Prior 3-years New Issues):					
Avg Participating GeoDiversity		**-0.641*** (-3.67)**			
Avg %Non-Relation Participants (for borrower)			**-0.611*** (-3.96)**		
Avg %Non-Relation Participants (for arranger)				**-0.311* (-1.90)**	
Avg Contracting Complexity					**-0.438*** (-2.73)**
Avg Borrower Reporting Complexity					**0.286 (1.14)**
Other Lagged Characteristics:					
Avg Loan Deal Arranged per Officer	-0.218***	-0.284***	-0.309***	-0.332***	-0.269***
	(-3.47)	(-5.27)	(-5.02)	(-5.42)	(-4.49)
# Arranging Loan Officers	-0.012	-0.017	-0.020	-0.019	-0.014
	(-0.99)	(-1.28)	(-1.55)	(-1.51)	(-1.06)
# Lagged Loan Deal Arranged	0.014	0.016	0.016	0.013	0.004
	(0.95)	(0.89)	(0.93)	(0.76)	(0.24)
# Lagged Leveraged Deal Arranged	-0.056*	-0.055	-0.048	-0.054	-0.034
	(-1.79)	(-1.52)	(-1.41)	(-1.57)	(-1.07)
Year FE	Yes	Yes	Yes	Yes	Yes
N	342	275	275	275	275
Log likelihood	-306.891	-268.402	-264.697	-272.501	-261.713
P value model test	0.000	0.000	0.000	0.000	0.000

Panel B: Loan-Level Determinants of Platform Adoption

	(1)	(2)	(3)	(4)
			Adoption	
Borrower Characteristics (Lagged):				
Debt/EBITDA	**0.023****			
	(2.51)			
Debt/EBITDA quartile		**0.168*****	**0.130*****	**0.093*****
		(3.30)	**(4.06)**	**(3.61)**
Assets			0.149***	0.070
			(2.73)	(1.25)
Tangibility			-0.339	-0.393
			(-1.22)	(-1.54)
OperatingCF			-3.776	-3.741
			(-1.61)	(-1.56)
MtB			-0.004	0.001
			(-0.44)	(0.14)
ROA			7.005***	5.980**
			(2.90)	(2.45)
SalesGrowth			0.095	0.085
			(0.58)	(0.41)
FirmAge			0.003	0.009*
			(0.56)	(1.72)
Loan Facility Characteristics:				
RelationBanking			-0.158	-0.258**
			(-1.25)	(-2.12)
LnAmount				0.211***
				(5.72)
Maturity				0.097***
				(3.15)
LnSpread				0.121
				(1.30)
NumCovenants				0.210***
				(6.21)
Secured				0.022
				(0.22)
Refinancing				0.084
				(0.58)
Revolver/Line				-0.044
				(-0.58)
Year FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	Yes
N	8,195	8,195	8,195	7,480
Pseudo R²	0.285	0.287	0.308	0.329

Panel C: Potential Participant Adoption Records and Platform Adoption

	(1)	(2)	(3)
		Adoption	
Potential Participants:			
# Participants in Market Joined Platform	**0.003*** **		
	(13.23)		
# Relation Participants Joined Platform (for borrowers)		**0.022**	
		(1.06)	
# Relation Participants Joined Platform (for arrangers)			**0.002*** **
			(3.75)
# Participants in Market	-0.000*		
	(-1.74)		
# Relation Participants (for borrowers)		-0.018	
		(-1.27)	
# Relation Participants (for arrangers)			-0.001**
			(-2.06)
Controls:			
Borrower Characteristics	Yes	Yes	Yes
Loan Facility Characteristics	Yes	Yes	Yes
Year FE	No	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes
N	7,480	7,480	7,480
Pseudo R^2	0.305	0.330	0.336

Table 4: Loans Issuance Around Initial Platform Adoption by Arrangers

Panel A estimates new loan issuances around the initial platform adoption by arrangers. Panel B separately estimates new loan issuances for first-time and repeat borrowing around the initial platform adoption by arrangers. First-time borrowing refers to the first syndication transaction between the arranger and the borrower. A seemingly unrelated estimation (SUEST) is used to test the equality of coefficients across models. Panel C estimates the cumulative outstanding loans under management around the initial platform adoption by arrangers. I restrict the sample to arrangers who entered the market before 1997 and continued operations at least until 2008. The sample begins when the arranger starts lending and ends either when the arranger ceases lending or, at the latest, in 2021. I drop all loans borrowed by financial companies. All columns use a TWFE model, and the unit of observation is arranger-year. In all panels, the dependent variables are the inverse hyperbolic sine of the number of loans (columns 1 and 2) and the logarithm of the loan amount (columns 3 and 4). The coefficients are *T*-statistics calculated with standard errors clustered at the arranger level and year level. All variable definitions and data sources are provided in Appendix C. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Newly Issued Loans

	(1)	(2)	(3)	(4)
	# Newly Issued Loans		***LnAmount (Newly Issued Loans)***	
InitialAdoption	**0.552*** **	**0.606*** **	**1.886*** **	**1.895*** **
	(4.24)	**(3.62)**	**(6.52)**	**(5.09)**
Arranger Characteristics:				
LnAssets		0.331*		0.766
		(1.75)		(1.55)
Assets-to-Equity		-0.021		-0.032
		(-1.29)		(-0.84)
Tier 1 Capital ratio		0.033		0.104
		(0.92)		(0.78)
Arranger FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	953	542	953	542
Adj. R²	0.721	0.766	0.561	0.608

Panel B: Newly Issued Loans (First Borrowing or Repeat Borrowing)

	(1)	(2)	(3)	(4)
	# Newly Issued Loans		***LnAmount (Newly Issued Loans)***	
	First	Repeat	First	Repeat
InitialAdoption	**0.582*** **	**0.339** **	**1.963*** **	**1.284** **
	(3.69)	**(2.18)**	**(4.65)**	**(2.49)**
Arranger Characteristics:				
LnAssets	0.380**	0.096	0.984*	-0.002
	(2.18)	(0.74)	(2.02)	(-0.00)
Assets-to-Equity	-0.020	-0.012	-0.026	-0.014
	(-1.19)	(-1.32)	(-0.69)	(-0.50)
Tier 1 Capital ratio	0.027	0.036*	0.148	0.072
	(0.76)	(1.71)	(1.16)	(0.84)
Arranger FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	542	542	542	542
Adj. R²	0.717	0.759	0.551	0.619
Chi-squared statistic and p-value from testing coefficient differences:				
InitialAdoption				
Chi-squared statistic	**2.63**		**1.60**	
P-value	**0.105**		**0.206**	

Panel C: Cumulative Loans Outstanding

	(1)	(2)	(3)	(4)
	# Loans Outstanding		***LnAmount (Loans Outstanding)***	
InitialAdoption	**0.717*****	**0.672****	**1.828*****	**1.699*****
	(3.85)	**(2.75)**	**(4.16)**	**(3.53)**
Arranger Characteristics:				
LnAssets		0.046		-0.129
		(0.22)		(-0.31)
Assets-to-Equity		-0.022		-0.008
		(-1.12)		(-0.31)
Tier 1 Capital ratio		0.054		0.096
		(1.32)		(1.16)
Arranger FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,009	570	1,009	570
Adj. R²	0.802	0.815	0.712	0.734

Table 5: Leveraged Loan Issuances Around Initial Platform Adoption by Arrangers

The tables estimate leveraged loan issuances around the initial platform adoption by arrangers. I restrict the sample to arrangers who entered the market before 1997 and continued operations at least until 2008. The sample begins when the arranger starts lending and ends either when the arranger ceases lending or, at the latest, in 2021. I drop all loans borrowed by financial companies. All columns use a TWFE model. In Panel A, the unit of observation is the arranger-year. The dependent variables are the logarithm of the loan amount outstanding (columns 1-4) and the proportion of the amount with a debt-to-EBITDA ratio in the top quartile by year and industry in the Compustat universe (columns 5-6). The coefficients are T-statistics calculated with standard errors clustered at the arranger level and year level. In Panel B, the unit of observation is the arranger-loan facility. The dependent variable is the debt-to-EBITDA quartile by year and industry in the Compustat universe. The coefficients are *T*-statistics calculated with standard errors clustered at the arranger, year, and borrower industry levels. All variable definitions and data sources are provided in Appendix C. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Arranger Portfolio Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	LnAmount (Loans Outstanding)				***% Amount Outstanding with high Debt/EBITDA (Quartile 4)***	
	Debt/EBITDA					
	Quartile 4		Others			
InitialAdoption	**2.233*** **	**2.225*** **	**0.787** **	**0.894**	**0.188*** **	**0.185** **
	(4.71)	**(3.57)**	**(2.07)**	**(1.50)**	**(3.64)**	**(2.54)**
Arranger Characteristics:						
LnAssets		0.043		-0.216		0.043
		(0.11)		(-0.38)		(0.70)
Assets-to-Equity		-0.082		-0.011		-0.006
		(-1.18)		(-0.34)		(-1.22)
Tier 1 Capital ratio		0.033		0.020		-0.004
		(0.27)		(0.19)		(-0.42)
Arranger FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,009	570	1,009	570	925	532
Adj. R²	0.616	0.648	0.618	0.671	0.149	0.241

Panel B: Loan Facility Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
			Debt/EBITDA Quartile			
InitialAdoption	**0.348*** **	**0.342*** **	**0.288** **	**0.163*** **	**0.181*** **	**0.159** **
	(3.72)	**(3.27)**	**(2.92)**	**(3.34)**	**(3.30)**	**(2.67)**
Borrower Characteristics (Lagged):						
Assets		0.122***	0.172***		0.318***	0.335***
		(6.87)	(9.93)		(7.53)	(7.79)
Tangibility		0.059	0.035		-0.374	-0.292
		(0.26)	(0.16)		(-1.40)	(-1.07)
MtB		-0.001	-0.002		0.007**	0.005
		(-0.11)	(-0.49)		(2.25)	(1.55)
ROA		-2.750**	-2.044**		-2.951***	-2.877***
		(-2.91)	(-2.55)		(-6.20)	(-5.60)
SalesGrowth		0.362**	0.340**		0.086	0.134
		(2.47)	(2.75)		(0.62)	(1.17)
FirmAge		-0.005***	-0.002*		0.013**	0.012**
		(-4.33)	(-1.89)		(2.43)	(2.97)
Loan Facility Characteristics:						
LnAmount			0.001			-0.007
			(0.04)			(-0.73)
Maturity			0.018			0.005
			(1.59)			(1.00)
LnSpread			0.256***			0.124**
			(8.23)			(3.03)
NumCovenants			0.040*			0.003
			(1.95)			(0.09)
Secured			0.121*			0.095
			(2.08)			(1.58)
Refinancing			0.103*			0.033
			(1.98)			(0.94)
Revolver/Line			-0.134***			-0.046**
			(-5.04)			(-2.30)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No	No	No
Borrower FE	No	No	No	Yes	Yes	Yes
N	7,844	7,844	7,192	7,110	7,110	6,463
Adj. R²	0.107	0.174	0.225	0.642	0.678	0.687

Table 6: Robustness Check – Stacked Regression (Pre-2004)

The tables estimate loan issuances around the initial platform adoption by arrangers. The stacked approach only considers not-yet adopters as the control group to the early adopter. I restrict the sample to arrangers who entered the market before 1997 and continued operations at least until 2008. The sample begins when the arranger starts lending and ends either when the arranger ceases lending or, at the latest, in 2003, ensuring that at least 40% of arrangers had not yet adopted. I drop all loans borrowed by financial companies. In Panels A and B, the sample is a panel of arranger-cohort-year observations, where each cohort includes all arrangers treated in the same year and those that have not yet adopted. Panel A focuses on new loan issuances, with dependent variables being the inverse hyperbolic sine of the number of loans (columns 1 and 2) and the logarithm of the loan amount (columns 3 and 4). Panel B examines leveraged loan issuances, with dependent variables being the logarithm of the loan amount outstanding (columns 1–4) and the proportion of the loan amount outstanding with a debt-to-EBITDA ratio in the top quartile, by year and industry, in the Compustat universe (columns 5–6). In Panel C, the observation is the arranger-loan facility-cohort-year, with the dependent variable being the debt-to-EBITDA quartile by year and industry in the Compustat universe. Across all panels, the coefficients are *T*-statistics calculated with standard errors clustered at the arranger×cohort level. All variable definitions and data sources are provided in Appendix C. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Newly Issued Loans

