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CEO inside debt holdings and credit ratings ☆

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ABSTRACT

In this paper we investigate the relationship between chief executive officer (CEO) inside debt holdings (pension benefits and deferred compensation) and long-term credit ratings. We provide evidence that firms with a higher level of inside debt holdings enjoy better credit ratings. Our results are robust to the use of alternative regression estimation and alternative measures of key variables. We employ instrumental variable–based two-stage least squares regression and instrumental variable regression estimation using heteroskedasticity-based instruments to mitigate the endogeneity concern. In addition, we employ propensity-matched sample and entropy balancing estimates to alleviate endogeneity concerns. Our cross-sectional analyses reveal that the relationship between CEO inside debt holdings and credit ratings is more pronounced in firms with a poor information environment, a weak monitoring mechanism, and powerful CEOs. Overall, findings from our study suggest that credit rating agencies evaluate CEO insider debt holdings positively in assessing the creditworthiness of a firm.

1. Introduction

"... in order to improve financial stability and rebuild the public trust, more compensation in finance needs to be deferred and for longer periods. Also, I think there needs to be a shift in the mix of deferred compensation away from equity and towards debt."

— William Dudley, President of the Federal Reserve Bank of New York (2009–2018)

Executive compensation has received considerable attention in corporate finance and corporate governance literature. Studies provide evidence that structures and forms of executive compensation have important implications for corporate performance, decisions, and information environment (Bhattacharyya et al., 2008; Brick et al., 2006; Core et al., 1999; White, 1996). While the vast majority of these studies focus on the compensation tied to future equity returns (e.g., stocks, stock options, and other instruments), an emerging body of literature centers on pensions and deferred compensation. These

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types of compensation resemble debt financing since they capture a firm's obligations to make future payments to the executives. Accordingly, these components of compensation are widely referred to as "inside debt." Prior studies show that the sensitivity of managerial wealth to stock return volatility (*vega*) and stock price (*delta*) affect a firm's creditworthiness and thus its credit rating (Kuang and Qin, 2013). However, it is not clear if credit rating agencies (CRAs) incorporate executive inside debt holdings in their credit risk evaluation. This study fills this void in the literature by examining the relationship between CEO inside debt holdings (CIDHs) and credit ratings.

In this study, we focus on CIDHs since the CEO is the highest ranking executive in a company who is primarily responsible for formulating key corporate strategies, policies, and decisions and managing overall business operations and resources (Cassell et al., 2012). The motivation for this study stems from the evidence that inside debt holdings are sizeable and constitute a major component of executive compensation (Anantharaman et al., 2014; Cassell et al., 2012; Phan, 2014). For instance, Wei and Yermack (2011) report an average CEO debt-to-equity ratio of 0.22 in 2006, while Kim et al. (2020) report a ratio of 0.23 during the 2006–2015 period; the difference suggests an increase in CIDHs over time. In our sample, we observe a similar increase in the CEO debt-to-equity ratio over the sample period. Thus, given the extensive use of insider debt and the significance of credit rating in determining a firm's access to external financing and related costs, understanding the relationship between CIDHs and credit ratings is important and timely.

Extant studies suggest that CIDHs (i.e., pension benefits and deferred compensation) are usually unsecured and unfunded obligations (Edmans and Liu, 2011). These features of inside debt holdings expose the CEO to the same level of default risk and insolvency treatment that unsecured external debtholders face (Cassell et al., 2012), which in turn strengthens the alignment of the interests of executives (the CEO in our case) and debtholders (Edmans and Liu, 2011; Jensen and Meckling, 1976). Wei and Yermack (2011) document that the disclosure of CIDHs results in a value transfer from the equity holders to the creditors. Therefore, CEOs with large inside debt incentives are expected to undertake less risky corporate policies. Indeed, consistent with such theoretical predictions, extant studies provide evidence that large CIDHs are associated with less risky investment and financial policies (Cassell et al., 2012). Moreover, CIDHs also associated with a lower likelihood of default (Sundaram and Yermack, 2007), lower payouts (Eisdorfer et al., 2015), lower marginal values of cash holdings (Liu et al., 2014), lower levels of outstanding convertible debt relative to total debt (Li et al., 2018), lower tax sheltering (Chi et al., 2017), lower abnormal accruals and higher quality accruals (Dhole et al., 2016; He, 2015), higher internal control quality (Chalmers et al., 2019), and lower income smoothing (Shu, 2021). In a recent study, Zhang et al. (2021) show that CEOs with more inside debt holdings invest more in building social capital.

Studies reveal that CIDHs lower yields and result in fewer covenants (Anantharaman et al., 2014), lower the cost of equity (Shen and Zhang, 2020), and lower refinancing risk (Dang and Phan, 2016). However, there is no direct evidence for how CRAs view CIDHs in evaluating the creditworthiness of the firm.

Credit ratings are independent opinions of a company's creditworthiness that serve to measure a firm's ability to repay its debt in a timely fashion. CRAs are well established to play a crucial role in reducing information asymmetry by providing information about the firm's likelihood to default (Frost, 2007). Credit ratings are thus useful to investors, regulators, customers, suppliers, financial counterparties, and the media (Kisgen, 2007). Extant studies provide substantial evidence that credit ratings have important implications for bond and stock prices and for major corporate outcomes (e.g., Basu et al., 2022; Gounopoulos and Pham, 2017; Gray et al., 2006; Hand et al., 1992; Kisgen, 2006). Using survey-based evidence, Graham and Harvey (2001) report that credit standing is the second most critical factor in corporate financing decisions.

Prior studies suggest that CRAs incorporate various forms of quantitative and qualitative information acquired from public and private sources in assigning credit ratings to firms. Quantitative information includes the firm's ability to service debt (interest coverage and debt coverage) and its leverage, profitability, solvency, liquidity, and volatility of returns, among other factors (Gray et al., 2006; Palepu et al., 2021). Prior evidence suggests that while assessing a firm's creditworthiness, CRAs also incorporate qualitative and non-financial information such as managerial ability, CEO decision-making power, industry characteristics, the information environment, the competitive position of the firm, and so on (Ashbaugh-Skaife et al., 2006; Cheng and Subramanyam, 2008; Cornaggia et al., 2017; Gray et al., 2006; Liu and Jiraporn, 2010).

