Debt Dynamics in Executive Compensation

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Abstract

The prevailing agency theory framework in executive compensation studies highlights the conflict of interest between managers and shareholders. Our study extends the literature by examining the incorporation of debt-related performance metrics (DPMs). 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 due to credit quality deterioration or debt maturity pressure. We demonstrate shareholders incorporate more non-debt metrics in their incentive programs in response to DPM inclusion. Our study contributes to understanding the agency costs of debt and debt-related factors in executive compensation.

Keywords: Debt Performance Metrics (DPMs), Executive Compensation, Agency Conflict
JEL Codes: G39, M12, M52, G30

1. Introduction

In the agency theory framework, the predominant focus in executive compensation research is the conflict between managers and shareholders. Most empirical studies have examined the role of stock-based compensation in addressing this concern. However, this is somewhat surprising given the substantial presence of debt financing in publicly traded companies. John and John (1993) argue that the ideal compensation structure should be determined by the composition and blend of all external claims issued by a firm, including both shareholders and debtholders. By solely concentrating on aligning managerial incentives with shareholder interests, the risk-shifting problem between shareholders and debtholders may be exacerbated, leading to increased agency costs of debt.

Contrary to the focus on stock-based performance metrics, our research offers new empirical evidence showing that companies integrate debt-related performance metrics (DPMs) (e.g., credit ratings, debt to EBITDA ratio) into executive compensation contracts. 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, debt to EBITDA ratio); (2) determine managerial compensation based on debt-related targets (e.g., debt reduction, debt financing); (3) plan to reward managers based on a financial metric with the explicit intention of addressing debt concerns. For instance, in Trinity Industries, Inc., "credit rating" is allocated a 15% weight in the 2010 stock program's performance measurement. Achieving a "BB+" (or "BBB-") rating allows the manager to obtain 70% (or 200%) of the compensation target. These metrics directly link debt performance to managerial compensation rather than through stock performance metrics, presumably aligning managerial interests more effectively with creditor interests.

We collect DPMs from annual proxy statements. We gathered 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, we find that roughly 19% of US publicly traded firms have incorporated DPMs into their compensation contracts at least once between 2007 and 2020. DPMs typically concentrate on debt or leverage levels, borrower repayment ability, and the firm's credit rating.

We explore the reasons behind including DPMs and find that lenders' demand for monitoring plays a crucial role. Specifically, our findings suggest that after lenders experience recent payment defaults in their portfolio, 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 find that borrowers are more likely to use DPMs in response to increases in their credit risks, as measured by their expected default frequency and credit rating, and when facing debt maturity pressure.

We rely on the exogenous default of the lender's other clients to provide identification. Our difference-in-difference results indicate focal companies are more likely to include DPMs in their compensation contracts after the lender's perception of future default likelihood increases. In response to including DPMs, we also find that shareholders introduce more non-debt metrics into their incentive programs.

In our last set of results, we explore the real activity consequence of DPMs. 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 likely to approve the inclusion of DPMs in the previous years.

Our findings also suggest that DPMs may have real activity consequences, as firms decrease their future R&D intensity and SG&A when they have DPMs in their compensation contract. In summary, our study provides evidence that including DPMs in executive compensation contracts may effectively mitigate the agency cost of debt.

In conclusion, our empirical findings suggest borrowers consider agency costs of debt when designing executive compensation contracts. 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 as well as inside debt included in managerial compensation (Sundaram & Yermack, 2007). Our study contributes to the compensation literature by offering initial evidence of using debt-related performance metrics (DPMs) in executive compensation contracts, complementing prior research by exploring another form of incorporating debtholders' interests into managerial compensation design.[1] Intuitively, DPMs target debtholders' concerns more directly than stock-based performance metrics.