	(1)	(2)	(3)	(4)
	# Newly Issued Loans		***LnAmount (Newly Issued Loans)***	
InitialAdoption	**0.572*** **	**0.670*** **	**1.352*** **	**1.450*** **
	(3.44)	**(3.26)**	**(3.49)**	**(3.39)**
Arranger Characteristics:				
LnAssets		0.021		0.802*
		(0.12)		(1.87)
Assets-to-Equity		-0.015		0.022
		(-0.89)		(0.28)
Tier 1 Capital ratio		0.000		0.073
		(0.02)		(0.84)
Cohort×Arranger FE	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes
N	1,073	578	1,073	578
Adj. R²	0.638	0.676	0.574	0.633

Panel B: Arranger Portfolio Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	LnAmount (Loans Outstanding)				***% Amount Outstanding with high Debt/EBITDA (Quartile 4)***	
	Debt/EBITDA					
	Quartile 4		Others			
InitialAdoption	**1.392*** **	**1.591** **	**0.967*** **	**1.045** **	**0.176*** **	**0.160** **
	(2.84)	**(2.52)**	**(3.04)**	**(2.54)**	**(2.87)**	**(2.20)**
Arranger Characteristics:						
LnAssets		-0.906**		0.330		-0.144**
		(-2.42)		(1.12)		(-2.51)
Assets-to-Equity		0.023		-0.062*		0.002
		(0.49)		(-1.90)		(0.41)
Tier 1 Capital ratio		-0.116**		-0.052		-0.008
		(-2.05)		(-1.41)		(-0.67)
Cohort×Arranger FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,042	546	1,042	546	939	514
Adj. R²	0.624	0.713	0.646	0.727	0.084	0.093

Panel C: Loan Facility Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
			Debt/EBITDA Quartile			
InitialAdoption	**0.455*** **	**0.381*** **	**0.332*** **	**0.388*** **	**0.379*** **	**0.409*** **
	(3.67)	**(3.01)**	**(2.66)**	**(3.45)**	**(3.61)**	**(4.50)**
Borrower Characteristics (Lagged):						
Assets		0.124***	0.190***		0.188***	0.167***
		(4.34)	(7.82)		(4.12)	(3.80)
Tangibility		0.222**	0.139		0.333	0.002
		(2.19)	(1.25)		(0.98)	(0.01)
MtB		-0.025***	-0.022***		-0.007	-0.006
		(-5.32)	(-5.56)		(-0.64)	(-0.56)
ROA		-0.495	0.304		-1.231	-1.760
		(-0.85)	(0.67)		(-0.78)	(-1.29)
SalesGrowth		0.202**	0.205***		-0.056	0.146
		(2.32)	(2.63)		(-0.34)	(1.65)
FirmAge		0.001	0.003*		0.047	0.048*
		(0.23)	(1.82)		(1.48)	(1.89)
Loan Facility Characteristics:						
LnAmount			0.036			0.017*
			(1.46)			(1.74)
Maturity			0.019			-0.000
			(0.98)			(-0.10)
LnSpread			0.339***			0.071*
			(9.19)			(1.95)
NumCovenants			0.062***			0.017
			(2.79)			(1.39)
Secured			0.169***			0.052
			(3.96)			(1.06)
Refinancing			-0.070			0.000
			(-1.24)			(0.00)
Revolver/Line			-0.095***			-0.007
			(-3.78)			(-0.69)
Cohort×Arranger FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No	No	No
Borrower FE	No	No	No	Yes	Yes	Yes
N	3,265	3,265	3,009	2,852	2,852	2,597
Adj. R²	0.132	0.186	0.262	0.904	0.908	0.922

Table 7: Platform Adoption and Syndicate Structure

The tables estimate the syndicate structure as a function of the platform adoption. All columns use a TWFE model (i.e., year and arranger fixed effects). I restrict the sample to arrangers who entered the market before 1997 and continued operations at least until 2008. The sample begins when the arranger starts lending and ends either when the arranger ceases lending or, at the latest, in 2021. I drop all loans borrowed by financial companies. In all panels, the unit of observation is the arranger-loan facility; and the independent variable is whether the loan adopts the platform. The dependent variables are participant geographic diversity, the percentage of non-relation participants (for the borrower), the percentage of non-relation participants (for the arranger), and retained shares by arrangers, separately, in a specific loan facility. The coefficients are *T*-statistics calculated with standard errors clustered at the arranger, year, and borrower industry levels. All variable definitions and data sources are provided in Appendix C. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Participant Geographic Diversity

	(1)	(2)	(3)	(4)
		Participant GeoDiversity		
Adoption	**0.077***	**0.065****	**0.042***	**0.030***
	(2.13)	**(2.53)**	**(1.92)**	**(2.10)**
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	7,464	7,464	6,863	6,134
Adj. R²	0.193	0.245	0.324	0.573

Panel B: Percentage of Non-Relation Participants (for Borrower)

	(1)	(2)	(3)	(4)
		% Non-Relation Participants (for borrower)		
Adoption	**0.091****	**0.083****	**0.057****	**0.058**
	(2.27)	**(2.58)**	**(2.42)**	**(1.77)**
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	7,844	7,844	7,192	6,463
Adj. R²	0.072	0.103	0.184	0.390

Panel C: Percentage of Non-Relation Participants (for Arranger)

	(1)	(2)	(3)	(4)
		% Non-Relation Participants (for arranger)		
Adoption	**0.029****	**0.028*****	**0.012**	**0.013**
	(2.85)	**(3.35)**	**(1.03)**	**(1.23)**
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	7,844	7,844	7,192	6,463
Adj. R²	0.382	0.390	0.427	0.624

Panel D: Lead Retained Share

	(1)	(2)	(3)	(4)
		Lead Retained Share		
Adoption	**-5.520**	**-4.422****	**-3.309****	**0.291**
	(-1.80)	**(-2.62)**	**(-2.42)**	**(0.14)**
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	2,585	2,585	2,467	1,928
Adj. R²	0.184	0.352	0.462	0.600

Table 8: Platform Adoption and Contracting

The tables estimate the loan contracting outcomes as a function of the platform adoption. All columns use a TWFE model (i.e., year and arranger fixed effects). I restrict the sample to arrangers who entered the market before 1997 and continued operations at least until 2008. The sample begins when the arranger starts lending and ends either when the arranger ceases lending or, at the latest, in 2021. I drop all loans borrowed by financial companies. In all panels, the unit of observation is the arranger-loan facility; and the independent variable is whether the loan adopts the platform. The dependent variables are the standardized contract file size (i.e., contract complexity) and the average number of loans processed by loan officers involved in a loan facility during the contracting year. The coefficients are T-statistics, calculated using standard errors clustered at the arranger, year, and borrower industry levels in Panel A, and at the arranger and year levels in Panel B. All variable definitions and data sources are provided in Appendix C. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Contract Complexity

	(1)	(2)	(3)	(4)
		Contract Complexity		
Adoption	**0.631*** **	**0.659*** **	**0.569*** **	**0.585*** **
	(5.28)	**(5.32)**	**(4.79)**	**(10.31)**
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	7,844	7,844	7,192	6,463
Adj. R²	0.291	0.336	0.410	0.703

Panel B: Average Processed Loans per Participating Officer

	(1)
	Average Processed Loans per Loan Officer
Adoption	**0.353*** **
	(2.84)
Controls:	
Year FE	Yes
Arranger FE	Yes
N	7,065
Adj. R²	0.145

Table 9: Platform Adoption and Negative Events

The tables estimate the association between platform adoption and the incidence of negative events. All columns use a TWFE model (i.e., year and arranger fixed effects). I restrict the sample to arrangers who entered the market before 1997 and continued operations at least until 2008. The sample begins when the arranger starts lending and ends either when the arranger ceases lending or, at the latest, in 2021. I drop all loans borrowed by financial companies. In all panels, the unit of observation is the arranger-loan facility; and the independent variable is whether the loan adopts the platform. In Panel A, the dependent variable indicates whether the borrower reports a financial covenant violation during the loan facility's outstanding period. The covenant violation dataset, collected by Nini et al. (2012), covers the period from the second quarter of 1997 to the fourth quarter of 2008. Accordingly, I restrict my sample to facilities that originated during this period. In Panel B, the dependent variable indicates whether the borrower defaulted during the loan facility's outstanding period. I only examine the universe of rated borrowers, using data provided by S&P rating agencies. The coefficients are *T*-statistics calculated with standard errors clustered at the arranger, year, and borrower industry levels. All variable definitions and data sources are provided in Appendix C. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Platform Adoption and Covenant Violation

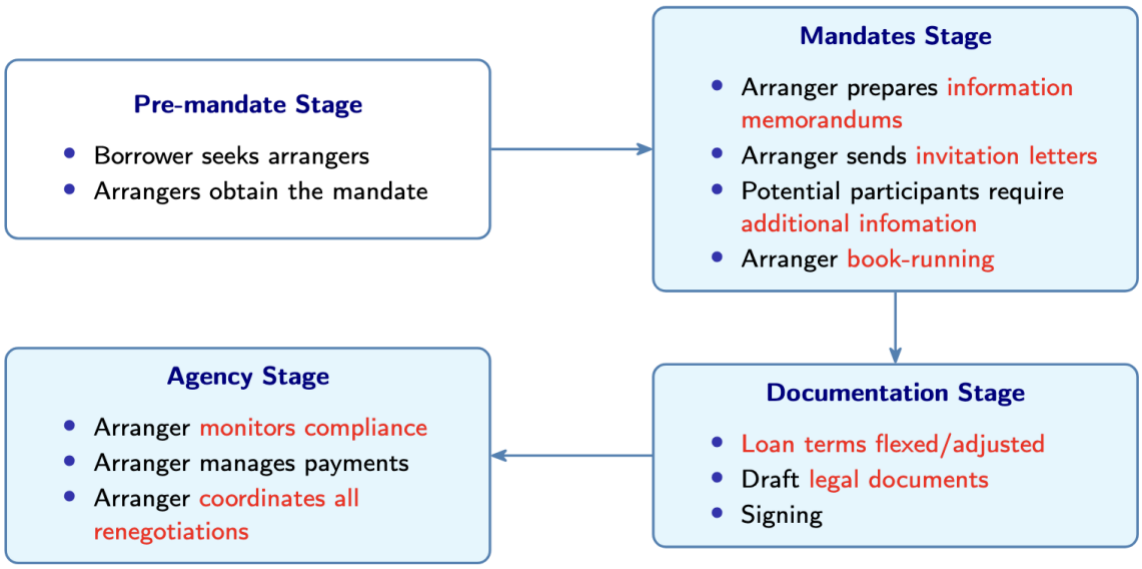
	(1)	(2)	(3)	(4)
		Covenant Violation		
Adoption	**-0.039**	**-0.011**	**-0.031**	**0.005**
	(-1.22)	**(-0.33)**	**(-0.89)**	**(0.20)**
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	3,899	3,899	3,625	3,036
Adj. R²	0.118	0.160	0.192	0.729

Panel B: Platform Adoption and Default Events

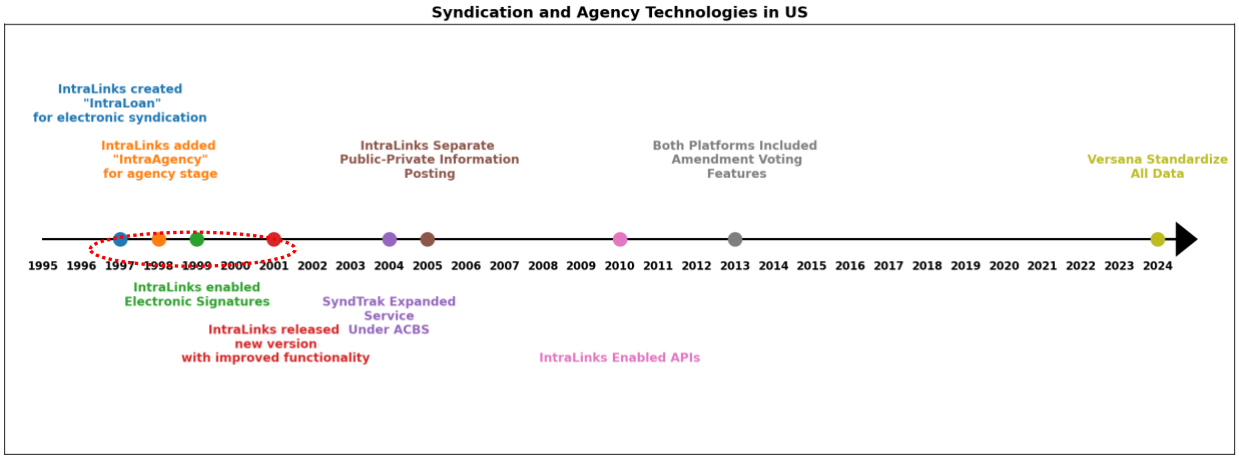
	(1)	(2)	(3)	(4)
		Default		
Adoption	**0.005**	**0.013**	**0.003**	**0.021**
	(0.25)	**(0.73)**	**(0.14)**	**(1.37)**
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	4,644	4,644	4,266	3,997
Adj. R²	0.093	0.142	0.165	0.668

Online Appendix I

Part I: Loan Syndication Process



Part II: Time-Series Updates of Information Exchange Technology in Syndicated Loan Market



Part III: An Example of Confidential Information Memorandum in the Syndication Stage

The public version of the Confidential Information Memorandum below is sourced from the 8-K filings of Reynolds American Inc. The original document can be viewed at:
https://www.sec.gov/Archives/edgar/data/1275283/000095012306006157/g01508exv99w1.htm

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ReynoldsAmerican

Part IV: An Example of Term Sheet in the Syndication Stage

The public version of the term sheet below is sourced from NPC International, Inc.