Anecdotal evidence indicates that CRAs pay close attention to the insider debt of key executives. For example, a report by Moody's Investors Service notes that "executive pay is incorporated into Moody's credit analysis of rated issuers because compensation is a determinant of management behavior that affects indirectly credit quality."[1] Moody's believes that enhanced disclosure surrounding defined benefit pension plans for executives is also a significant improvement, and they use these disclosures in their analytical framework (Moody's Investors Service, 2016). Similarly, Standard & Poor's (S&P) notes that it uses several dimensions of executive compensation in evaluating issuers' performance and profitability. In particular, when deferred compensation constitutes a major rating consideration, S&P delves more deeply into the company's specific circumstances and its benefit plans (Standard & Poor's, 2007).

We hypothesize that CIDHs are positively associated with credit ratings for two reasons. Our first argument is based on the incentive alignment view, which suggests that CEOs with debt-like incentives have the same default risk and insolvency treatment as that faced by unsecured external debtholders (Cassell et al., 2012), strengthening the alignment of the interests of CEO and debtholders (Edmans and Liu, 2011; Jensen and Meckling, 1976). This incentive alignment curbs CEO risk-taking behavior, reflected in a decrease in the volatility of future stock returns, research and development expenditures, financial

[1] https://www.complianceweek.com/ceo-pay-and-credit-ratings-rumor-control/5426.article.

leverage, and default risks (Cassell et al., 2012; Sundaram and Yermack, 2007). Studies also show that debt-like compensation precludes unethical and illegal misconduct by managers (Chi et al., 2017). Mary Jo White, a former *SEC* chair, also supports this view, arguing that deferred compensation "would impose liability on executives for misconduct they did not engage in or condone and thus would expand liability considerably beyond current law."[2] Such a reduction in opportunistic, unethical, and illegal misconduct tends to increase expected cash flows and a firm's market value (Brown et al., 2021), while decreasing the probability of default and debtholders' risk (Fisher, 1959; Ogden, 1987). Because incentive alignment reduces the riskiness of investment and financial policies vis-à-vis debtholder risk, CRAs should view this development positively, leading to better credit ratings for a firm.

Our second argument for a positive relationship between CIDHs and credit ratings stems from information risk-based theory. Prior studies suggest that information opacity and higher information processing cost creates uncertainty about a bond's default risk, which in turn leads to less favorable credit ratings (Bonsall and Miller, 2017; Merton, 1974). In this study, we argue that since CIDHs are related to lower abnormal accruals, a lower probability of an earnings misstatement, better accruals quality, and a lower prevalence of earnings benchmark beating (He, 2015), debt-like compensation incentives tend to decrease uncertainty and information asymmetry in the markets, resulting in less information risk (Easley and O'Hara, 2004). Building on this argument, we predict that a better information environment associated with inside debt holdings tends to reduce default risk, which in turn results in better credit ratings.

Using a sample of 753 unique US-listed firms, we construct a sample of 4,646 firm-year observations over the period 2006 to 2016. In line with prior theoretical and empirical studies (Cassell et al., 2012; Chi et al., 2017; Edmans and Liu, 2011; Wei and Yermack, 2011), we employ-four different measures of CIDHs. We use long-term credit ratings issued by S&P available from COMPUSTAT as our main measure of credit ratings. Similar to Kim et al. (2013) and Cornaggia et al. (2017), we translate alphanumeric ratings into numerical scores, with the lowest being C = 1 and the highest being AAA = 21.

Consistent with our expectation, we find robust evidence for a positive relationship between CIDHs and a firm's credit rating. This result is consistent with the theoretical prediction that large inside debt holdings reduce a firm's risk-seeking incentives, improve information environment, and curb managerial opportunistic and unethical behavior, which produces more favorable ratings from CRAs. We also find that the economic magnitude of our estimates is nontrivial. For example, ordinary least squares (OLS) regression estimation suggests that a one standard deviation increase in CIDHs is related to a 7.6 % increase in the credit ratings of a firm, which may be further interpreted as a one rating step (approximately) upgrade for an average firm (e.g., A to A +). The statistical and economic significance of our estimate remains robust when we use alternative regression specifications such as the Fama–MacBeth model (1973) or the ordered probit regression model. Our findings also remain qualitatively unaffected when we employ alternate measures of key variables.

Of course, endogeneity is a common concern in corporate finance and governance studies. We take multiple steps to mitigate this concern. Earlier studies suggest that lagged modeling specification mitigates endogeneity concerns arising from reverse causality to a large extent (Adams et al., 2009; Hossain et al., 2021). For this reason, we use lagged independent and control variables in our regression model. Additionally, we show that findings from our analysis continue to hold when we employ-two- and three-year lagged versions of CIDHs.

To formally alleviate endogeneity problems, we first use State Wage Tax and State Mortgage Subsidy as instruments. We find that regression results from two-stage least squares (2SLS) largely corroborate the findings from our main analysis. Second, we employ instrumental variable (IV) regression estimation using heteroskedasticity-based instruments to mitigate the endogeneity concern (Lewbel, 2012). Again, we continue to find that the positive relationship between CIDHs and credit ratings remains robust. We then estimate the main regression using a propensity score matched (PSM) sample and obtain qualitatively similar results. Finally, we employ balancing regression estimates. Again, we find that our findings are unlikely to be driven by endogeneity problems.

To provide additional insights into the relationship between CIDHs and credit ratings, we perform two sets of cross-sectional analyses. We first examine whether firm-level governance and monitoring moderate the documented positive relationship between CIDHs and credit ratings. Following prior studies, we construct a CEO Power Index to proxy for firm-level governance (Bebchuk et al., 2002; Core et al., 1999). This index captures five components of power that include CEO/chair duality, CEO equity ownership, board co-option, CEO tenure, and CEO pay slice. The CEO Power Index score ranges from zero to five with a higher score indicating more power. Our analysis reveals that the positive relationship between CIDHs and credit ratings is significantly more pronounced for the subsample of firms with more CEO power. When we use financial leverage as a monitoring mechanism (Méndez et al., 2015; Shin and Seo, 2011), we find that our documented positive relationship is significantly more pronounced for the subsample of firms with a low level of leverage. These findings support our incentive alignment-based argument.