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[1] In the work of Carter et al. (2020), we find indications of debt performance metrics. They conjecture that cash-flow-related measures are in sync with the interests of creditors, and that firms react to the emergence of financial distress by establishing incentives geared towards enhancing cash flows. Our research diverges from theirs in three notable ways. First, they postulate they focus on cash-flow-related metrics to capture debt effects. In contrast, in our dataset, the borrowers designate only a few cash-flow (or EBITDA) metrics as debt-related. Second, they rely on data obtained from the Incentive Lab Database, which encompasses a relatively diminutive proportion (1.36%) of debt performance metrics. At the same time, our identification method contributes to a much larger number of such metrics. Third, they expound upon the changes in compensation policy during financial distress, whereas we adopt a more comprehensive viewpoint.

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.[2] 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 discretionary performance metrics (DPMs) in executive compensation contracts, can be a viable solution. Although debt contract covenants are

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[2] 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.

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 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, DPMs 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 between the borrower and each individual lender in a syndicated loan, 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 vantage point of borrowers, Dynamic Performance Metrics (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. Shareholders, as residual claimholders, 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, 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 instance, 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 & Yogo, 2009).

Conversely, debt overhang theory suggests that the pressure exerted by maturing debt may cause shareholders or management compensated with stock options to internalize only a fraction of the potential benefits of investment, thereby leading to underinvestment.[3] 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. 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:

H3: *Firms with higher debt maturity pressure 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'

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

proxy.[4] 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 any 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.[5] We download all proxy statements during the 2007-2020 proxy seasons through the EDGAR system and

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[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. Although shareholders could approve several business criteria for setting performance goals and authorize the compensation committee to pick the suitable measures annually, using multiple criteria usually necessitated a re-approval of the plan by shareholders at least once every five years.

[5] 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.

then identify DPM contracts using manually summarized regular expressions[6]. Section 3.2 and Appendix A provides more details about our data collection.

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*)[7]. (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-performance plan that awarded improving "EBITDA" which would provide cash flows to stabilize and improve the business and refinance our credit facility."

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[6] Details on our summarized regular expressions can be requested.

[7] 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.

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 DPMs 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. Appendix A provides more details about our data collection.

3.3 Expected Default Frequency (EDF)

We propose the expected default frequency as a proxy of credit quality. We compute the expected default frequency (EDF) using the Merton (1974) model and the procedure in Bharath and Shumway (2008). That is, for firm *i,* we compute:

$$EDF_{it} = N\left(\frac{-log\frac{V_{it}}{B_{it}} - \left(\mu_{V_{it}} - \frac{\sigma_{V_{it}}^2}{2}\right)}{\sigma_{V_{it}}}\right)$$

Where $N(\cdot)$ denotes the standard normal cumulative density function, V_{it} is the market value of the firm *i*’s assets, B_{it} is the book value of debt coming due that quarter, μ_{Vit} is the expected asset return, and σ_{Vit} its asset return volatility. To compute μ_{Vit} and σ_{Vit}, we use monthly returns. Details on the computation of these values and STATA code refer to the appendix of Gomes, Grotteria and Wachter (2018). We use the median value of quarterly EDF in that fiscal year as our measure of expected default frequency.

3.4 Summary Statistics

Figure 1 Panel A displays the time trend of the number 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.[8] Before discussing changes in the number of firms with DPM contracts over time, we note that the average leverage ratio (debt/assets) increases 50% between 2007 to 2020, while the number of firms with DPM contracts increase 210% in the same periods. Interestingly, we notice a significant increasing trend between 2007-2009 and 2015-2020. Figure 1 Panel B displays the industry distribution (Fama & French 12 industries classification) of the number of firm-years with DPMs contracts during the fiscal year 2007-2020. DPMs are common across industries. About 31.4% 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]

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

[8] 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.

incorporated (i.e., *Debt Reduction, Debt financing, Debt payment*).[9] 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]

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, something we explore further in Section 4.2. Interestingly, these firm-years with DPM contracts usually have larger size, higher tangibility, higher operating cash

[9] 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.

flow, higher market value, 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 compensation designs. These statistics seem to suggest that outside monitoring may trigger the use of DPMs.