Summary Description of the Senior Secured Credit Facilities

Preliminary Senior Secured Credit Facilities Term Sheet	
Borrower:	NPC International, Inc. ("Lead Borrower") and certain of its direct subsidiaries (together with the Lead Borrower, the "Borrowers")
Facility Description:	$460 million Senior Secured Credit Facilities comprised of: – $85 million Revolving Credit Facility (the "Revolver") – $375 million 1st Lien Term Loan (the "TL")
Maturity:	Revolver: 5 years from closing TL: 7 years from closing
Incremental Facility:	▪ $125 million provided that the Lead Borrower's senior secured leverage is no greater than the Lead Borrower's senior secured leverage at closing and subject to 50 bps MFN provision ▪ Additional $15 million incremental revolver subject to same terms and pricing as the Revolver – Decreased dollar-for-dollar if commitments under the Revolver on the closing date are greater than $85 million
Use of Proceeds:	Proceeds to be used to fund the LBO of NPC International and related fees and expenses
Security:	Obligations of the Borrowers and the Guarantors secured by a perfected first priority security interest in substantially all tangible and intangible assets of the Borrowesr and the Guarantors (excluding franchise agreements and voting stock)
Guarantee:	Obligations guaranteed by all existing and future material wholly owned domestic restricted subsidiaries (the "Guarantors")
Ranking:	Pari passu with all existing and future senior indebtedness and senior to all existing and future subordinated indebtedness
Optional Prepayments:	Prepayable at par; 101 soft-call for the first year on the term loan
Mandatory Prepayments:	100% debt (excluding permitted debt), insurance proceeds and asset sales (subject to normal reinvestment requirements), 50% excess cash flow with step downs based on leverage
Mandatory Amortization:	1.0% per annum
Financial Covenants:	Maximum leverage, minimum interest coverage
Negative Covenants:	Usual and customary for transactions of this type, including but not limited to: limitations on indebtedness, liens, investments, asset sale / leaseback transactions, capital expenditures, restricted payments and transactions with affiliates

Part V: An Example of Communication between Arrangers and Participants in the Syndication Stage
The table is sourced from the book *Syndicated Lending: Practice and Documentation (Third Edition),* published in July 2000.

Name of Bank	Location	Contact Name	Fax Number	Telephone Number	Acceptance US$ million	Information Memorandum	Decline	Comment
Banca de la Creme	Milan	Adele Bechamel				Yes		11/9 – Currently reviewing
Bank of Good Hope	London	Horatio Cape				Yes		11/9 – Seeking US$75m
Banque de Tremble	Paris	Marie Brave				Yes	11/9	No NY office
Bargain Banking Co	Atlanta	Terry Basement				Yes	28/8	Pricing
Best Bank NA	Amsterdam	Gerald Verity			75	Yes		
Bonanza Banking Corp	New York	Walter Gold				Yes	27/8	Pricing
First and Best Bank NA	London	Gordon Highest			50	Yes		
First and Last Banking Corp	New York	Ingrid Stayer				Yes		Decision on US$50m 23/9
Flash Banking Corp	London	James Gordon				Yes	11/9	Sector
Forever Bank	London	George True			50	Yes		
Leading Bank NA	Frankfurt	Harry First			50	Yes		
Looking Good Bank	Amsterdam	Miranda Glass				Yes		10/9 – Likes deal
National Bank of Good Credit	New York	Joseph Savewell				Yes		15/9 – Wants more info
Nononsense Credit Bank	London	Jane Plaine				Yes		15/9 – Looking at US$50m
Perhaps Banking Corp	Luxembourg	Robert le Farceur				Yes	15/9	Cannot meet deadline
Possible Bank NA	London	Gerry Thinkalot				Yes	15/9	Pricing
Premier Bank and Trust Co	Luxembourg	Phillip Toppe				Yes		9/9 – Exposure problem
Resolute Banking Corp	Zurich	Anthony Strong			50	Yes		
Sometimes Bank Ltd	London	Sam Dithers				Yes		28/8 – Exposure
Strong Bank NA	London	Tom Hearty				Yes		8/9 – Processing US$75m
Summit Bank	London	Rosemary Topp			75	Yes		
Sure Banking Inc	Nassau	Roland Firmin				Yes		9/9 – Positive Responding 29/9
Tip Top Bank	London	George Sharp			75	Yes		
Treble Chance Bank	Geneva	Hugh Roller				Yes	27/8	27/8 – Fees too low
Wonder Bank	Dusseldorf	Max Marvel			75	Yes		

Part VI: An Example of Required Information Exchange in the Agency Stage

Section 5.01. *Financial Statements and Other Information.* The Borrower will furnish to the Administrative Agent and each Lender:

(a) within 105 days after the end of each Fiscal Year, its audited consolidated balance sheet and related statements of operations, stockholders' equity and cash flows as of the end of and for such year……

(b) within 60 days after the end of each of the first three fiscal quarters of each Fiscal Year, its consolidated balance sheet and related statements of operations, stockholders' equity and cash flows as of the end of and for such fiscal quarter……

(c) concurrently with any delivery of financial statements under clause (a) or (b) above, a certificate of a Financial Officer of the Borrower (i) certifying as to whether a Default has occurred ……, and (iii) stating whether any change in GAAP or in the application thereof has occurred ……..

(d) concurrently with any delivery of financial statements under clause (a) above, a certificate of the accounting firm that reported on such financial statements stating whether they obtained knowledge during the course of their examination of such financial statements of any Default (which certificate may be limited to the extent required by accounting rules or guidelines);

(e) promptly after the same become publicly available, copies of all periodic and other reports, proxy statements and other materials filed ……

(f) (i) at least 90 days (subject to the parenthetical at the end of the second paragraph in Section 6.02(a) hereof) prior to entering into a Restricted Guaranty notice of its intent to do so, which notice shall set forth the terms of the Guaranteed Parent Indebtedness proposed to be Guaranteed pursuant to such Restricted Guaranty and (ii) on the date of granting of such Restricted Guaranty, a certificate of the chief financial officer or the chief accounting officer of the Parent, stating whether the Parent is in compliance with the covenants referred to in clause (2) of Section 6.02(a) and with respect to any such covenants that are financial covenants, setting forth reasonably detailed calculations of compliance therewith……

Online Appendix II

Table IA.1: The Association Between Contract Complexity and Other Measures

The tables estimate the association between my measure of contract complexity (i.e., standardized contract length) and other potential indicators of contracting complexity. All columns control for year, arranger, and borrower industry fixed effects. In this test, I use the full sample from 1993 to 2021. I drop all loans borrowed by financial companies. In all panels, the unit of observation is the arranger-loan facility level. The coefficients are *T*-statistics calculated with standard errors clustered at the arranger, year, and borrower industry levels. All variable definitions and data sources are provided in Appendix C. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
		Contract Complexity		
Debt/EBITDA Quartile	**0.065****			
	(2.80)			
Participant GeoDiversity		**0.461*****		
		(4.01)		
% Non-Relation Participants (for borrower)			**0.452*****	
			(4.57)	
% Non-Relation Participants (for arranger)				**0.289*****
				(4.20)
LnAmount	0.077***	0.049**	0.046**	0.071***
	(5.27)	(3.06)	(2.83)	(4.71)
Maturity	0.074***	0.065***	0.063***	0.072***
	(11.87)	(13.46)	(15.51)	(11.24)
LnSpread	0.142***	0.159***	0.149***	0.148***
	(4.19)	(5.35)	(4.93)	(4.51)
Controls:				
Borrower Characteristics	Yes	Yes	Yes	Yes
Loan Facility Characteristics	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	Yes
N	8,695	8,350	8,702	8,702
Adj R²	0.394	0.396	0.405	0.393

Table IA.2: Platform Adoption and Loan Contract Outcomes (Control Public-Side Lender)
In 2005, IntraLinks separated public and private information posting, and some lenders chose to remain on the public side. The tables estimate the syndicate structure as a function of platform adoption, while also controlling for the presence of public-side lenders, as studied in Amiraslani et al. (2023). All columns use a TWFE model (i.e., year and arranger fixed effects). I restrict the sample to arrangers who entered the market before 1997 and continued operations at least until 2008. The sample begins when the arranger starts lending and ends either when the arranger ceases lending or, at the latest, in 2021. I drop all loans borrowed by financial companies. In all panels, the unit of observation is the arranger-loan facility; and the independent variable is whether the loan adopts the platform. In Panels A–D, the dependent variables are, respectively, the retained shares by arrangers, participant geographic diversity, the percentage of non-relation participants for the borrower, and the percentage of non-relation participants for the arranger, in a specific loan facility. The coefficients are *T*-statistics calculated with standard errors clustered at the arranger, year, and borrower industry levels. All variable definitions and data sources are provided in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Contract Complexity

	(1)	(2)	(3)	(4)
		Contract Complexity		
Adoption	**0.497*** **	**0.538*** **	**0.474*** **	**0.511*** **
	(5.00)	**(5.04)**	**(4.63)**	**(10.80)**
Ind_PublicLender	0.457***	0.412***	0.341***	0.272***
	(7.96)	(7.40)	(6.46)	(4.59)
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	7,844	7,844	7,192	6,463
Adj. R²	0.317	0.357	0.424	0.708

Panel B: Lead Retained Share

	(1)	(2)	(3)	(4)
		Lead Retained Share		
Adoption	**-4.777**	**-3.647** **	**-2.737***	**1.000**
	(-1.57)	**(-2.37)**	**(-1.95)**	**(0.42)**
Ind_PublicLender	-4.027*	-4.168**	-3.094	-5.368***
	(-2.00)	(-3.00)	(-1.62)	(-3.31)
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	2,585	2,585	2,467	1,928
Adj. R²	0.186	0.355	0.463	0.603

Panel C: Participant Geographic Diversity

	(1)	(2)	(3)	(4)
		Participant GeoDiversity		
Adoption	**0.070***	**0.056****	**0.037***	**0.027***
	(2.13)	**(2.57)**	**(1.86)**	**(1.97)**
Ind_PublicLender	0.027	0.030*	0.018	0.011
	(1.49)	(1.94)	(1.71)	(0.69)
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	7,464	7,464	6,863	6,134
Adj. R²	0.194	0.246	0.325	0.573

Panel D: Percentage of Non-Relation Participants (for Borrower)

	(1)	(2)	(3)	(4)
		% Non-Relation Participants (for borrower)		
Adoption	**0.078****	**0.071****	**0.052****	**0.056**
	(2.24)	**(2.64)**	**(2.55)**	**(1.72)**
Ind_PublicLender	0.043	0.041	0.020	0.008
	(1.61)	(1.66)	(0.88)	(0.41)
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	7,844	7,844	7,192	6,463
Adj. R²	0.074	0.105	0.184	0.390

Panel E: Percentage of Non-Relation Participants (for Arranger)

	(1)	(2)	(3)	(4)
		% Non-Relation Participants (for arranger)		
Adoption	**0.025****	**0.024****	**0.011**	**0.011**
	(2.35)	**(2.65)**	**(0.91)**	**(1.03)**
Ind_PublicLender	0.015	0.013	0.004	0.010
	(0.97)	(0.89)	(0.34)	(0.96)
Controls:				
Borrower Characteristics	No	Yes	Yes	Yes
Loan Facility Characteristics	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	No
Borrower FE	No	No	No	Yes
N	7,844	7,844	7,192	6,463
Adj. R²	0.382	0.390	0.427	0.624

Chapter 3: Do Private Lenders Learn from Disclosed Loan Contracts?