We then examine whether the firm-level information environment moderates the documented relationship between CIDHs and credit ratings. We use discretionary accruals, 10-K file size, and weak modal words[3] to proxy for the information environment. We find that the positive relationship between CIDHs and credit ratings is significantly more pronounced for the subsample of firms with higher discretionary accruals, a larger 10-K file size, and a higher percentage of weak modal words in

[2] See https://www.sec.gov/news/speech/chair-white-speech-new-york-university-111816.html.

[3] Weak modal words (e.g., may, might, could, possible, and somewhat) indicate a lack of confidence and represent ambiguity in financial disclosures (Ertugrul et al., 2017). Prior studies suggest that using weak model words in corporate disclosures raises a firm's perceived information risk while reducing its perceived creditworthiness (Loughran and McDonald, 2011, 2016).

their 10-K files. These findings are consistent with our information risk-based argument that CIDHs improve corporate informational transparency, which results in lower debtholder risk and better credit ratings.

Finally, we examine the direct and indirect effect of CIDHs on credit ratings. Prior research has documented that a high degree of CIDHs significantly improves the financial reporting quality (Dhole et al., 2016; He, 2015). Moreover, Akins (2018) shows that financial reporting quality reduces the informational uncertainty of rating agencies. Therefore, it is possible that CIDHs affect a firm's credit rating indirectly through its effect on financial reporting quality. To isolate the extent to which CIDHs directly and indirectly (through financial reporting quality) affect credit ratings, we use the simultaneous equations model. Our finding suggests that the positive relationship between CIDHs and credit ratings is driven by the direct channel (and not the indirect channel), supporting our main finding.

This study contributes to the literature in a few important ways. First, our study contributes to the growing literature on CIDHs. Building on the theories of Jensen and Meckling (1976) and Edmans and Liu (2011), extant studies show that CIDHs encourage CEOs to pursue conservative investment and financing decisions, which in turn reduces the cost of equity (Shen and Zhang, 2020) and debt (Anantharaman et al., 2014), debt covenants (Chava et al., 2010), the agency cost of debt (Edmans and Liu, 2011), and firm risk (Wei and Yermack, 2011). In addition, CIDHs increase cash holdings (Liu et al., 2014), bond value (Wei and Yermack, 2011), and audit fees (Sun et al., 2014). Moreover, Han and Pan (2016) show that firms with higher CIDHs rely more on internal cash flows when financing their investments. We extend this literature by showing that CRAs value the beneficial role of CIDHs, which helps these firms obtain higher credit ratings. As far as we are aware, the current study is the first to empirically examine the role of CIDHs on a firm's long-term credit ratings.

Second, we contribute to the credit ratings literature. Cornaggia et al. (2017) find that managerial ability is a significant factor in determining a firm's credit rating. They show that high-ability managers defuse many of the negative nuances that firms face and achieve relatively higher credit ratings. In a recent study, Ma et al. (2021) show that generalist CEOs are associated with lower credit ratings. Our study extends their findings by showing CIDHs as a contributing factor in a firm's long-term credit ratings. Our results also complement the studies of Liu and Jiraporn (2010) and Du et al. (2019), who find that CEO power and intra-firm tournament incentives affect credit ratings of a firm. Finally, by documenting a direct relationship between CIDHs and credit ratings we complement the empirical studies of Anantharaman et al. (2014), Chava et al. (2010), and Wei and Yermack (2011).

Our study has important policy implications as well. CRAs serve as valuable information intermediaries in alleviating information opacity and improving contracting (Beaver et al., 2006; Frost, 2007). Thus, credit ratings clearly have considerable influence on corporations, and corporations are in turn cognizant of behavior that could harm their ratings. Our findings suggest that firms should consider CIDHs as a tool to not only to lessen the riskiness of CEO actions, but also to improve their credit ratings. Moreover, since CIDHs reduce default risk and improves credit ratings, policymakers and regulators should take the beneficial role of CIDHs into account when designing optimal compensation packages.

2. Sample selection, data, and research design

2.1. Sample and data

In this study, we use data from several sources. For example, we collect CEO compensation and attributes data from ExecuComp, financial and long-term credit ratings data issued by S&P from COMPUSTAT, institutional holding data from Thomson Reuters 13f files, and board data from Boardex databases. We start our sample with the interaction of COMPUSTAT North America and ExecuComp databases for the period spanning the years from 2006 to 2017. Our sample starts from 2006 because it is the first year for which data for deferred compensation are available.[4] We obtain 23,130 firm-year observations in the intersection of Compustat and ExecuComp data files. We remove firm-year observations pertaining to financial (Standard Industrial Classification [SIC]: 6000–6999) and utility (SIC: 4900–4999) industries from the sample (5,721 firm-years). Then, we drop observations with missing rating data (10,148 firm-years). Finally, we remove firm-year observations with missing control variables, including financial and governance data (2,615 firm-years). Our final sample comprises 4,646 firm-year observations (753 unique firms).[5]

2.2. Research design

To investigate the relationship between CIDHs and credit rating, we estimate the following multivariate regression[6]:

$$RATING_{t+1} = \alpha_0 + \beta_1 CIDH_t + \theta' Controls_t + INDFE + YEARFE + \varepsilon \tag{1}$$

where the dependent variable is credit rating (*RATING*) (see Section 2.3), and our main variable of interest is CEO inside debt (*CIDH*) (see Section 2.4). The regression model also includes CEO attributes, firm attributes, corporate governance measures,

[4] Wang et al. (2018, p. 2133) also note that "... in 2006 the *SEC* adopted new disclosure requirements for executive compensation mandating that firms with fiscal year ends on or after December 15, 2006, report the accumulated deferred compensation and pension benefits of their five highest paid executives.".

[5] Since we use CEO inside debt holdings data available in year t to predict credit ratings in year t+1, our final sample covers the years from 2006 to 2016.

[6] We employ OLS, ordered probit, and the Fama–MacBeth regression specification. These regression models have been widely used in prior credit rating literature (Attig et al., 2013; Bhandari and Golden, 2021; Bonsall et al., 2018; Cornaggia et al., 2017; Lobo et al., 2017; Ma et al., 2021, among others).

and dummy variables to capture industry and year fixed effects (see Section 2.5). In the regression estimate, we correct standard errors by using a two-way clustering at both firm and year (Cameron et al., 2011). We define the variables in Appendix A.