4. Empirical Findings

4.1 Lender Monitoring and DPM Contracting

We first examine whether lenders' demand for monitoring explains the existence of DPMs. Using a lender-specific shock - defaults in a lender's corporate loan portfolio as a 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.

To identify payment defaults, following Murfin (2012), we use borrowers reported to be in default or selective default by S&P in Capital IQ S&P credit ratings database. This captures borrowers that have had a payment default on at least one obligation.[10] 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 are left with a record of all the defaults for a given loan arranger[11] and the timing of those defaults. We identify the current borrowers of the loan arranger that experiences recent payment defaults in its portfolio as the treatment group.[12] 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 DPMs 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.[13] 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 experience recent payment

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

[11] 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.spglobal.com/marketintelligence/en/documents/lcd-primer-leveraged-loans_ltr.pdf).

[12] We consider their initial treatment as their treatment time. 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). See Online Appendix Table IA.1 Panel A.

[13] 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.

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 3]

Table 3 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 for each firm.

Table 3 Panel A reports the tests on the full sample of firms that have accessed the syndicated loan market during our sample period, excluding defaulting borrowers. Table 3 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, 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 Columns (1) and (2), we report results 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 suggest that DPMs can serve as a monitoring tool for lenders. This also provides evidence in support of hypothesis one, in which firms with stringent lenders' monitoring are more likely to use DPMs in executive compensation contracts.

As with any difference-in-difference design our approach assume 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 lenders experience 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. Online Appendix Table IA.1 Panel B 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.

4.2 Credit Quality and DPM Contracting

We use two measures of credit quality to estimate the impact of a credit quality decline on the likelihood of observing a DPM compensation contract in a firm. First, for the full sample, we proxy credit quality by using the expected default frequency (*EDF*) calculated based on Merton's (1974) model. Higher *EDF* indicates a higher default probability. The calculation of *EDF* values can be found in Section 3.3[14]. Second, we use the borrower's credit rating (*CreditRating*) in the previous year as a measure of credit quality. Larger *CreditRating* indicates better ratings. The draw-back of the credit rating measure is that it is only available for rated firms, which comprise 29% of our sample.

[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 measures of borrower credit quality. All regressions control for firm-specific characteristics (including *Assets, Tangibility, OperatingCF, MtB, ROA, Sales-Growth, FirmAge*), year-fixed effects, and firm (or industry) fixed effects. In all regressions, standard errors are clustered for each firm. 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)

[14] The calculation method of *EDF* causes some missing values. Following Nini et al. (2009), we also use the borrower's debt-to-EBITDA ratio to 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. All core results are robust when we use *Debt / EBITDA* to measure credit quality, see Online Appendix Table IA.2.

NumDPM is the number of debt performance metrics used in the given year by a firm.

Almost in all specifications (except for column (1) in Table 4 Panel A), 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 *EDF* increases or when the value of *CreditRating* decreases. The results suggest that, even within a firm, the worse credit quality is highly associated with the presence of DPMs.

In Table 4 Panel A, we further use the *EDF* quantile indicator variables to explore the impact of a credit quality decline. 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., 5.4% increase) to use DPMs. Given the mean likelihood of 7%, this effect represents a 77% 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., 3.9% decrease) to use DPMs, which represents a 56% decrease in the likelihood evaluated relative to the mean.

In Table 4 Panel B, we also use the credit rating category indicator to explore the impact of a credit quality decline. 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 9.3% 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 to 1 if there exist split ratings 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 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.

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 principle 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.[15] 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, 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 all specifications, our results show that borrowers are more likely to use DPMs in response 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

[15] 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.

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 a 0.23% increase of the likelihood of using DPMs. However, the debt maturity pressure due in the 3rd, 4th, and 5th year does not have a significant impact on 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 response of the shareholders 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, only 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 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 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) (2), we conduct the estimation in the full sample; while in columns (3) (4), we conduct the estimation in a subsample of firms that have used DPMs during the sample period. In columns (5) (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 re-balance the executive incentives in the presence of DPMs, thereby tilting incentives away from the interests of creditors.