ABSTRACT

This study examines whether and how private lenders use disclosed loan information to overcome contracting frictions in the syndicated lending market. While the SEC requires borrowers to publicly file material loan agreements, the broader implications for the lending market remain underexplored. Using SEC log file data, I document that disclosed contracts are actively accessed by outside lenders, with interest particularly concentrated in contracts involving riskier borrowers, larger loan arrangements, or more complex contract structures. These search behaviors persist over time. I further investigate how these search patterns influence subsequent contract designs. The results indicate that a lender's prior search history is not significantly associated with her subsequent pricing strategies but is strongly linked to covenant design, reflecting the unique value of detailed contract texts available through full regulatory disclosures. Overall, these findings highlight the informational role of disclosed loan contracts for outside lenders and contribute to our understanding of the information production process in debt contracting.

Keywords: Private Lenders, Debt Contracting, Information Acquisition, EDGAR

JEL Codes: G20, M40, D82, D83

1. INTRODUCTION

The Securities and Exchange Commission (SEC) mandates disclosure of material agreements either as an exhibit to Form 8-K or the company's next periodic report, and syndicated loan contracts fall under this category.[49] Therefore, outside lenders can access the negotiated loan information disclosed by borrowers through the EDGAR database. I refer to lenders listed in a loan contract as "inside lenders" and other lenders in the market as "outside lenders". Despite this regulatory oversight, very little is known about the lending market implications of this type of disclosure. Theory suggests that prices perform a well-articulated role in conveying information from the informed to the uninformed (e.g., Grossman, 1976; Grossman and Stiglitz, 1980). Applying this insight to the lending market, I argue that the disclosed loan contracts can convey hidden signals to outside lenders, as they are privately negotiated outcomes with informational advantaged lenders—who gather information costly through private communication. This study examines whether and how outside lenders use disclosed loan information, a less-explored information channel, to overcome contracting frictions.

It is well-established that private lenders produce information through delegated monitoring (Diamond 1984), deriving benefits over time through developing lending relationships and acquiring expertise (e.g., Hauswald and Marquez, 2006). The learning processes necessitate real lending activities, which are associated with high costs, particularly for risky borrowers. Consequently, some lenders actively seek alternative, less costly information sources to mitigate their informational disadvantage relative to more informed inside lenders. Recent research shows that public media coverage (Bushman et al., 2017), analyst reports (Call et al., 2022), expanded auditor's reports (Porumb et al., 2021), stock prices (De George et al., 2024), and financial reports (Chi et al., 2022) can serve as such informational channels. My study extends this literature by showing that loan contract disclosures in SEC filings can provide new information to outsider

[49] In 1980, Exhibits disclosure requirements were moved from Securities Act and Exchange Act forms and reconciled into uniform disclosure requirements in Regulation S-K (adopting Item 7, Exhibits (now Item 601)). In 2004, the SEC started encouraging companies to file the exhibit with Form 8-K when feasible rather than in the company's next periodic report, particularly when no confidential treatment is requested. Since May 2019, Registrants can omit confidential information in material contracts without submitting a confidential treatment request to the Commission. The need for confidential treatment generally can no longer be the basis for declining to file the material definitive agreement as an exhibit to the Item 1.01 Form 8-K.

lenders, thereby contributing to our understanding of the information production process in private debt contracting.

I argue that the informational role of disclosed syndicated loan contracts is an empirical question. In classic models of information flows between traders, prices should be noisy signals (Grossman, 1976), and an increase in noise reduces the informativeness of the price system (Grossman and Stiglitz, 1980). If the noise is significant enough, "uninformed" traders would have no incentive to learn from prices. This insight may apply to syndicated loan contracts. Such contracts often include implicit information rents and various terms, such as interest rates, pricing provisions, collaterals, covenants, reporting requirements, and default clauses, making them more costly to process. Moreover, loan contracts are disclosed as exhibits in SEC filings, which require high information acquisition costs. The significant effort needed to process such information may discourage traders from utilizing it. Private lenders, with their relatively low costs of information production through private communication compared to equity investors, further intensify this tension. This tension is greater for publicly traded companies, where lenders can rely on stock performance, analyst reports, or credit ratings as alternative screening tools.

I start by checking whether outside lenders acquire disclosed loan information of public companies via the EDGAR database. To capture their loan information acquisition, I take advantage of the server log files provided by the SEC, which contain search records on SEC filings by a specific IP address. Previous empirical studies have extensively used this dataset to measure investors' and other stakeholders' public information acquisition (e.g., Loughran and McDonald 2017). By accessing the ARIN database, I have successfully identified the IP address ranges of 98 lender groups reported in sampled loan contracts during the 2007-2016 period. The statistics indicate that about 80% of loan contracts involve the 98 lenders as leads or participants, suggesting that the sample likely represents the broader population. As shown in Figure 1, 83% of disclosed loan contracts were searched by outsider lenders during the sample period, a pattern consistent across all industries. Notably, outsiders searched for both historical and recent loan contracts.

I document that the informational value of loan contracts varies. Searches are concentrated on borrowers with higher levels of debt financing, particularly for loans with larger amounts, longer maturities, and higher credit spreads, even after controlling for other borrower- and loan-level

characteristics. Compared to credit lines, term loans, which involve more institutional lenders, receive more attention. More importantly, I find that more complex contracts, proxied by loan contract length, are significantly positively associated with searches by outside lenders, even after controlling for loan information available in DealScan, such as loan pricing.[50] This indicates that, beyond the summarized information in DealScan, the full contract texts and detailed structures available through SEC filings provide unique value to lenders, an aspect often overlooked in the current literature.

To rule out the possibility that searches are driven by simultaneous filings rather than specific loan information, I provide evidence of the persistence in lenders' tracking behavior over time. The results indicate that when an outside lender searches for a loan contract filing, the likelihood of them searching for the amendment of the same loan increases by over 57%. For reference, the unconditional probability of a lender searching for a loan amendment filing is 3.92%. I find similarly strong persistence at both the borrower and lender levels. Specifically, when an outside lender searches for a loan contract filing, the likelihood of them searching for other loan contracts by the same borrower (lender) increases by 19% (11.4%).

If the searches are associated with information production, I expect lenders' subsequent decisions to be associated with their past search activities. I further investigate how these loan information search behaviors affect lenders' subsequent loan contract designs. I focus on recent information searches by lenders conducted before origination activities. Specifically, I define loan information searches as those conducted by a specific lender between 30 and 180 days before the new loan's origination date. I chose the window because it aligns with the typical syndication period. I expect these searched loans to have a greater influence on loan originations compared to unsearched loans, which serve as the control group. The control loans are one-to-one matched with the searched loans based on loan disclosure type (i.e., origination or amendment), disclosure timing, borrower industry, loan facility type (i.e., credit line or not), maturity, and credit ratings.

The empirical results indicate no significant difference in the impact of searched versus

[50] In untabulated analyses, I estimate the association between my measure of contract complexity and other potential indicators of contracting complexity. The results show that this measure is positively associated with established metrics, such as borrower leverage ratio, loan amount, maturity, and credit spread, even after controlling for arranger, year, and borrower industry fixed effects. A similar verification is presented in Chapter 2 of this thesis.

unsearched loans on the credit spreads of lenders' newly issued loans. However, the covenant design of searched loans is strongly associated with the covenant structure of newly issued loans. Specifically, when the contracts of searched loans contain covenants, the lenders' subsequent loans are more likely to include covenants as well, even after controlling for lender and borrower fixed effects. Moreover, the types of covenants show a similar association. For example, if the searched loans include a debt-to-EBITDA financial covenant, the new loans are more likely to include this type of covenant as well. I argue that the limited covenant detail in other databases may explain these findings, highlighting the unique informational value of full contract texts available through SEC filings. In conclusion, this study documents the importance of disclosed loan contract information for outside lenders, reflecting the critical role of detailed contract terms in debt contracting.

A related study is Murfin et al. (2019), which argues that lenders set loan interest spreads based on the analysis of recently closed, comparable transactions. The authors leverage the timing of loan spread disclosed in DealScan as an information shock to market lenders and find that the interest rate of an individual comparable is associated with the rate set on subsequent loans. However, Murfin et al. (2019) simply assume that lenders acquire and process loan information immediately upon disclosure, an assumption that has been challenged by recent accounting literature (e.g., Blankespoor et al., 2020). While they try to provide robust evidence based on matching comparables, they cannot rule out the possibility that the results are influenced by other confounding factors. In contrast, my empirical strategy makes it possible to trace out lenders' information acquisition (through their search behavior in the EDGAR database, which I can map to the IP addresses of lenders), thereby deriving direct insights into the informational value of loan contracts.

More importantly, while Murfin et al. (2019) focus solely on loan interest rates disclosed in DealScan, my research emphasizes the broader informational value of loan contracts in SEC filings, including covenant structures, which are crucial for the SEC's regulatory oversight. In other words, beyond the basic contract terms available in DealScan (which also sources data from filings), the additional contract details disclosed in SEC filings provide significant informational value, offering lenders a more comprehensive view of borrower risk and contractual protections. This is crucial

for regulators. Recent studies (e.g., Caskey et al. 2023; Li et al. 2024) document that borrowers strategically disclose loan information (i.e., delay or hide full contracts), yet the SEC does not rigorously enforce compliance with 8-K loan disclosures. Note that noisy or even fraudulent public loan information could have adverse consequences if it drives market expectations away from fundamentals, especially when "information cascades" occur.[51]

This study also contributes to the emerging literature on how decision-makers learn investor information from price signals to guide their decisions. Most studies provide evidence supporting this informational feedback from the stock market to institutional investors (Chen et al., 2020) corporate managers (Zuo, 2016), and private lenders (De George et al., 2023). I add to this growing literature by examining loan contracts as price signals that convey investor information.

2. DATA COLLECTION

To identify lenders' acquisition of loan information, I take advantage of the server log files provided by the SEC, which contain search records on SEC filings by a specific IP address. Previous empirical studies have extensively used this dataset to measure investors' and other stakeholders' public information acquisition (e.g., Loughran and McDonald 2017).[52] I combine data from a variety of sources: the SEC filings in EDGAR, the SEC's server log files, the American Registry of Internet Numbers (ARIN), and the DealScan database. My sample starts in 2007 as the log files between September 2005 and May 2006, are either missing or corrupt (e.g., Loughran and McDonald 2017); it ends in 2016 as the SEC discontinued updating EDGAR log data for specific IP addresses in 2017. In this section, I describe the steps of how I collect this acquisition data, including: a) filtering loan contracts in SEC filings; b) identifying IP addresses of lenders reported in the loan contracts; c) identifying lenders' search behaviors on loan contracts via EDGAR.

2.1 Filtering loan contracts in SEC filings

I identify loan contracts from SEC filings of all publicly traded firms (domestic firms traded

[51] In a sequential trading game, "information cascades" denotes a scenario where late traders may rationally choose to ignore their own signal if another signal revealed through preceding trading actions is dominant.
[52] Other studies using this dataset include works by Lee et al. (2015), Drake et al. (2016, 2019, 2020), Bernard et al. (2020), Chen et al. (2020), Gibbons et al. (2021), Coles et al. (2022), Chi et al. (2022) and Crane et al. (2023), etc.

on NYSE, AMEX, or NASDAQ) filed on or before December 2016. These contracts are material public disclosures generally filed as exhibits to a firm's 8-K reports.[53] I searched for any 8-K filing that contains an attached Exhibit 10, which relates to "material agreements". Following Nini et al. (2009), I identify loan contract documents by employing terms-searching at the beginning part of each "material agreement" exhibit.[54] To ensure the disclosure of complete contracts, I only retain those loan filings with signature pages.