2.3. Dependent variable (credit ratings — RATING)

Following previous studies, we use domestic long-term issuer credit ratings in our empirical analysis (Attig et al., 2013; Baghai et al., 2014; Kisgen, 2006). Typically, S&P ratings fall into 21 categories, from high to low: AAA, AA+, AA, AA−, A+, A, A−, BBB+, BBB, BBB−, BB+, BB, BB−, B+, B, B−, CCC+, CCC, CCC−, CC, and C. The lower the rating, the higher the expected default risk. While credit ratings of BBB − and above are considered to be investment grade, any ratings below BBB − are considered to be non-investment (or junk) grade. For our empirical tests, we transform the alphanumeric ratings into a numeric scale. In particular, following Kim et al. (2013) and Cornaggia et al. (2017), we assign a value of 21 to the highest rated bonds (i.e., AAA) and a value of 1 to the lowest rated bonds (i.e., C), to imply that a higher credit rating score indicates a better credit rating.

2.4. Independent variable (CEO inside debt holdings — CIDHs)

Following prior literature on CIDHs (Anantharaman et al., 2014; Cassell et al., 2012; Chi et al., 2017; Edmans and Liu, 2011; Hasan et al., 2021; Wei and Yermack, 2011), in our baseline analysis we measure CIDHs as the natural logarithm of one plus CEO debt-to-equity ratio (*CIDH*). This measure captures the incentive arising from a CEO's inside debt holdings in comparison with their equity holdings. As noted by Chi et al. (2017), CIDHs consist of the present values of accumulated pension and deferred incentives as reported in ExecuComp. Moreover, we obtain CEO total equity holdings from ExecuComp which include accumulated stock holdings and stock options.

In the sensitivity analysis, we also use three alternative measures of CIDHs. The motivation for these alternative measures stems from the seminal studies of Jensen and Meckling (1976) and Edmans and Liu (2011), who suggest that alignment of debt-to-equity ratios of a CEO and a firm makes the CEO agnostic about reallocating wealth between stockholders and debtholders of the firm. In particular, these studies argue that if the CEO debt-to-equity ratio surpasses that of the firm, then the CEO will act more for the debtholders than for the stockholders, and vice versa. Consistent with these theories and recent empirical work on CIDHs, our first alternative measure is the natural logarithm of the ratio of CEO-to-firm debt-to-equity (*CIDH_ALT1*). Our second alternative measure is a dummy variable that takes a value of one if the ratio of CEO's debt-to-equity to firm's debt-to-equity is greater than 1, and zero otherwise (*CIDH_ALT2*). This alternative measure is important since Jensen and Meckling (1976) state that impacts of debt incentive are predominant when CEO debt-to-equity is in fact greater than that of the firm. Finally, to avoid any biases in terms of measurement issues, as discussed in Chi et al. (2017), we measure CIDHs as the ratio of CEO debt compensation to a firm's lagged total assets (*CIDH_ALT3*).

2.5. Controls

In the regressions, we include a set of CEO attributes, corporate governance variables, and firm-level characteristics following related studies (e.g., Ashbaugh-Skaife et al., 2006; Cornaggia et al., 2017; Jiang et al., 2018; Zhang and Schloetzer, 2021). CEO-specific variables include the natural logarithm of CEO age (*CEO Age*), a CEO's tenure in the current role (*CEO Tenure*), and the natural logarithm of one plus total CEO compensation as reported in ExecuComp (*Total Pay*). The controls for corporate governance include the percentage of total institutional ownership (*INST Total Ownership*) and the percentage of outside/independent directors (*Board Independence*). Our firm-specific controls include the natural logarithm of market capitalization (*Firm Size*); financial leverage measured as total debt scaled by total assets (*Leverage*); return on assets (*ROA*); an indicator variable that takes a value of one if net income before extraordinary items is negative and zero otherwise (*LOSS*); property, plant, and equipment scaled by total assets (*Tangibility*); interest coverage ratio, a dummy variable that takes a value of one if the firm has subordinated debt and zero otherwise (*SUBORD*); the rolling standard deviation of cashflow over the past five years (*Cash Flow Volatility*); and the financing constraints score (*KZ*; Kaplan and Zingales, 1997). Since the CEO compensation structure could vary across industries and over time (Hoi et al., 2019), we control for industry (Fama–French 48) and year fixed effects. Appendix A contains definitions of the variables and measurements.

3. Results

3.1. Descriptive statistics

In Table 1, we provide the year-by-industry and industry-by-industry distribution of credit ratings. In Panel A, we find that the majority of the ratings (about 60 %) in our sample belong to investment grade (BBB − or better). This distribution is not surprising given that we are drawing our sample from ExecuComp, which covers well-established S&P 1500 firms. We do not observe any unusual distribution of ratings over the years. Panel B exhibits the distribution of the sample across the

Table 1
Sample distribution. This table reports the distribution of samples across year (Panel A) and Fama–French 12 industry groups (Panel B).

Panel A: Sample distribution by year and rating category

Year	AAA	AA	A	BBB	BB	B	CCC/CC/C	Total
2006	5	10	75	152	123	43	2	410
2007	6	12	76	146	100	48	2	390
2008	4	12	70	137	95	56	2	376
2009	3	12	77	148	105	52	1	398
2010	4	12	79	153	126	52	0	426
2011	4	14	81	161	124	49	0	433
2012	4	17	83	166	117	55	1	443
2013	3	18	85	169	118	52	0	445
2014	3	20	74	172	127	54	2	452
2015	1	20	69	165	136	45	2	438
2016	2	17	68	167	143	37	1	435
Total	39	164	837	1,736	1,314	543	13	4,646

Panel B: Sample distribution by Fama–French 12 industry and rating category

Industry Description	AAA	AA	A	BBB	BB	B	CCC/CC/C	Total
Consumer Non-Durables	0	6	107	164	91	39	0	407
Consumer Durables	0	3	21	68	38	21	1	152
Manufacturing	0	19	190	318	310	79	1	917
Energy	9	17	61	129	65	32	1	314
Chemicals	0	16	57	132	70	34	2	311
Business Equipment	17	23	113	244	214	75	1	687
Telecom	0	0	33	57	38	32	0	160
Shops	0	28	90	254	157	85	3	617
Healthcare	10	38	111	75	65	49	0	348
Other	3	14	54	295	266	97	4	733
Total	39	164	837	1,736	1,314	543	13	4,646

Fama–French 12 industry groups. We find that the manufacturing industry represents the largest percentage of our sample (19.74 %), whereas the consumer durables industry represents the smallest percentage (3.27 %).