It is possible that this increasing trend of non-debt metrics is driven by the worse credit quality. In Online Appendix Table IA.3, we conduct a similar estimation as in Section 4.2 (Table 4) but use the *Number of Non-debt metrics* as the dependent variable. First, we use *EDF* and *EDF* quantile indicator variables as measures of credit quality, and the results show that a credit quality decline does not significantly influence the number of non-debt metrics utilized by the firm. Second, we use *CreditRating* and *CreditRating* category indicators as measures of credit quality. The results show, within a firm, the value of *CreditRating* has a negative association with the number of non-debt metrics utilized by this firm. However, when we look at the industry-level effects (i.e., control for industry-fixed effects), this association reverses (i.e., a positive association between *CreditRating* and the *Number of Non-debt metrics*). We argue that, within a firm, the increasing number of non-debt metrics may be caused by the worse operating situations, rather than the worse credit quality. Given that credit analysis is industry-based, we conclude that we find little evidence to support the argument that the increasing trend of non-debt metrics is driven by the worse credit quality rather than the presence of DPMs.

4.5 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. Following prior 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 7]

Table 7 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 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 $RDIntensity_{t+1}$, $RDIntensity_{(t+1)\text{-}(t+3)}$, $SG\&A_{t+1}$, $SG\&A_{(t+1)\text{-}(t+3)}$, 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 having 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 the inclusion of 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

We present novel empirical evidence that some companies incorporate debt-related performance metrics (DPMs) (e.g., credit ratings, debt to EBITDA ratio) into their executive compensation contracts. 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. 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 having a DPM contract 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. Our study contributes to the compensation literature by providing initial evidence on the utilization of debt-related performance metrics (DPMs).

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Appendix A: Examples of DPM compensation contracts

Example 1: Trinity Industries, Inc.

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: 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 4: 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.

Example 5: 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 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

……

Example 6: 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

……

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*
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*

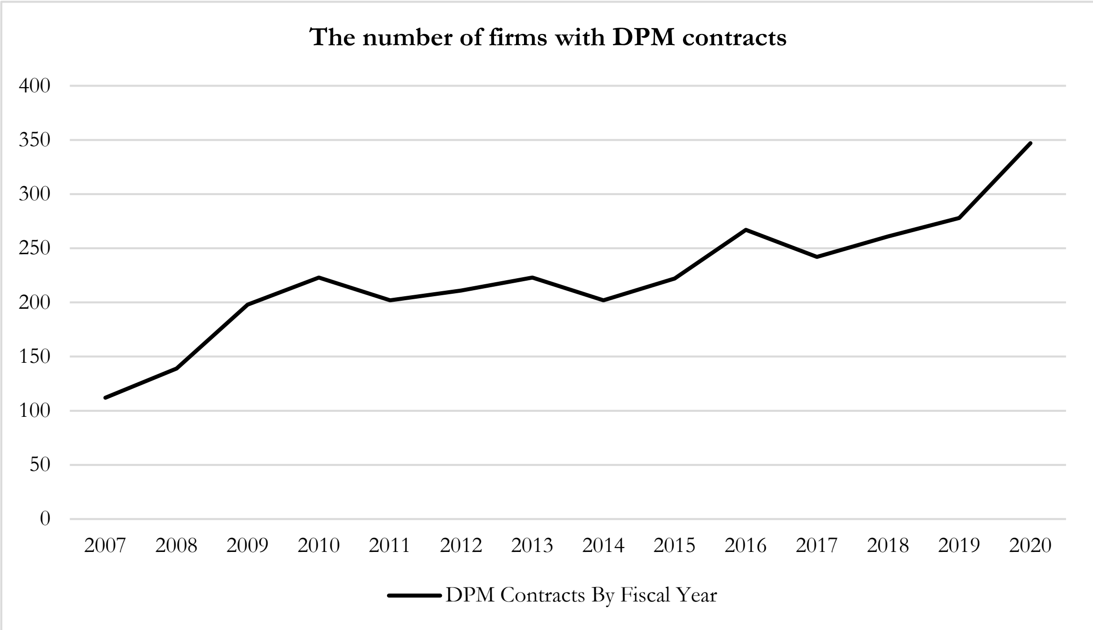
RDIntensity	R&D expenses scaled by sales.	*Compustat/CRSP*
SG&A	SG&A costs scaled by operating expense.	*Compustat/CRSP*
Control Variables		
Debt / EBITDA	Ratio of total debt to earnings before interest, taxes, depreciation, and amortization.	*Compustat/CRSP*
Debt / Equity	Ratio of total debt to shareholder 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*