Next, I match loan contracts in SEC filings with the corresponding records in the DealScan database. In detail, I obtain the Compustat identifier "gvkey" for both the filers of loan contracts in EDGAR and borrowers in the DealScan database by using the Roberts Dealscan-Compustat Linking Database. I match these two datasets based on the common identifier "gvkey". Afterward, for each "gvkey", I match loan contracts to corresponding DealScan records, ensuring that the reporting dates of loan contracts fall within a 90-day window centered around the "tranche active date" specified in the DealScan records (Bushman et al. 2021). I perform the matching process separately for loan originations and loan amendments.

2.2 Identifying IP addresses of lenders reported in the loan contracts

To identify the IP address for specific lenders, I begin by constructing a list of lenders in the filtered loan contracts for the sample period 2007-2016. Large organizations, such as lenders, often register large blocks of IP addresses on the ARIN (Gibbons et al. 2021), this helps me to identify major lenders' IP addresses and then locate their information searches using SEC log files. [55]

I manually identify the IP address ranges of each specific lender using "Entity Search" (i.e., lender's full name) in WHOIS/RDAP database from the ARIN. For each search, I obtain a JSON-formatted link under "Self" column which contains all active IP addresses registered by this entity.

[53] Despite the SEC's encouragement for companies to file the exhibit with Form 8-K since 2004, there are cases where borrowers may choose to file the loan contracts in their subsequent periodic reports, such as Form 10-K and 10-Q. This study primarily focuses on search activities related to 8-K loan filings to mitigate the impact of simultaneous disclosures with financial reports. Moreover, 8-K loan contracts are generally filed in a timely manner without the submission of a confidential treatment request, potentially containing more informational value.

[54] Terms include: "credit agreement", "loan agreement", "credit facility", "loan and security agreement", "loan & security agreement", "revolving credit", "financing and security agreement", "financing & security agreement", "credit and guarantee agreement", and "credit & guarantee agreement".

[55] ARIN claims that it will not collect any personal information for inclusion in its public Whois. The only information that is published in ARIN's public Whois is organizational information.

There could be cases where some lenders are not listed in the database as registered organizations. For example, some lenders may have their IP address ranges registered under different entities (e.g., their parent company) or may use IP addresses that are not easily traceable through WHOIS/RDAP databases. To mitigate this issue, I also manually identify the official website of each lender by using Google search (i.e., the first record in Google search) and then locate the IP address of each website by using WHOIS query. Next, I search this identified IP address and obtain its registered entity from WHOIS/RDAP database. It is important to note that, in some cases, websites may be hosted on external servers or use content delivery networks (CDNs) (e.g., Amazon Server), which can result in the IP address being linked to a different entity than the website owner. After manual checks, I only keep those cases where the registered entity is the owner of the specific lender.[56]

In the loan contracts sample, multiple lender names may belong to the same company group or essentially be the same company, sharing identical IP address ranges. For example, "JP Morgan", "JP Morgan Trust Co", and "Morgan Bank, N.A." are all subsidiaries of JPMorgan. My method clusters these subsidiaries as the same lender. Another example is "Emigrant Savings Bank", the former name of "Emigrant Bank"; although DealScan defines these two names as different banks, the IP address hosting its official website helped me identify them as the same bank.

2.3 Identifying lenders' search behaviors on loan contracts via EDGAR

The SEC's server log file contains the following variables for each search: IP address, search date, and SEC accession associated with the document requested. The IP addresses in the dataset are partially anonymized, providing the first three octets with the fourth octet obfuscated with a 3-character string (###.###.###.xxx). As large organizations often register the full range of possible IPs available in the fourth octet (Crane et al. 2022), following prior studies, I link search activities in the log file to specific lender groups by using the first three octets. After this step, I am able to track search behaviors on loan information by 98 lender groups through the SEC log file. In this study, I focus on lenders' searches for loan information when they are not party to the

[56] For example, the lender name "40/86 Advisors Inc" cannot be traced directly by using "Entity Search" in the ARIN database. However, I obtained the IP address hosting the official website of "40/86 Advisors Inc" and then located it as a subsidiary of CNO Financial Group.

contracts, referred to as outside loan information.

2.4 Sample Construction

Table 1 describes the lenders in our sample. Panel A presents the number of loan contracts and the involvement of lenders in the sampled loans. The statistics indicate that about 80% (85%) of loan origination (amendment) involve the 98 lenders as leads or participants, suggesting that the sample likely represents the broader population. Panel B presents the top 10 sample lenders, sorted by the number of loan contracts they initiated; and Panel C presents the top 10 sample lenders, sorted by the number of outside contracts they searched. Note that one loan contract may include multiple loan facilities, which are structured as one deal. Overall, institutional lenders with less direct monitoring experience have a greater likelihood of searching for public loan information, such as "Hartford Life Insurance Co." and "DE Shaw & Co.". Given that these institutional investors usually have multiple investment lines, including both equity and loans, I cannot simply conclude that these searches are specifically for loan information. Other simultaneous filings may influence the observed search behaviors, rather than being solely related to loan-specific purposes. Therefore, I design several empirical tests in the next section to further investigate whether the searches are driven by loan-related purposes.

[Insert Table 1]

3. EMPIRICAL RESULTS

3.1 Overview of Sample

I start by checking the time trends and types of loan information searched by outside lenders through the EDGAR database. Figure 1 Panel A displays the time trend of the number of loan contracts searched by sampled outside lenders and the number of loan contracts disclosed in EDGAR over the period 2007-2016. I notice a significant increasing trend of loan contracts searching between 2007-2016, while the trend in the number of newly disclosed loan contracts remains relatively flat. Figure 1 Panel B shows the industry distribution (i.e., Fama & French 12 industries classification) of loan contracts searched by sampled outside lenders over the period

2007-2016. Among all industries, over 83% of disclosed loan contracts have been searched by outsiders during my sample period. Overall, Figure 1 suggests that private lenders search for both historical and recent loan contracts, and most of the disclosed loan contracts have been searched by my sampled outside lenders.

[Insert Figure 1]

3.2 Characteristics of Searched Loan Contracts

Next, I investigate the characteristics that influence the informational value of loan contracts searched by outside lenders.

I simply start my analysis by comparing firm and loan characteristics between two groups: highly-searched loan contracts (i.e., those with more outside lenders searching, above the median in the sample) and lowly-searched loan contracts. Table 2, Panel A, demonstrates that attention varies across loan deals with differing characteristics. Variable definitions are provided in Appendix A. The unit of observation is the loan-deal level, and all loans issued to financial companies are excluded from the sample. The univariate analysis suggests that borrowers with high leverage ratios and low growth opportunities are more likely to be searched by outside lenders. This finding supports the idea that these risky borrowers necessitate information production, leading outsiders to rely on public loan information to mitigate informational asymmetries. Furthermore, I find that loans with larger amounts, longer maturities, and higher credit spreads receive more attention. Compared to credit lines, term loans, which involve more institutional lenders, receive more attention.

Table 2, Panel B, presents results from OLS regressions that examine the relationship between firm and loan characteristics of a loan contract and the frequency of its being searched. The dependent variable, *Number of Outside Lenders Searching*, is the number of outside lenders searching for a specific loan contract from 2007 to 2016. All firm and loan characteristics are defined at the time of loan filing. All tests are conducted at the loan contract level. Note that one loan contract may include multiple loan facilities, structured as one deal; as such, I use the maximum value of loan terms within a deal to define its contract-level characteristics. In Panel B, all regressions control for disclosure year fixed effects (representing the year the filing was disclosed), and the number of

sampled lenders participating in the loan contract (*NumInsider*). I begin by including variables *Leverage*, *Assets*, and industry fixed effects in columns (1)-(2), add other firm characteristics in column (3), and then add loan characteristics in column (4). In column (5), I replace industry-fixed effects with firm-fixed effects. Robust standard errors are clustered at the firm level and t-statistics are reported in parentheses. I winsorize all the firm-level variables at the 1st and 99th percentiles.

In all specifications, there is a statistically significant increase in the frequency of a contract being searched as leverage or total assets increase, even after controlling for other borrower- and loan-level characteristics. These results suggest that searches are concentrated on borrowers with higher levels of debt financing. In Columns (4) and (5), I also observe a statistically significant increase in the frequency of a contract being searched as loan amount, maturity, and credit spread increase, even after accounting for other borrower- and loan-level characteristics. It suggests the notion that lenders focus their searches on riskier or larger loan arrangements, which may potentially contain more informational value. Furthermore, compared to credit lines, term loans—typically involving more institutional lenders who lack direct monitoring experience—receive greater attention.

[Insert Table 2]

Next, I explore whether other types of loan information in SEC filings, beyond the basic contract terms available in DealScan (which also sources data from filings), hold unique value for outside lenders. Table 3 reports results from OLS regressions that relate the complexity of a loan contract (i.e., the length of the loan contract) to the frequency of its being searched. The dependent variable, *Number of Outside Lenders Searching*, is the number of outside lenders searching for a specific loan contract from 2007 to 2016. All firm and loan characteristics are defined at the time of loan filing. All tests are conducted at the loan contract level. All regressions control for borrower-level characteristics, disclosure year fixed effects (representing the year the filing was disclosed), and the number of sampled lenders participating in the loan contract (*NumInsider*). I use contract length as a proxy for contracting complexity, capturing the potential informational content of the agreement. In untabulated analyses, I estimate the association between this measure and other potential indicators of informational value. The results show that this measure is positively associated with

established metrics, such as borrower leverage ratio, loan amount, maturity, and credit spread, even after controlling for arranger, year, and borrower industry fixed effects. A similar verification is presented in Chapter 2 of this thesis.

In all specifications, the results show that more complex contracts, proxied by loan contract length, are significantly and positively associated with searches by outside lenders, even after controlling for loan information available in DealScan, such as loan amount, maturity, and credit spread. This indicates that, beyond the information summarized in DealScan, other loan details in filings are valuable to lenders. Such information is often overlooked in the current literature.

[Insert Table 3]

3.3 Persistence of Searching Behaviors

To rule out the possibility that searches are driven by simultaneous filings rather than specific loan information, I provide evidence of the persistence in lenders' tracking behavior over time. If the searches are for loan-specific purposes, I expect lenders to persistently track changes in the same loans, the same borrowers, or the same inside lenders over time.

Table 4 examines the persistence in loan tracking behavior of lenders. Panel A reports whether a lender tracks changes in loan terms (i.e., amendment) after reviewing the original loan contract (i.e., origination), or vice versa. I retain only those facilities with origination and amendment records between 2007 and 2016. Panel B reports whether a lender tracks the new contract of a specific borrower after reviewing her old loan contract, or vice versa. I retain only those facilities with multiple loan originations between 2007 and 2016. Panel C reports whether a lender tracks the new contract of a specific lender after reviewing her old loan contract, or vice versa. I retain only those lenders with multiple loan originations between 2007 and 2016. Panel D reports whether a lender tracks the new contract of a specific lead arranger after reviewing her old loan contract, or vice versa. I retain only those lead arrangers with multiple loan originations between 2007 and 2016. Robust standard errors are clustered at the lender level and t-statistics are reported in parentheses.

[Insert Table 4]

The results indicate that when an outside lender searches for a loan contract filing, the

likelihood of them searching for the amendment of the same loan increases by over 57%. For reference, the unconditional probability of a lender searching for a loan amendment filing is 3.92%. I find similarly strong persistence at both the borrower and lender levels. Specifically, when an outside lender searches for a loan contract filing, the likelihood of them searching for other loan contracts by the same borrower (lender) increases by 19% (11.4%). The results remain robust across all specifications, after controlling for different levels of fixed effects.

3.4 Impact of Past Loan Searches on Loan Contract Design

If the searches are associated with information production, I expect lenders' subsequent decisions to be associated with their past search activities. Next, I further investigate how these loan information search behaviors affect lenders' subsequent loan contract designs. I focus on recent information searches by lenders conducted before origination activities. Specifically, I define loan information searches as those conducted by a specific lender between 30 and 180 days before the new loan's origination date. I chose the window because it aligns with the typical syndication period. I expect these searched loans to have a greater influence on loan originations compared to unsearched comparable loans.

The empirical challenge is to identify loans that are not searched but share comparable characteristics with the searched loans, ensuring that the observed effects are driven by the loan search itself rather than by other confounding factors. My identification approach follows the spirit outlined in Murfin et al. (2019). The control loans are matched to the searched loans based on the following criteria: the same report type (i.e., origination or amendment), reporting within (-180, +180) days of the searched contracts, the same Fama-French 30-industry classification, the same loan type (i.e., credit line or not), and a maturity difference of less than 360 days. Within these groups, loans are matched one-to-one based on the closeness of their "S&P Ratings".