In Panel A of Table 2, we report descriptive statistics of the variables used in the regression models. We find that the mean (median) score for *RATING* is 12.24 (12) with a standard deviation of 3.09. This finding indicates that the average (median) firm in our sample has an investment grade. This rating score is also consistent with that reported in earlier studies (Ashbaugh-Skaife et al., 2006; Cornaggia et al., 2017). Our main measure of *CIDH* (i.e., the natural logarithm of CEO debt-to-equity ratio) has a mean of 0.23, which is largely consistent with prior studies (e.g., Wei and Yermack, 2011). Our alternate measures of CIDHs (e.g., *CIDH_ALT1, CIDH_ALT2*, and *CIDH_ALT3*) are also comparable to other related studies (e.g., Chi et al., 2017). Panel A also shows that average firms in our study are relatively large (market value of $6.15 billion (exp(8.725)), profitable (*ROA* = 14.4 %), are less leveraged (*Leverage* = 28 %), with a higher interest coverage ratio (16.75) and a lower level of cash flow volatility (2.7 %). As for firm-level governance, we observe a relatively high level of institutional ownership (81 %) and a high proportion of independent board members (87 %), implying better firm-level governance. This finding is not surprising given that our study covers relatively large firms from the post-Sarbanes–Oxley Act era, both of which contribute to stronger monitoring. In Panel B, we provide a year-by-year mean distribution of the CIDHs measures used in this study.

3.2. Correlation

Table 3 presents the correlation between variables used in the baseline regression. We find that the correlation between *RATING* and *CIDH* is positive and statistically significant ($\rho = 0.119$; $p < 0.01$), which provides preliminary support for our hypothesis. We find qualitatively similar correlations for other proxies of *CIDH* (untabulated).[7] We also find that the correlation between credit rating and other control variables is significant and consistent with expectation. For example, credit rating is positively correlated with firm size ($\rho = 0.784$; $p < 0.01$) and profitability ($\rho = 0.384$; $p < 0.01$), while it is negatively correlated with leverage ($\rho = -0.307$; $p < 0.01$), loss ($\rho = -0.338$; $p < 0.01$), cash flow volatility ($\rho = -0.137$; $p < 0.01$), financial distress (*KZ*: $\rho = -0.450$; $p < 0.01$), and the presence of subordinated debt ($\rho = -0.189$; $p < 0.01$).[8]

[7] Untabulated results are available upon request.

[8] To mitigate the concern with the multicollinearity problem, we also check the variance inflation factor (VIF) of the variables included in the analysis. We find that the highest VIF is 2.72 for *Firm Size*, followed by 2.57 for *Tangibility*. The rest of the VIFs are below 1.94. These VIFs indicate that multicollinearity is not a concern for our analysis.

Table 2
Descriptive statistics. Panel A of this table presents summary statistics of the variables used in this study. Panel B reports the year-by-year means of *CIDH*. We winsorize the continuous variables at the 1% and 99% levels. Variable definitions are provided in Appendix A.

Panel A: Summary statistics

Variables	N	Mean	S.D.	25th	50th	75th
RATING	4,646	12.241	3.093	10.000	12.000	14.000
CIDH	4,646	0.231	0.362	0.001	0.094	0.311
CIDH_ALT1	4,646	0.178	0.227	0.001	0.090	0.271
CIDH_ALT2	4,646	0.331	0.471	0.000	0.000	1.000
CIDH_ALT3	4,646	1.147	2.241	0.009	0.325	1.217
CEO Age	4,646	64.430	6.968	59.000	64.000	69.000
CEO Tenure	4,646	6.939	6.246	2.000	5.000	9.000
Total Pay	4,646	8.526	0.823	8.026	8.586	9.069
INST Total Ownership	4,646	0.810	0.133	0.740	0.841	0.909
Board Independence	4,646	0.866	0.069	0.833	0.889	0.909
Firm Size	4,646	8.725	1.529	7.665	8.657	9.770
Leverage	4,646	0.280	0.147	0.176	0.263	0.371
ROA	4,646	0.144	0.064	0.101	0.136	0.177
LOSS	4,646	0.110	0.313	0.000	0.000	0.000
Tangibility	4,646	0.280	0.223	0.105	0.207	0.401
Interest Coverage Ratio	4,646	16.747	13.538	6.037	12.863	22.824
SUBORD	4,646	0.091	0.287	0.000	0.000	0.000
Cash Flow Volatility	4,646	0.027	0.028	0.011	0.019	0.032
KZ	4,646	0.606	0.894	0.155	0.638	1.179
CEO Power Index	4,646	2.563	1.534	1.000	3.000	4.000
Discretionary Accruals	4,406	0.033	0.031	0.011	0.024	0.045
10-K File Size	4,609	1.954	0.495	1.457	2.153	2.351
Weak Modal	4,609	0.525	0.137	0.429	0.508	0.605

Panel B: Year-by-year distribution of CEO debt incentive

Year	Obs.	*CIDH*	*CIDH_ALT1*	*CIDH_ALT2*	*CIDH_ALT3*
2006	410	0.14	0.11	0.26	1.23
2007	390	0.15	0.12	0.28	1.27
2008	376	0.23	0.18	0.26	1.14
2009	398	0.31	0.22	0.40	1.45
2010	426	0.25	0.20	0.37	1.26
2011	433	0.26	0.20	0.33	1.18
2012	443	0.25	0.19	0.36	1.13
2013	445	0.23	0.18	0.38	1.03
2014	452	0.22	0.17	0.35	1.05
2015	438	0.26	0.19	0.34	1.04
2016	435	0.24	0.18	0.31	0.89
Total	4,646	0.23	0.18	0.33	1.15

3.3. Univariate results

Table 4 presents the univariate test of differences in the mean of variables between high (if *CIDH* is above sample median) and low (if *CIDH* is below sample median) CIDHs groups. We find that firm-level credit rating is significantly higher ($p < 0.01$) for firms within the high *CIDH* subsample (12.93) compared with those in the low *CIDH* counterpart (11.56). This score indicates that, on average, credit ratings of firms within the high (low) *CIDH* subsample are of investment (non-investment) grades. This finding provides further support for our hypothesis.