Appendix C Figures and Tables

Figure 1: DPM Characteristics

The figures present the fraction of 3,127 firm-years with DPM contracts collected from the annual proxy statement over the period 2007-2020, sorted by fiscal year and industry.

Panel A: Number of Firms with DPM contracts



Panel B: Number of Firm-Years with DPM contracts by Industry

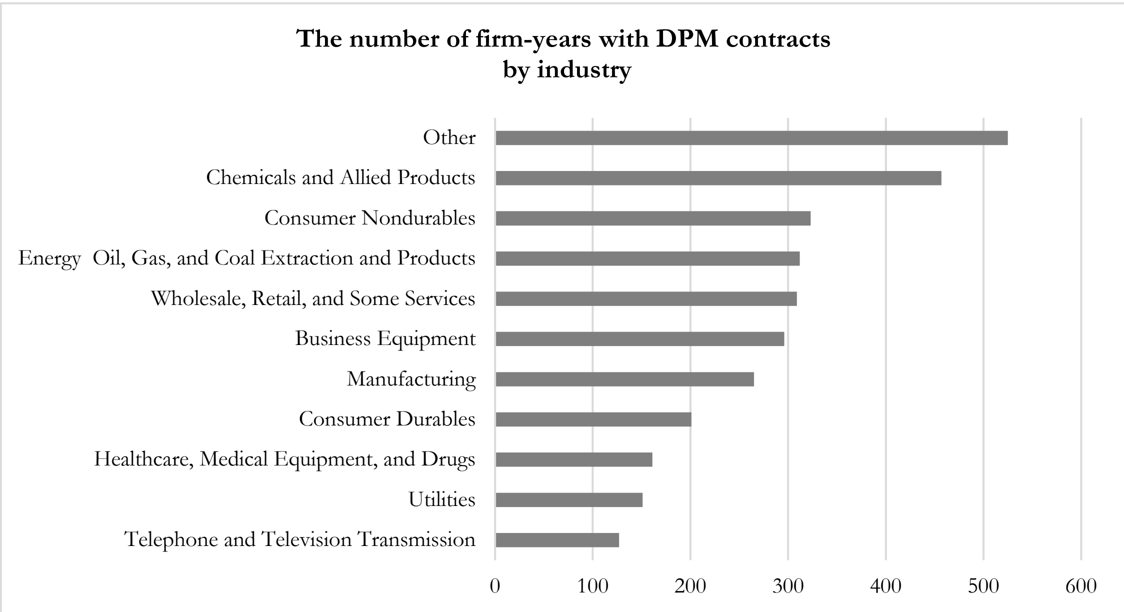


Table 1: Type of DPMs used by Firms

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 their 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	0.06	0.12	0.00	0.01	0.02	0.05	0.84
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	14.63	0.00	5.00	13.00	25.00	55.00
EDF	30,237	0.00	0.01	0.00	0.00	0.00	0.00	0.13
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	0.00	0.00	0.00	0.00	-0.002***
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	0.06	0.02	0.03	0.01	0.035***
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	23.05	19.00	-6.475***
Rated	0.26	0.00	0.62	1.00	-0.360***
Syndicated	0.61	1.00	0.92	1.00	-0.308***

Table 3: 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. Panel A contains the full sample of firms that have accessed the syndicated loan market excluding 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. $Post_t \times Default_i$ 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. 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 firm-specific characteristics (including *Debt/EBITDA*, *Assets, Tangibility, OperatingCF, MtB, ROA, Sales-Growth, FirmAge*), year fixed effects and firm fixed effects. In all regressions, standard errors are clustered for each firm. In Column (1) and (2), we 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*.