I compare the influence of searched versus unsearched loans on the design of newly issued loans by a lender. The empirical specification is shown as below:

$$NewLoanDesign = \alpha + \boldsymbol{\beta_1}(\boldsymbol{DisclosedLoanDesign} * \boldsymbol{Searched}) + \beta_2 DisclosedLoanDesign + \beta_3 Searched + \beta_4 DiffDate + \beta_5 DiffRating + \beta_6(DisclosedLoanDesign * DiffDate) + \beta_7(DisclosedLoanDesign * DiffRating) + LenderFE + BorrowerFE + \varepsilon$$

NewLoanDesign denotes the contract terms of newly issued loans by a specific lender. *DisclosedLoanDesign* refers to the loan terms of either a loan contract searched by that lender or an unsearched loan contract that is comparably matched to the searched loan contract. *Searched* indicates whether the contract was searched within the 30 to 180 days preceding the origination date of the new loan. I further control for the fundamental gap between the disclosed loan information and the new loan transactions. Specifically, I account for the differences in transaction time and credit quality between the new loans and the disclosed loan information. *Diff_Date* represents the number of days between the closing date of the new loan and that of the disclosed loan of interest. *Diff_Rating* represents the absolute value of the rating difference between the new loan and the disclosed loan of interest. Each of these two measures interacts with *DisclosedLoanDesign*.

Table 5 reports the impact of search on loan spread design. Panel A includes all lenders, while Panels B focus on arrangers and participants, respectively. The coefficient on *DisclosedLoanSpread *Searched* captures the difference in the impact of searched versus unsearched loan information on subsequent loan spread design. The empirical results indicate no significant difference in the effect of searched versus un-searched loans on the loan spreads of newly issued loans. These findings are consistent across all specifications.

[Insert Table 5]

Table 6 reports the impact of past loan searches on the likelihood of the lender's new loan origination being covenant lite. Panel A includes all lenders, while Panels B focus on arrangers and participants, respectively. The coefficient on *DisclosedCovenant-Lite*Searched* captures the difference in the impact of searched versus unsearched loan information on subsequent loan covenant-lite choice. I expect these searched loans to have a greater influence on loan originations compared to

unsearched loans. The empirical results show that, the covenant design of searched loans is strongly associated with the covenant design of the new loans. Specifically, when the loan contracts of searched loans contain covenants, the new loans are more likely to include covenants, even after controlling for lender and borrower fixed effects.

[Insert Table 6]

Moreover, the types of covenants are also significantly associated. Table 7 reports the impact of past loan searches on the financial covenant choice of the lender's new loan origination. Following Christensen and Nikolaev (2012), I categorize covenants into capital-based and performance-based. I find that: 1) when the searched loans include a capital-based covenant, the new loans are more likely to include it as well, as shown in Table 7 Panel A; 2) when the searched loans include a performance-based covenant, the new loans are more likely to include it as well, as shown in Table 7 Panel B; 3) when the searched loans include a debt-to-EBITDA financial covenant, the new loans are more likely to include it as well, as shown in Table 7 Panel C. I argue that the inadequacy of covenant details in other databases may explain these findings.

[Insert Table 7]

4. CONCLUSION

The SEC mandates the disclosure of syndicated loan contracts, yet little is known about the implications of this type of disclosure for the lending market. In this paper, I argue that the disclosed loan contracts can convey hidden signals to outside lenders. Using SEC log file data, I document that disclosed contracts are actively accessed by outside lenders, with interest particularly concentrated in contracts involving riskier borrowers, larger loan arrangements, or more complex contract structures. These search behaviors persist over time. I further investigate how these search patterns influence subsequent contract designs. The results indicate that a lender's prior search history is not significantly associated with her subsequent pricing strategies but is strongly linked to covenant design, reflecting the unique value of detailed contract texts available through full regulatory disclosures. Overall, these findings highlight the informational role of disclosed loan contracts for outside lenders and contribute to our understanding of the information production process in debt contracting.

Recent research shows that some lenders actively seek public, less costly information sources to mitigate their informational disadvantage relative to more informed inside lenders. My study extends this literature by showing that loan contract disclosures in SEC filings can provide new information to outsider lenders, thereby contributing to our understanding of the information production process in private debt contracting. This is also crucial for the SEC's regulatory oversight. Beyond the basic contract terms available in DealScan (which also sources data from filings), additional loan information disclosed in SEC filings also provides significant informational value. Recent studies (e.g., Caskey et al. 2023; Li et al. 2024) document that borrowers strategically disclose loan information (i.e., delay or hide full contracts), yet the SEC does not rigorously enforce compliance with 8-K loan disclosures. Note that noisy or even fraudulent public loan information could have adverse consequences if it drives market expectations away from fundamentals. Lastly, this study contributes to the emerging literature on how decision-makers use investor information from price signals (in this case, loan information) to guide their decisions.

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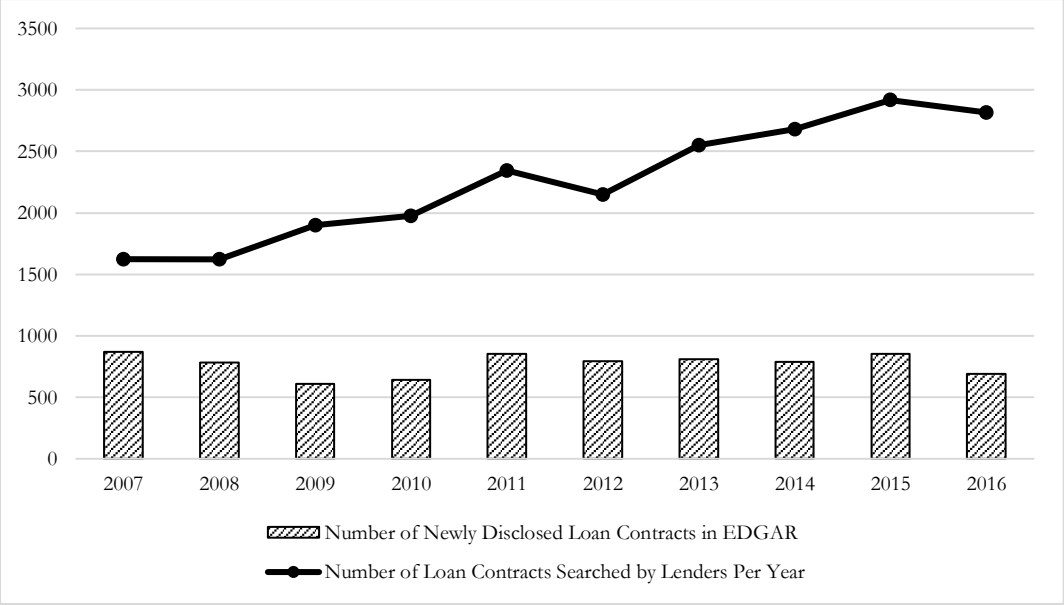
Appendix A Variable definition

Variables	Description	Source
Debt/EBITDA	Ratio of total debt to earnings before interest, taxes, depreciation, and amortization.	*Compustat/CRSP*
Leverage	Ratio of total debt to total asset (book leverage).	*Compustat/CRSP*
Assets	Logged book value of total assets.	*Compustat/CRSP*
Tangibility	The ratio of net PP&E to total assets	*Compustat/CRSP*
OperatingCF	Ratio of operating income before depreciation to lagged total assets.	*Compustat/CRSP*
MtB	Ratio of Market Cap to Book Value of Equity, omitted for negative Book Equity	*Compustat/CRSP*
ROA	Ratio of earnings before interest and taxes to lagged total assets.	*Compustat/CRSP*
SalesGrowth	Calculated as sales minus previous year sales scaled by previous year sales.	*Compustat/CRSP*
Rated	Dummy equal to 1 if borrower has a current credit rating by S&P	*Capital IQ S&P Credit Ratings*
LnAmount	Logged value of facility amount (dollar)	*DealScan*
Secured	Dummy equal to 1 if the loan is secured	*DealScan*
Covenant	Dummy equal to 1 if the loan has at least one covenant	*DealScan*
Spread	All-in spread drawn above LIBOR	*DealScan*
LnMaturity	Logged value of loan maturity (days)	*DealScan*
TopArranger	Dummy equal to 1 if any of the lead arrangers of the facility is a top five lead arranger based on market share, and zero otherwise.	*DealScan*
PerformancePricing	A dummy variable equal to 1 if performance pricing exists	*DealScan*
Term Loan A	Dummy equal to 1 if the loan is term loan A	*DealScan*
Term Loan B+	Dummy equal to 1 if the loan is term loan B or plus	*DealScan*
Revolver/Line	Dummy equal to 1 if the loan is credit line	*DealScan*
NumLenders	Number of lenders in a facility	*DealScan*
Complexity	Standardized value of the length of loan contract	*SEC filings*

Figure 1: Characteristics of Loan Contracts Searched by Outside Lenders

The figures present the number of loan contracts searched by sampled outside lenders and the number of loan contracts newly disclosed in EDGAR over the period 2007-2016, sorted by year and industry (i.e., Fama-French 12-industry classification).

Panel A: Yearly Trend of Number of Loan Contracts Searched by Outside Lenders



Panel B: Industry Distribution of Loan Contracts Searched by Outside Lenders

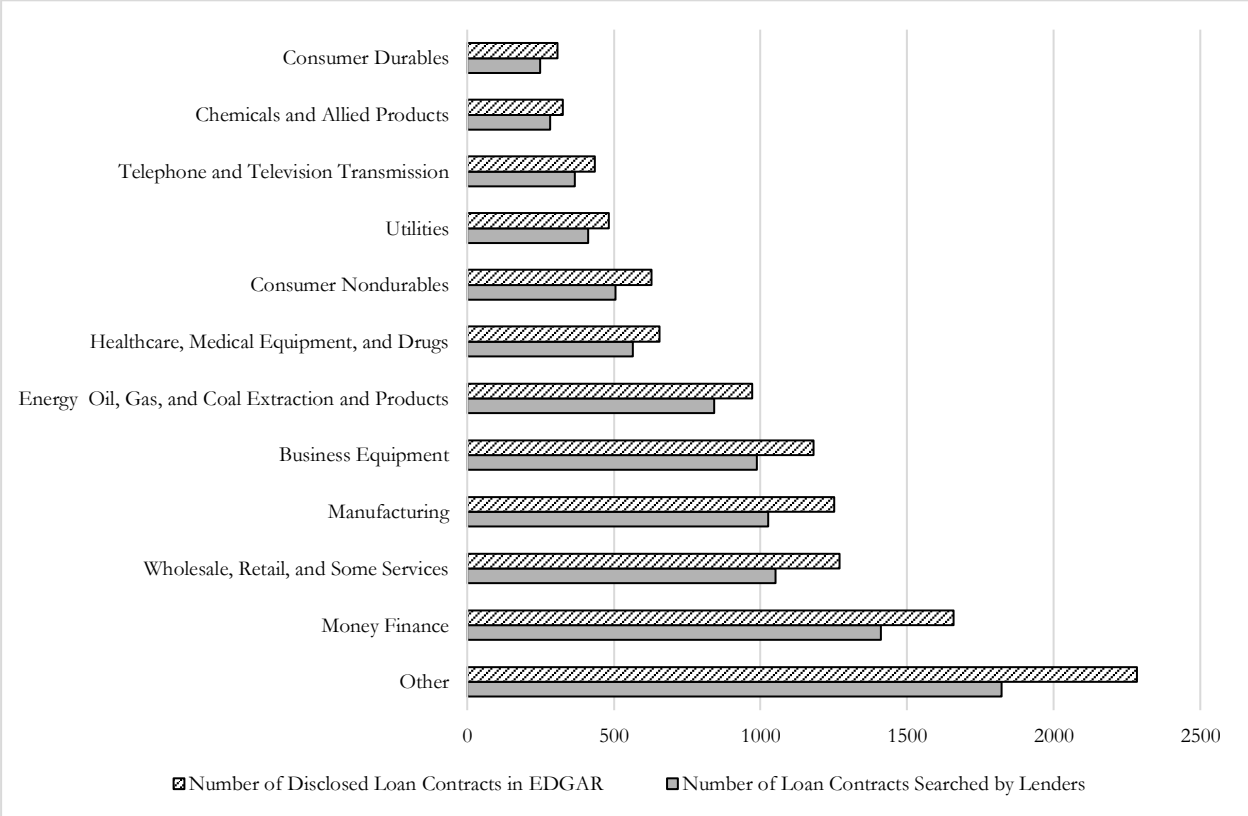


Table 1: Lenders in the Sample

This table describes the lenders in my sample. Panel A presents the number of loan contracts and the involvement of lenders in the sampled loans. Panel B presents the top 10 sample lenders, sorted by the number of loan contracts they initiated. Panel C presents the top 10 sample lenders, sorted by the number of outside contracts they searched. Note that one loan contract may include multiple loan facilities, which are structured as one deal.