In addition, we notice that average firms in the high *CIDH* group are relatively larger in size, have greater board independence, have fewer incidents of loss, possess more tangible assets, have less subordinated debt and cash flow volatility, and are less financially distressed.

3.4. Main regression results

We present the main regression results of the relationship between CIDHs and credit ratings in Table 5. In the regression models, our dependent variable is credit ratings (*RATING*), the main independent variable is CEO inside debt holdings (*CIDH*), and the regression includes controls that prior studies suggest affect credit ratings. We predict a positive relationship between *CIDH* and *RATING*.

In column (1), we report the OLS regression estimate that controls for year and industry effects only. We find a strong positive relationship between *CIDH* and *RATING* (coefficient = 0.880; $p < 0.01$), suggesting that firms with more CIDHs have better credit ratings. In column (2), we report the OLS results that control for firm-specific characteristics, CEO-specific attributes, and corporate governance along with the year and industry effects. This increases the adjusted R^2 and reduces the coefficient and standard errors. Importantly, we continue to find that the relationship between *CIDH* and *RATING* is positive

Table 3
Pearson correlation. This table presents correlations between variables used in this study. Correlation coefficients in bold are significant at $p < 0.01$. Variable definitions are provided in Appendix A.

	Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
[1]	*RATING*	1							
[2]	*CIDH*	**0.119**	1						
[3]	*CEO Age*	0.036	0.045	1					
[4]	*CEO Tenure*	**−0.073**	**−0.076**	**0.388**	1				
[5]	*Total Pay*	**0.461**	**0.078**	−0.007	−0.006	1			
[6]	*INST Total Ownership*	**−0.235**	**−0.060**	**−0.090**	0.009	**−0.075**	1		
[7]	*Board Independence*	0.183	**0.114**	**−0.126**	**−0.188**	**0.180**	0.039	1	
[8]	*Firm Size*	**0.784**	**0.085**	−0.007	**−0.061**	**0.649**	**−0.237**	**0.189**	1
[9]	*Leverage*	**−0.307**	0.005	−0.034	0.043	**−0.067**	**−0.077**	**−0.077**	**−0.200**
[10]	*ROA*	**0.384**	−0.027	0.036	−0.046	**0.131**	**−0.109**	0.010	**0.297**
[11]	*LOSS*	**−0.338**	0.010	−0.010	−0.009	**−0.142**	−0.013	−0.047	**−0.284**
[12]	*Tangibility*	**−0.114**	0.035	**0.088**	0.043	**−0.061**	**−0.118**	−0.049	−0.018
[13]	*Interest Coverage Ratio*	**−0.332**	**−0.068**	0.024	−0.006	**−0.165**	**0.096**	−0.007	**−0.279**
[14]	*SUBORD*	**−0.189**	−0.029	**0.051**	**0.056**	**−0.117**	0.038	**−0.162**	**−0.173**
[15]	*Cash Flow Volatility*	**−0.137**	−0.045	0.015	−0.004	−0.064	−0.018	−0.031	**−0.051**
[16]	*KZ*	**−0.450**	**−0.125**	**−0.063**	**0.115**	**−0.145**	**0.172**	**−0.137**	**−0.321**
	Variables	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
[9]	*Leverage*	1							
[10]	*ROA*	**−0.143**	1						
[11]	*LOSS*	**0.155**	**−0.335**	1					
[12]	*Tangibility*	**0.138**	**0.075**	**0.115**	1				
[13]	*Interest Coverage Ratio*	**−0.052**	**−0.202**	**0.280**	0.027	1			
[14]	*SUBORD*	**0.170**	**−0.113**	**0.076**	0.021	0.013	1		
[15]	*Cash Flow Volatility*	**−0.080**	**0.080**	**0.123**	**0.157**	0.021	−0.002	1	
[16]	*KZ*	**0.503**	**−0.320**	**0.209**	**0.028**	**0.095**	**0.186**	**−0.043**	1

Table 4
Univariate mean difference test results. This table presents univariate mean difference test results of the variables included in the regression analysis. We classify the sample into two groups based on the median level of CEO debt holdings. Firm-year observations with higher (lower) than sample median CEO debt holdings are defined as the high (low) CEO inside debt holdings group. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Appendix A.

Variables	High Debt Incentive (*CIDH* > median)		Low Debt Incentive (*CIDH* ≤ median)		Difference of mean (High − Low)	
	Mean	S.D.	Mean	S.D.	Diff.	t-stat
RATING	12.926	3.000	11.556	3.032	1.370	15.48***
CEO Age	64.890	5.851	63.969	7.904	0.921	4.52***
CEO Tenure	6.304	5.058	7.573	7.186	−1.269	−6.96***
Total Pay	8.638	0.749	8.414	0.877	0.224	9.37***
INST Total Ownership	0.806	0.128	0.814	0.138	−0.008	−2.10**
Board Independence	0.879	0.058	0.853	0.075	0.026	13.16***
Firm Size	8.947	1.545	8.502	1.481	0.445	10.03***
Leverage	0.278	0.133	0.282	0.160	−0.004	−0.96
ROA	0.145	0.062	0.144	0.067	0.001	0.49
LOSS	0.094	0.292	0.127	0.333	−0.033	−3.57***
Tangibility	0.290	0.217	0.271	0.228	0.019	2.88***
Interest Coverage Ratio	0.121	0.197	0.165	0.246	−0.044	−6.70***
SUBORD	0.080	0.271	0.102	0.302	−0.022	−2.61***
Cash Flow Volatility	0.025	0.026	0.028	0.031	−0.003	−4.17***
KZ	0.468	0.825	0.744	0.937	−0.276	−10.66***

and significant (coefficient = 0.210; $p < 0.05$), which provides support for our hypothesis, that firms with higher CIDHs tend to have better credit ratings. We also note that the economic magnitude of our estimates is nontrivial. For example, the coefficient in column (2) suggests that a one standard deviation increase in *CIDH* (=0.362) is related to a 7.6 % increase in the *RATING* of a firm (calculated as 0.362×0.21), which may be further interpreted as a one rating step (approximately) upgrade for an average firm (e.g., A to A +).