Panel A: Defaults

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DPM_t	$NumDPM_t$	DPM_t	$NumDPM_t$	DPM_t	$NumDPM_t$	DPM_t	$NumDPM_t$
	Full Sample		Entropy Balance: three moments		PSM: nearest		PSM: three nearest	
$Post_t \times Default_i$	0.042***	0.051**	0.039***	0.046**	0.038***	0.040*	0.041***	0.048**
	(3.10)	(2.30)	(2.82)	(2.00)	(2.76)	(1.76)	(2.98)	(2.11)
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	18,107	18,107	22,073	22,073
Adj. R^2	0.322	0.332	0.326	0.331	0.313	0.328	0.318	0.328

Panel B: Defaults different region and SIC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DPM_t	$NumDPM_t$	DPM_t	$NumDPM_t$	DPM_t	$NumDPM_t$	DPM_t	$NumDPM_t$
	Full Sample		Entropy Balance: three moments		PSM: nearest		PSM: three nearest	
$Post_t \times Default_i$	0.040***	0.052**	0.037**	0.044*	0.036**	0.038	0.040***	0.050**
	(2.78)	(2.12)	(2.49)	(1.77)	(2.44)	(1.51)	(2.78)	(2.03)
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	16,049	16,049	20,137	20,137
Adj. R^2	0.318	0.333	0.323	0.334	0.311	0.331	0.317	0.333

Table 4: 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 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.

Panel A: Expected Default Frequency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DPM_t				$NumDPM_t$			
EDF_t	0.157		0.526**		1.078**		1.553***	
	(0.81)		(2.33)		(2.24)		(3.04)	
EDF_High_t		0.036***		0.054***		0.076***		0.112***
		(4.10)		(5.76)		(4.61)		(6.45)
EDF_Low_t		-0.013***		-0.039***		-0.009		-0.048***
		(-2.79)		(-7.72)		(-1.29)		(-6.13)
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	29,772	29,772	30,237	30,237	29,772	29,772	30,237	30,237
Adj. R^2	0.317	0.319	0.062	0.073	0.325	0.326	0.060	0.072

Panel B: Credit Rating

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DPM_t				$NumDPM_t$			
$CreditRating_{t-1}$	-0.022***	-0.021***			-0.042***	-0.040***		
	(-4.58)	(-7.34)			(-4.91)	(-7.50)		
$A\ rated\ or\ better_{t-1}$			-0.093***				-0.159***	
			(-5.86)				(-6.27)	
$BB\ rated\ or\ worse_{t-1}$			0.080***				0.153***	
			(4.93)				(5.59)	
$RatingDisagree_{t-1}$				0.033***				0.054***
				(2.74)				(2.62)
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	0.040

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 the measures of 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, i.e., when the firm incorporates debt performance metrics in their executive compensation designs. 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. 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.

Panel A: The presence of DPMs

	(1)	(2)	(3)	(4)	(5)	(6)
			DPM_t			
Due_1st_Year % $_{t-1}$	0.023***					
	(3.13)					
Due_2nd_Year % $_{t-1}$		0.023***				
		(3.07)				
Due_3rd_Year % $_{t-1}$			0.010			
			(1.35)			
Due_4th_Year % $_{t-1}$				0.002		
				(0.26)		
Due_5th_Year % $_{t-1}$					-0.008	
					(-1.26)	
Due_Other_Year % $_{t-1}$						-0.028***
						(-3.57)
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

Panel B: The number of DPMs

	(1)	(2)	(3)	(4)	(5)	(6)
			$NumDPM_t$			
Due_1st_Year % $_{t-1}$	0.034***					
	(3.24)					
Due_2nd_Year % $_{t-1}$		0.031***				
		(2.94)				
Due_3rd_Year % $_{t-1}$			0.013			
			(1.21)			
Due_4th_Year % $_{t-1}$				0.016		
				(1.53)		
Due_5th_Year % $_{t-1}$					-0.013	
					(-1.39)	
Due_Other_Year % $_{t-1}$						-0.049***
						(-3.75)
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	0.329	0.329	0.329	0.329	0.329	0.330

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, Sales-Growth, 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.