Panel A: Sample Lenders and Loan Contracts in EDGAR

	(1)	(2)
	# Loans	**% Loans**
Loan Originations		
# Loan Contracts in EDGAR (On and before 2016)	7,152	100%
# Loan Contracts with Sample Lenders as Leads or Participants	5,756	80%
# Loan Contracts with Sample Lenders as Leads	3,921	55%
# Loan Contracts with Sample Lenders as Participants	4,744	66%
Loan Amendments		
# Loan Contracts in EDGAR (On and before 2016)	4,300	100%
# Loan Contracts with Sample Lenders as Leads or Participants	3,659	85%
# Loan Contracts with Sample Lenders as Leads	2,534	59%
# Loan Contracts with Sample Lenders as Participants	3,051	71%

Panel B: Top 10 Lenders (sorted by the number of contracts they initiated)

		Loan Origination Contracts	
	Lender Group	# Lead or Participant	# Lead
1	['JP Morgan', 'JP Morgan Trust Co', 'Morgan Bank, N.A.']	3,523	2,411
2	['Citi']	2,085	1,091
3	['Elavon Financial Services Limited', 'US Bancorp', 'US Bank National Association Canada Branch', 'USA Bank', 'USBanCorp']	2,030	250
4	['PNC Bank']	1,837	332
5	['Deutsche Bank AG']	1,356	479
6	['HSBC Banking Group']	1,024	137
7	['Bank of New York Mellon']	979	54
8	['Fifth Third Bank']	966	70
9	['UBS AG']	879	171
10	['Northern Trust Corp']	749	1

Panel C: Top 10 Lenders (sorted by the number of outside contracts they searched)

		The Search for Outside Contracts	
	Lender Group	# Origination	# Amendment
1	['Hartford Life Insurance Co']	3,268	2,650
2	['DE Shaw & Co']	2,536	2,155
3	['UBS AG']	2,167	1,171
4	['Deutsche Bank AG']	2,007	1,027
5	['JP Morgan', 'JP Morgan Trust Co', 'Morgan Bank, N.A.']	1,983	947
6	['Citi']	1,938	1,149
7	['Elavon Financial Services Limited', 'US Bancorp', 'US Bank National Association Canada Branch', 'USA Bank', 'USBanCorp']	1,079	510
8	['Raymond James Financial Inc']	844	473
9	['Fifth Third Bank']	758	432
10	['Prudential Financial Inc']	747	522

Table 2: Characteristics of Searched Loan Contracts

Panel A compares firm and loan characteristics between two groups: highly-searched loan contracts (i.e., those with more outside lenders searching, above the median in the sample) and lowly-searched loan contracts. Panel B reports results from OLS regressions that relate firm and loan characteristics of a loan contract to the number of outside lenders searching for it. The dependent variable, *Number of Outside Lenders Searching*, is the number of outside lenders searching for a specific loan contract from 2007 to 2016. All firm and loan characteristics are defined at the time of loan filing. All tests are conducted at the loan contract level. Note that one loan contract may include multiple loan facilities, structured as one deal; as such, we use the maximum value of loan terms within a deal to define its contract-level characteristics. In Panel B, all regressions control for disclosure year fixed effects (representing the year the filing was disclosed), and the number of sampled lenders participating in the loan contract (*NumInsider*). I begin by including variables *Leverage*, *Assets,* and industry fixed effects in columns (1)-(2), add other firm characteristics in column (3), and then add loan characteristics in column (4). In column (5), I replace industry-fixed effects with firm-fixed effects. Robust standard errors are clustered at the firm level and t-statistics are reported in parentheses. I winsorize all the firm-level variables at the 1st and 99th percentiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Univariate Analysis

	Loan Contracts						Difference in Mean
	Highly Searched			**Lowly Searched**			
	Sample	Mean	Median	Sample	Mean	Median	
Borrower-Level Characteristics							
Debt/EBITDA	3,376	3.28	2.73	3,992	2.83	2.42	0.442***
Leverage	3,376	0.34	0.33	3,992	0.30	0.30	0.032***
Assets	3,376	7.94	7.85	3,992	6.98	6.91	0.952***
Tangibility	3,376	0.33	0.24	3,992	0.32	0.24	0.01
OperatingCF	3,376	0.12	0.11	3,992	0.11	0.11	0.00
MtB	3,376	0.02	0.01	3,992	0.04	0.02	-0.021***
ROA	3,376	0.07	0.07	3,992	0.07	0.07	0.00
SalesGrowth	3,376	0.12	0.07	3,992	0.14	0.08	-0.026***
Rated	3,376	0.54	1.00	3,992	0.41	0.00	0.134***
Deal-Level Characteristics							
LnAmount	3,376	6.38	6.40	3,992	5.47	5.53	0.904***
Spread	3,376	239.92	200.00	3,992	214.38	175.00	25.541***
LnMaturity	3,376	7.36	7.51	3,992	7.17	7.44	0.181***
Secured	3,376	0.55	1.00	3,992	0.63	1.00	-0.078***
Covenant	3,376	0.68	1.00	3,992	0.84	1.00	-0.165***
TopArranger	3,376	0.84	1.00	3,992	0.76	1.00	0.084***
NumInsiders	3,376	3.95	3.00	3,992	3.29	3.00	0.656***
Term Loan A	3,376	0.18	0.00	3,992	0.09	0.00	0.085***
Term Loan B+	3,376	0.20	0.00	3,992	0.16	0.00	0.036***
Revolver/Line	3,376	0.86	1.00	3,992	0.88	1.00	-0.023***

Panel B: Multivariate Analysis

	(1)	(2)	(3)	(4)	(5)
	Number of Outside Lenders Searching				
Borrower-Level Characteristics					
Leverage	**1.595*** **	**1.196*** **	**1.130*** **	**0.529*** **	**0.641***
	(9.69)	**(7.49)**	**(6.38)**	**(2.91)**	**(1.94)**
Assets		0.479***	0.463***	0.332***	0.291***
		(18.52)	(15.23)	(8.53)	(3.24)
Tangibility			-0.335**	-0.263*	-0.599
			(-2.13)	(-1.67)	(-1.17)
OperatingCF			3.856***	3.522***	1.507
			(3.52)	(3.28)	(0.70)
MtB			-0.403	0.005	-0.071
			(-1.09)	(0.01)	(-0.11)
ROA			-3.911***	-3.617***	-3.090
			(-3.59)	(-3.36)	(-1.44)
SalesGrowth			0.386***	0.247***	0.196*
			(4.50)	(2.92)	(1.81)
Rated			0.173***	0.145**	0.160
			(2.69)	(2.30)	(1.35)
Deal-Level Characteristics					
LnAmount				**0.272*** **	**0.207*** **
				(6.53)	**(3.96)**
Spread				**0.001*** **	**0.001*** **
				(4.54)	**(3.19)**
LnMaturity				**0.269*** **	**0.253*** **
				(5.08)	**(4.46)**
Secured				0.063	0.027
				(1.00)	(0.27)
Covenant				-0.173**	-0.190**
				(-2.40)	(-2.19)
PerformancePricing				0.351***	0.379***
				(6.96)	(7.03)
TopArranger				-0.060	0.011
				(-0.95)	(0.11)
Revolver/Line				-0.291***	-0.171*
				(-3.27)	(-1.68)
NumInsiders	-0.043***	-0.165***	-0.162***	-0.188***	-0.233***
	(-4.65)	(-14.53)	(-14.35)	(-14.75)	(-13.52)
Industry FE	Yes	Yes	Yes	Yes	No
Borrower FE	No	No	No	No	Yes
Disclosure Year FE	Yes	Yes	Yes	Yes	Yes
N	7,368	7,368	7,368	7,368	6,482
Adj. R²	0.471	0.517	0.521	0.537	0.594

Table 3: Loan Contract Complexity and Searching Behaviors

This table reports results from OLS regressions that relate the complexity of a loan contract (i.e., the length of the loan contract) to the number of outside lenders searching for it. The dependent variable, *Number of Outside Lenders Searching*, is the number of outside lenders searching for a specific loan contract from 2007 to 2016. All firm and loan characteristics are defined at the time of loan filing. All tests are conducted at the loan contract level. Note that one loan contract may include multiple loan facilities, structured as one deal; as such, we use the maximum value of loan terms within a deal to define its contract-level characteristics. All regressions control for borrower-level characteristics, disclosure year fixed effects (representing the year the filing was disclosed), and the number of sampled lenders participating in the loan contract (*NumInsider*). I winsorize all the firm-level variables at the 1st and 99th percentiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Number of Outside Lenders Searching			
Complexity	**0.273*** **	**0.265*** **	**0.190*** **	**0.202*** **
	(9.37)	**(7.65)**	**(6.12)**	**(5.50)**
LnAmount			0.251***	0.183***
			(6.04)	(3.49)
Spread			0.001***	0.001***
			(4.07)	(3.00)
LnMaturity			0.230***	0.228***
			(4.33)	(4.02)
Secured			0.012	-0.008
			(0.19)	(-0.08)
Covenant			-0.160**	-0.182**
			(-2.24)	(-2.11)
PerformancePricing			0.295***	0.313***
			(5.75)	(5.65)
TopArranger			-0.059	0.014
			(-0.95)	(0.14)
Revolver/Line			-0.315***	-0.213**
			(-3.51)	(-2.08)
NumInsiders	-0.172***	-0.220***	-0.190***	-0.235***
	(-15.01)	(-14.39)	(-14.85)	(-13.50)
Controls:				
Borrower Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Borrower FE	No	Yes	No	Yes
Disclosure Year FE	Yes	Yes	Yes	Yes
N	7,368	6,482	7,368	6,482
Adj. R²	0.529	0.590	0.540	0.597

Table 4: Persistence of Searching Behaviors

This table examines the persistence in loan tracking behavior of lenders. Panel A reports whether a lender tracks changes in loan terms (i.e., amendment) after reviewing the original loan contract (i.e., origination), or vice versa. I retain only those facilities with origination and amendment records between 2007 and 2016. Panel B reports whether a lender tracks the new contract of a specific borrower after reviewing her old loan contract, or vice versa. I retain only those facilities with multiple loan originations between 2007 and 2016. Panel C reports whether a lender tracks the new contract of a specific lender after reviewing her old loan contract, or vice versa. I retain only those lenders with multiple loan originations between 2007 and 2016. Panel D reports whether a lender tracks the new contract of a specific lead arranger after reviewing her old loan contract, or vice versa. I retain only those lead arrangers with multiple loan originations between 2007 and 2016. Robust standard errors are clustered at the lender level and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Tracking Loan Renegotiation

	(1)	(2)	(3)	(4)
		Search_Amendment		
Search_Origination	**0.722*** **	**0.571*** **	**0.569*** **	**0.570*** **
	(13.43)	**(19.51)**	**(19.60)**	**(19.65)**
Outside Lender FE	No	Yes	Yes	Yes
Borrower FE	No	No	Yes	No
Loan Facility FE	No	No	No	Yes
N	470,547	470,547	470,547	470,547
Adj. R²	0.489	0.552	0.554	0.554

	(5) Search Loan Origination	(6) Search Loan Amendment
Unconditional Probability	3.66%	3.92%

Panel B: Tracking Borrowers

	(1)	(2)	(3)
		Search_Borrower_New_Loan	
Search_Borrower_Old_Loan	**0.459*** **	**0.195*** **	**0.190*** **
	(7.01)	**(10.20)**	**(9.91)**
Outside Lender FE	No	Yes	Yes
Borrower FE	No	No	Yes
N	192,888	192,888	192,888
Adj. R²	0.190	0.371	0.375