As a further test of robustness, we employ the Fama–MacBeth regression specification (Fama and MacBeth, 1973) in column (3) and obtain qualitatively similar results (coefficient = 0.226; $p < 0.01$). As described earlier, we use the OLS regression specification in line with the literature (Baghai et al., 2014; Cornaggia et al., 2017). Extant credit rating studies also employ the ordered probit model in regression analysis (Attig et al., 2013). To check if our results are sensitive to model specification, we re-run our main model using the ordered probit specification and report the results in column (4). We continue to

Table 5
Baseline regression results. This table reports main regression results. The dependent variable is *RATING* score, and the main independent variable is CEO inside debt holdings (*CIDH*). Column (1) presents results without any firm-level controls, and column (2) presents results with all the controls. Results from Fama–MacBeth and ordered probit regressions are presented in columns (3) and (4), respectively. Robust *t*-statistics are reported in parentheses below the coefficients. We correct standard errors by using a two-way clustering at both firm and year levels (Cameron et al., 2011). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Appendix A.

Variables	Main Model (univariate) with fixed effects but no controls	Main Model with all controls and fixed effects	Main Model Fama–MacBeth specification	Main Model Ordered Probit specification
	(1)	**(2)**	**(3)**	**(4)**
CIDH	**0.880*****	**0.210****	**0.226*****	**0.140****
	(3.04)	**(1.99)**	**(4.24)**	**(1.99)**
CEO Age		−0.0004	0.003	−0.001
		(−0.05)	(1.13)	(−0.22)
CEO Tenure		0.004	0.004	0.004
		(0.47)	(0.80)	(0.76)
Total Pay		−0.159**	−0.188***	−0.106**
		(−2.00)	(−4.45)	(−1.99)
INST Total Ownership		−0.866*	−0.880***	−0.339
		(−1.82)	(−6.96)	(−1.07)
Board Independence		0.245	0.164	0.121
		(0.36)	(0.34)	(0.26)
Firm Size		1.427***	1.4282***	0.977***
		(26.46)	(71.65)	(21.73)
Leverage		−0.980*	−0.983***	−0.715*
		(−1.78)	(−3.63)	(−1.95)
ROA		5.524***	6.431***	3.899***
		(5.19)	(10.43)	(5.62)
LOSS		−0.262**	−0.455***	−0.244***
		(−2.41)	(−11.03)	(−3.35)
Tangibility		−0.810**	−0.946***	−0.582**
		(−2.02)	(−6.04)	(−2.16)
Interest Coverage Ratio		−1.142***	−1.155***	−0.906***
		(−5.10)	(−7.19)	(−5.22)
SUBORD		−0.208	−0.173**	−0.137
		(−1.20)	(−2.25)	(−1.26)
Cash Flow Volatility		−12.301***	−16.308***	−8.522***
		(−3.74)	(−5.85)	(−3.75)
KZ		−0.469***	−0.435***	−0.319***
		(−6.59)	(−12.70)	(−6.74)
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	No	Yes
Observations	4,646	4,646	4,646	4,646
Adjusted/Pseudo R^2	0.169	0.765	0.762	0.290

observe a positive and significant relationship between *CIDH* and *RATING* (coefficient = 0.140; $p < 0.05$). Taken together, we provide a robust positive relationship between CIDHs and credit ratings.

The coefficients for controls are largely in line with expectations. For example, we report that larger firms with low leverage, good operating performance, profitability, low level of cash flow volatility, and low financial constraints obtain better ratings (Cornaggia et al., 2017).

3.5. Sensitivity tests

3.5.1. Our findings are robust to the use of non-continuous measure of CIDHs

To show the robustness of our findings, we employ-two alternate non-continuous measures of the main variable of interest, *CIDH*. First, we replace *CIDH* with a quintile ranking (*CIDH_q*) in our main model. The result reported in column (1) of Table 6 shows that our main result continues to hold (coefficient = 0.163; $p < 0.01$). Second, we use a dichotomous variable (*CIDH_d*), which takes a value of one if the firm's *CIDH* are greater than the sample median, and zero otherwise. Results in column (2) continue to show a significant positive relationship between CIDHs (represented here by *CIDH_d*) and credit ratings (represented by *RATING*). These results suggest that the positive relationship between CIDHs and credit ratings we have documented is not driven by continuous measure of CIDHs.

3.5.2. Our findings are robust to the use of alternate proxies for CIDHs

As discussed in Section 2.4, we employ-three well-established alternate proxies for our main independent variable, *CIDH*, to examine the robustness of findings. In particular, in columns (3), (4), and (5), we use *CIDH_ALT1* (i.e., the natural logarithm

Table 6
Sensitivity Tests. This table reports results from sensitivity analysis. Columns (1) and (2) employ non-continuous variations of our variable of interest (*CIDH*) (see Section 3.5.1); columns (3) to (5) use three alternate proxies for CIDHs (see Section 3.5.2); columns (6) and (7) use lagged versions of *CIDH* (see Section 3.5.3); and columns (8) and (9) use OLS and logit models using a dummy specification for all variables involved in the main model (see Section 3.5.4). Robust *t*-statistics are reported in parentheses below the coefficients. We correct standard errors by using two-way clustering at both firm and year levels (Cameron et al., 2011). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Appendix A.