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$_t$	0.184***		0.176***		0.162***	
	(3.78)		(3.64)		(2.88)	
NumDPM$_t$		0.116***		0.113***		0.108***
		(3.76)		(3.66)		(3.25)
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	0.522	0.523	0.553	0.553

Table 7: 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 $RDIntensity_{t+1}$, $RDIntensity_{(t+1)\text{-}(t+3)}$, $SG\&A_{t+1}$, $SG\&A_{(t+1)\text{-}(t+3)}$, 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.

Panel A: The presence of DPMs

	(1)	(2)	(3)	(4)
	$RDIntensity_{t+1}$	$RDIntensity_{(t+1)\text{-}(t+3)}$	$SG\&A_{t+1}$	$SG\&A_{(t+1)\text{-}(t+3)}$
DPM_t	-0.108***	-0.038***	-0.035***	-0.031***
	(-3.68)	(-6.92)	(-5.58)	(-4.44)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	37,144	28,711	33,433	25,623
Adj. R^2	0.226	0.490	0.428	0.405

Panel B: The number of DPMs

	(1)	(2)	(3)	(4)
	$RDIntensity_{t+1}$	$RDIntensity_{(t+1)\text{-}(t+3)}$	$SG\&A_{t+1}$	$SG\&A_{(t+1)\text{-}(t+3)}$
$NumDPM_t$	-0.059***	-0.022***	-0.023***	-0.022***
	(-3.99)	(-6.48)	(-6.17)	(-5.21)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	37,144	28,711	33,433	25,623
Adj. R^2	0.227	0.491	0.429	0.405

Online Appendix

Table IA.1: 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. Table IA.1 Panel A use the same specification as in Table 3 Panel B but eliminate borrowers for which the first treatment falls before 2007 (i.e., the starting year of our sample period). In all columns in Table IA.1 Panel A, we use the full sample of firms that have accessed the syndicated loan market. In Table IA.1 Panel B, to evaluate treatment effects of the pre- and post- treatment periods, we also use a difference-in-difference event study specification within a six-years window around the treatment. $Default_{i,t}$ takes a value of one if the borrower's current loan arranger experiences a payment default in its portfolio in 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. 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*.

Panel A: Eliminate borrowers for which the first treatment falls before 2007

	(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	
$Post_t \times Default_i$	0.047***	0.063***	0.044***	0.053**	0.044***	0.045**	0.045***	0.057**
	(3.47)	(2.85)	(3.24)	(2.37)	(3.15)	(1.98)	(3.34)	(2.55)
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	18,440	18,440	18,440	18,440	11,214	11,214	15,352	15,352
Adj. R^2	0.297	0.309	0.304	0.317	0.289	0.303	0.298	0.309

Panel B: 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*	-0.020	-0.043*	-0.019	-0.045*	-0.019	-0.046*
	(-1.28)	(-1.89)	(-1.22)	(-1.71)	(-1.17)	(-1.78)	(-1.21)	(-1.83)
$Pre(-2)_t \times Default_i$	-0.013	-0.011	-0.012	-0.008	-0.011	-0.007	-0.011	-0.009
	(-1.05)	(-0.54)	(-0.96)	(-0.39)	(-0.91)	(-0.34)	(-0.89)	(-0.42)
$Default_{i,t}$	0.017	-0.002	0.016	-0.002	0.016	-0.003	0.018	-0.001
	(1.42)	(-0.10)	(1.35)	(-0.11)	(1.32)	(-0.17)	(1.50)	(-0.04)
$Post(+1)_t \times Default_i$	0.046***	0.046**	0.043***	0.043*	0.043***	0.041*	0.046***	0.045*
	(3.08)	(2.03)	(2.87)	(1.87)	(2.80)	(1.75)	(3.07)	(1.94)
$Post(+2)_t \times Default_i$	0.047***	0.051**	0.044***	0.045*	0.043***	0.045*	0.048***	0.049*
	(2.93)	(2.01)	(2.67)	(1.73)	(2.61)	(1.71)	(2.92)	(1.90)
$Post(+3)_t \times Default_i$	0.048***	0.067**	0.042**	0.058**	0.041**	0.056**	0.046***	0.062**
	(2.85)	(2.49)	(2.45)	(2.09)	(2.35)	(2.02)	(2.72)	(2.31)
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	10,416	10,416	14,382	14,382
Adj. R^2	0.343	0.370	0.344	0.357	0.336	0.374	0.340	0.365