	(4) Search Loan
Unconditional Probability	5.64%

Panel C: Tracking Lenders

	(1)	(2)	(3)
		Search_Lender_New_Loan	
Search_Lender_Old_Loan	**0.363*** **	**0.114** **	**0.114** **
	(3.66)	**(2.36)**	**(2.36)**
Outside Lender FE	No	Yes	Yes
Inside Lender FE	No	No	Yes
N	1,347,396	1,347,396	1,347,396
Adj. R²	0.131	0.290	0.290

	(4)
	Search Loan
Unconditional Probability	5.0%

Panel D: Tracking Lead Arrangers

	(1)	(2)	(3)
		Search_Arranger_New_Loan	
Search_Arranger_Old_Loan	**0.378*** **	**0.106** **	**0.106** **
	(3.80)	**(2.55)**	**(2.54)**
Outside Lender FE	No	Yes	Yes
Inside Lender FE	No	No	Yes
N	381,922	381,922	381,922
Adj. R²	0.143	0.312	0.312

	(4)
	Search Loan
Unconditional Probability	5.38%

Table 5: Impact of Past Loan Searches on Loan Spread Design

This table reports the impact of past loan searches on the loan spread of the lender's new loan origination. I define loan information searches as loans searched by the lender between 30 and 180 days before the new loan origination date. I expect these searched loans to have a greater influence on loan originations compared to unsearched loans, which serve as the control group. The control loans are matched to the searched loans based on the following criteria: the same report type (i.e., origination or amendment), reporting within (-180, +180) days of the searched contracts, the same Fama-French 30-industry classification, the same loan type (i.e., credit line or not), and a maturity difference of less than 360 days. Within these groups, loans are matched one-to-one based on the closeness of their "S&P Ratings". Panel A includes all lenders in the new loan origination, while Panels B focus on arrangers and participants, respectively. Robust standard errors are clustered at the lender level and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: All Lenders

	(1)	(2)	(3)
		Origination LoanSpread	
Loan Information Characteristics:			
DisclosedLoanSpread*Searched	**-0.001**	**0.003**	**-0.001**
	(-0.32)	**(0.69)**	**(-0.29)**
DisclosedLoanSpread	0.073***	0.441***	0.186***
	(6.97)	(5.76)	(4.71)
Searched	0.001	-0.022	0.001
	(0.03)	(-0.86)	(0.08)
Diff_Date		0.000***	0.000***
		(3.65)	(3.75)
Diff_Rating		0.075***	0.008***
		(10.83)	(8.33)
*DisclosedLoanSpread*Diff_Date*		-0.000***	-0.000***
		(-4.08)	(-4.03)
*DisclosedLoanSpread*Diff_Rating*		-0.013***	-0.001***
		(-11.42)	(-8.25)
Lender FE	Yes	Yes	Yes
Borrower FE	No	No	Yes
N	3,271,790	3,271,790	3,271,787
Adj. R²	0.023	0.034	0.769

Panel B: Arrangers or Participants

	(1)	(2)	(3)	(4)	(5)	(6)
			Origination LoanSpread			
	Subsamples: Arrangers			Subsamples: Participants		
Loan Information Characteristics:						
DisclosedLoanSpread*Searched	**-0.001**	**-0.001**	**-0.002**	**-0.002**	**0.002**	**-0.001**
	(-0.37)	**(-0.32)**	**(-1.18)**	**(-0.29)**	**(0.27)**	**(-0.34)**
DisclosedLoanSpread	0.056***	0.193***	0.056***	0.082***	0.219***	0.078***
	(8.35)	(23.39)	(8.13)	(4.44)	(7.91)	(12.60)
Searched	0.001	-0.001	0.006	0.003	-0.017	0.001
	(0.08)	(-0.07)	(0.80)	(0.09)	(-0.57)	(0.03)
Diff_Date		0.000***	0.000***		0.001***	0.000***
		(5.66)	(6.87)		(6.08)	(13.90)
Diff_Rating		0.083***	0.008***		0.063***	0.008***
		(9.13)	(7.26)		(11.13)	(7.08)
*DisclosedLoanSpread*Diff_Date*		-0.000***	-0.000***		-0.000***	-0.000***
		(-5.74)	(-7.36)		(-6.76)	(-15.13)
*DisclosedLoanSpread*Diff_Rating*		-0.014***	-0.001***		-0.011***	-0.001***
		(-9.85)	(-6.38)		(-11.16)	(-7.21)
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	No	No	Yes	No	No	Yes
N	1,741,156	1,741,156	1,741,153	1,530,634	1,530,634	1,530,630
Adj. R²	0.051	0.064	0.817	0.032	0.044	0.775

Table 6: Impact of Past Loan Searches on Loan Covenant-Lite Choice

This table reports the impact of past loan searches on the likelihood of the lender's new loan origination being covenant lite. I define loan information searches as loans searched by the lender between 30 and 180 days before the new loan origination date. I expect these searched loans to have a greater influence on loan originations compared to unsearched loans, which serve as the control group. The control loans are matched to the searched loans based on the following criteria: the same report type (i.e., origination or amendment), reporting within (-180, +180) days of the searched contracts, the same Fama-French 30-industry classification, the same loan type (i.e., credit line or not), and a maturity difference of less than 360 days. Within these groups, loans are matched one-to-one based on the closeness of their "S&P Ratings". Panel A includes all lenders in the new loan origination, while Panels B focus on arrangers and participants, respectively. Robust standard errors are clustered at the lender level and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: All Lenders

	(1)	(2)	(3)
		Origination Covenant-Lite	
Loan Information Characteristics:			
DisclosedCovenant-Lite*Searched	**0.007****	**0.007****	**0.005*****
	(2.59)	**(2.54)**	**(3.51)**
DisclosedCovenant-Lite	0.021***	0.032***	0.011***
	(10.97)	(5.89)	(7.86)
Searched	-0.001	-0.001	-0.001**
	(-1.05)	(-0.67)	(-2.33)
Diff_Date		0.000***	0.000***
		(9.61)	(11.91)
Diff_Rating		0.002***	0.000***
		(7.10)	(5.06)
*DisclosedCovenant-Lite*Diff_Date*		-0.000	-0.000**
		(-0.63)	(-2.56)
*DisclosedCovenant-Lite*Diff_Rating*		-0.001***	0.000
		(-5.18)	(1.52)
Lender FE	Yes	Yes	Yes
Borrower FE	No	No	Yes
N	3,592,695	3,592,695	3,592,695
Adj. R²	0.007	0.008	0.621

Panel B: Arrangers or Participants

	(1)	(2)	(3)	(4)	(5)	(6)
			Origination Covenant-Lite			
	Subsamples: Arrangers			Subsamples: Participants		
Loan Information Characteristics:						
DisclosedCovenant-Lite*Searched	**0.006****	**0.005****	**0.004****	**0.008****	**0.008****	**0.004*****
	(2.57)	**(2.57)**	**(2.41)**	**(2.32)**	**(2.31)**	**(2.77)**
DisclosedCovenant-Lite	0.020***	0.034***	0.010***	0.018***	0.023***	0.007***
	(6.70)	(4.30)	(3.58)	(8.18)	(8.19)	(4.12)
Searched	-0.001	-0.000	-0.001*	-0.001	-0.001	-0.001
	(-1.20)	(-0.76)	(-1.71)	(-0.94)	(-0.61)	(-1.34)
Diff_Date		0.000***	0.000***		0.000***	0.000***
		(7.99)	(7.07)		(9.41)	(12.85)
Diff_Rating		0.002***	0.000***		0.001***	0.000***
		(4.68)	(5.91)		(4.66)	(3.09)
*DisclosedCovenant-Lite*Diff_Date*		-0.000	-0.000**		-0.000	-0.000
		(-0.70)	(-2.08)		(-0.43)	(-1.48)
*DisclosedCovenant-Lite*Diff_Rating*		-0.001***	-0.000		-0.000	0.000
		(-5.10)	(-0.55)		(-0.32)	(0.79)
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	No	No	Yes	No	No	Yes
N	1,922,277	1,922,277	1,922,277	1,670,418	1,670,418	1,670,418
Adj. R²	0.009	0.010	0.667	0.006	0.007	0.664

Table 7: Impact of Past Loan Searches on Loan Financial Covenant Design

This table reports the impact of past loan searches on the financial covenant choice of the lender's new loan origination. Following Christensen and Nikolaev (2012), I categorize covenants into capital-based and performance-based. I define loan information searches as loans searched by the lender between 30 and 180 days before the loan origination date of interest. I expect these searched loans to have a greater influence on loan originations compared to unsearched loans, which serve as the control group. The control loans are matched to the searched loans based on the following criteria: the same report type (i.e., origination or amendment), reporting within (-180, +180) days of the searched contracts, the same Fama-French 30-industry classification, the same loan type (i.e., credit line or not), and a maturity difference of less than 360 days. Within these groups, loans are matched one-to-one based on the closeness of their "S&P Ratings". Robust standard errors are clustered at the lender level and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Number of Capital-based Covenant

	(1)	(2)	(3)
		Origination #CapitalCovenant	
Loan Information Characteristics:			
#DisclosedCapitalCovenant*Searched	**0.005*** **	**0.004*** **	**0.002** **
	(4.53)	**(5.19)**	**(2.51)**
#DisclosedCapitalCovenant	0.008***	0.017***	0.005***
	(5.44)	(21.89)	(7.27)
Searched	-0.002***	-0.001***	-0.001**
	(-6.92)	(-5.83)	(-2.50)
Diff_Date		-0.000***	-0.000***
		(-5.49)	(-3.01)
Diff_Rating		-0.002***	-0.000**
		(-6.20)	(-2.57)
*#DisclosedCapitalCovenant*Diff_Date*		-0.000	-0.000**
		(-1.05)	(-2.22)
*#DisclosedCapitalCovenant*Diff_Rating*		-0.001***	-0.000*
		(-3.15)	(-1.87)
Lender FE	Yes	Yes	Yes
Borrower FE	No	No	Yes
N	3,592,695	3,592,695	3,592,695
Adj. R²	0.008	0.008	0.778

Panel B: Number of Performance-based Covenant

	(1)	(2)	(3)
		Origination #PerformanceCovenant	
Loan Information Characteristics:			
#DisclosedPerformanceCovenant*Searched	**0.010*** **	**0.010*** **	**0.005*** **
	(2.78)	**(2.69)**	**(3.96)**
#DisclosedPerformanceCovenant	0.018***	0.029***	0.010***
	(14.93)	(11.00)	(9.69)
Searched	-0.012***	-0.013***	-0.006***
	(-3.26)	(-3.39)	(-5.39)
Diff_Date		-0.000***	-0.000***
		(-6.72)	(-4.44)
Diff_Rating		0.000	-0.001***
		(0.93)	(-10.80)
*#DisclosedPerformanceCovenant*Diff_Date*		-0.000*	-0.000***
		(-1.74)	(-8.16)
*#DisclosedPerformanceCovenant*Diff_Rating*		-0.001***	0.000
		(-6.15)	(0.62)
Lender FE	Yes	Yes	Yes
Borrower FE	No	No	Yes
N	3,592,695	3,592,695	3,592,695
Adj. R²	0.009	0.010	0.693

Panel C: Existence of Debt-to-EBITDA Covenant

	(1)	(2)	(3)
	Origination Any Debt-to-EBITDA Covenant		
Loan Information Characteristics:			
AnyDisclosed Debt-to-EBITDA Covenant*Searched	**0.005****	**0.005****	**0.003*****
	(2.43)	**(2.49)**	**(6.90)**
AnyDisclosed Debt-to-EBITDA Covenant	0.010***	0.018***	0.006***
	(9.42)	(6.53)	(9.12)
Searched	-0.004***	-0.004***	-0.002***
	(-3.14)	(-3.61)	(-9.30)
Diff_Date		-0.000***	-0.000**
		(-6.22)	(-2.64)
Diff_Rating		0.000*	-0.000***
		(1.67)	(-6.99)
*AnyDisclosed Debt-to-EBITDA Covenant*Diff_Date*		-0.000	-0.000***
		(-1.57)	(-6.06)
*AnyDisclosed Debt-to-EBITDA Covenant*Diff_Rating*		-0.001***	0.000*
		(-3.86)	(1.78)
Lender FE	Yes	Yes	Yes
Borrower FE	No	No	Yes
N	3,592,695	3,592,695	3,592,695
Adj. R²	0.005	0.006	0.722