Table IA.2: Credit Quality (Debt-to-EBITDA) 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. Following Nini et al. (2009), we also use the borrower's ratio of debt to EBITDA as a measure of credit quality. Higher Debt/EBITDA indicates lower credit quality. We collect the sample over the period 2007–2020. 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. We 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 for each firm.

	(1)	(2)	(3)	(4)	(5)	(6)
		DPM_t			$NumDPM_t$	
Debt / EBITDA $_{t-1}$	0.007***	0.002***	0.004***	0.012***	0.003***	0.007***
	(12.63)	(4.56)	(8.61)	(11.90)	(4.76)	(8.38)
Controls	No	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	No	No	Yes	No
Industry FE	No	No	Yes	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	39,326	38,856	39,326	39,326	38,856	39,326
Adj. R^2	0.017	0.330	0.057	0.018	0.334	0.054

Table IA.3: Credit Quality and Non-debt metrics

This table presents estimated coefficients from linear regressions that relate number of *Non-debt metrics* to the measures of borrower credit quality. We collect the sample over the period 2007–2020. 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. Panel A contains the full sample, while Panel B only contains those firms with credit ratings. The dependent variable is *Number of Non-debt metrics*, which represents the number of non-debt metrics utilized by the firm in the given year. 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 control for firm-specific characteristics (including *Assets, Tangibility, OperatingCF, MtB, ROA, SalesGrowth, FirmAge*), the inclusion of DPM (*DPM*), year fixed effects and firm (or industry) fixed effects. In all regressions, standard errors are clustered for each firm.

Panel A: Expected Default Frequency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Number of Non-debt Metrics$_t$				
EDF$_t$	-0.296	-0.348			-1.238	-1.608		
	(-0.19)	(-0.23)			(-0.52)	(-0.68)		
EDF_High$_t$			0.084	0.075			-0.117	-0.144*
			(1.38)	(1.22)			(-1.40)	(-1.72)
EDF_Low$_t$			-0.062*	-0.060*			-0.250***	-0.231***
			(-1.71)	(-1.66)			(-4.12)	(-3.82)
DPM$_t$		0.166***		0.161***		0.322***		0.309***
		(3.42)		(3.33)		(4.87)		(4.66)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	No	No	No	No
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,428	11,428	11,428	11,428	11,495	11,495	11,495	11,495
Adj. R^2	0.580	0.581	0.580	0.581	0.144	0.148	0.147	0.150

Panel B: Credit Rating

	(1)	(2)	(3)	(4)	(5)	(6)
			Number of Non-debt Metrics$_t$			
CreditRating$_{t-1}$	-0.055**	0.055***		-0.051**	0.060***	
	(-2.35)	(3.09)		(-2.21)	(3.39)	
A rated or better$_{t-1}$			0.195*			0.214*
			(1.71)			(1.88)
BB rated or worse$_{t-1}$			-0.235***			-0.255***
			(-2.62)			(-2.83)
DPM$_t$				0.141**	0.230***	0.232***
				(2.49)	(3.47)	(3.50)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	Yes	No	No
Industry FE	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7,211	7,273	7,273	7,211	7,273	7,273
Adj. R^2	0.541	0.152	0.153	0.542	0.155	0.155