	Main Model CEO debt as quantile	Main Model CEO debt as a dummy	Main Model CEO debt incentive alternate measure 1	Main Model CEO debt incentive alternate measure 2	Main Model CEO debt incentive alternate measure 3 OLS	Main Model CEO debt two-year lagged	Main Model CEO debt three-year lagged	Main Model with dummy specification (all variables are dummies) OLS	Main Model with dummy specification (all variables are dummies) *LOGIT*
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
CIDH_q	**0.163*****								
	(4.98)								
CIDH_d		**0.392*****						**0.078*****	**0.643*****
		(4.79)						**(4.00)**	**(4.12)**
CIDH_ALT1			**0.480*****						
			(2.68)						
CIDH_ALT2				**0.243*****					
				(3.00)					
CIDH_ALT3					**0.068*****				
					(3.90)				
CIDH_lag2						**0.209****			
						(2.03)			
CIDH_lag3							**0.125***		
							(1.91)		
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,646	4,646	3,804	3,273	4,646	4,646	4,646	4,646	4,646
Adjusted/ Pseudo R^2	0.769	0.468	0.774	0.776	0.497	0.455	0.766	0.766	0.767

of the ratio of CEO-to-firm debt-to-equity ratio), *CIDH_ALT2* (i.e., a dummy variable that takes a value of one if the ratio of CEO's debt-to-equity to firm's debt-to-equity is greater than 1, and zero otherwise), and *CIDH_ALT3* (i.e., the ratio of CEO debt holdings to a firm's lagged total assets) as our main independent variable. We re-estimate our main model (equation (1)) using each of these alternates and report the summary results in columns (3)–(5) of Table 6. The coefficients of these three alternative measures of CIDHs are 0.480 ($p < 0.01$), 0.243 ($p < 0.01$), and 0.068 ($p < 0.01$) respectively. These results indicate that findings from our main regression are not driven by the specific measure of CIDHs, providing robustness of our findings.

3.5.3. Our results are robust to the use of lagged CEO debt incentive variables

Prior literature suggests a lagged model specification can mitigate the reverse causality concern (Adams et al., 2009; Hossain et al., 2021). As mentioned earlier, in our main regressions we use a one-year lagged independent variable since *CIDH* was calculated at the end of the previous period. To further examine the sensitivity of our findings, we use two- and three-year lagged versions of our main variable (*CIDH*). The results presented in columns (6) and (7) of Table 6 show that inference from our analysis remains qualitatively unaltered when the two- or three-year lagged independent variable is used in the regressions. For example, the coefficient of *CIDH_lag2* is 0.209 ($p < 0.05$), and that of *CIDH_lag3* is 0.125 ($p < 0.10$).

3.5.4. Our results are robust to the use of alternate specifications

In Table 6 we use two alternate model specifications, namely Fama–Macbeth and ordered probit. To show the further robustness of our finding, we use a dummy model in which all the continuous variables are converted into dichotomous ones. The dummy version of each continuous variable takes a value of one if it is greater than the sample median, and zero otherwise. We run both OLS (see column (8)) and probit (see column (9)) models for this dummy specification. We find that the positive relationship between *CIDH* and *RATING* continues to hold ($p < 0.01$).

3.5.5. Our results are robust to the inclusion of additional controls

In our baseline regression, we control for a set of firm characteristics that prior studies suggest affect the credit rating. To examine the robustness of our finding, we further control for discretionary accruals, the readability of financial reports (*10-K*

File Size), and financial distress (the *Altman Z Score*). In columns (1) to (3) of Table 7, we re-run the baseline regression after including these controls separately. In column (4), we include all these additional controls together. We find that the positive relationship between *CIDH* and *RATING* remains robust after including these additional controls.

3.6. Endogeneity tests

We report a strong positive relationship between CIDHs and credit ratings. However, there may be a concern that our empirical tests are subject to endogeneity problems. Endogeneity could arise if the omitted unobservable factors influence both CIDHs and credit ratings. Another concern is reverse causality. For example, firms with higher credit ratings could choose to provide CEOs with more insider debt. In our regressions, the independent variable (*CIDH*) is lagged by one year relative to *RATING*, which partially mitigates the reverse causality issue. Nevertheless, we address potential endogeneity concerns in several additional ways.

3.6.1. Two-stage least squares tests

As a first attempt to alleviate the endogeneity concerns, we employ IV-based 2SLS regression estimates. Following Shen and Zhang (2020), we use the state-level maximum tax rate for personal wage income in each year (State Wage Tax) and the state-level mortgage subsidy rate in each year (State Mortgage Subsidy) as two instruments. In the spirit of Shen and Zhang (2020), we argue that CEOs of firms headquartered in states with higher wage tax rates are expected to defer compensation (i.e., use more inside debt) to reduce the current tax burden. On the other hand, a higher mortgage subsidy rate tends to increase the use of CIDHs to reduce a CEO's overall tax burden. Thus, in the context of this study, we expect a positive and significant correlation between State Wage Tax and CIDHs, as well as a negative and significant correlation between State Mortgage Subsidy and CIDHs. However, we do not have any a priori reason to believe that these exogenous instruments (State Wage Tax and State Mortgage Subsidy) affect firm-level credit ratings. Thus, our instruments satisfy the essential requirements.

We report results from two-stage least squares in Table 8. Column (1) reports the first-stage regression result. As expected, we find a positive and significant relationship between State Wage Tax and *CIDH* (coefficient = 0.008; $p < 0.10$). In addition, we document a negative and significant relationship between State Mortgage Subsidy and *CIDH* (coefficient = -0.018; $p < 0.01$). Moreover, the Cragg–Donald Wald *F*-statistics in column (1) are higher than 10, which confirms that our selected instrument is not weak (Larcker and Rusticus, 2010). Finally, the insignificant Hansen *J*-statistics confirm that our instruments satisfy the exclusion restriction. We report results from the second-stage regression in column (2). We continue to find a positive and significant relationship between our instrumented *CIDH* (represented by *CIDH instrumented*) and credit ratings (coefficient = 4.426; $p < 0.05$).[9] We therefore conclude that our documented positive relationship between CIDHs and credit ratings is not driven by the endogeneity problem.[10]

3.6.2. Instrumental variable regression estimation using heteroskedasticity-based instruments

As a further attempt to mitigate endogeneity concerns, we use an IV approach with heteroskedasticity-based instruments following Lewbel (2012). This method does not require an external instrument and instead uses heterogeneity in the error term of the first-stage regression model to generate instruments from the existing model. Lewbel (2012) suggests that this method is particularly useful in applications in which other sources of identification, such as external IVs, are weak or nonexistent. Contemporary studies apply this identification method to mitigate endogeneity problems (Habib et al., 2017; Mavis et al., 2020). We report the results from this analysis in column (3) of Table 8. We find that our documented positive relationship between CIDHs and credit rating remains robust when heteroskedasticity-based instruments are used in the regression model (coefficient = 0.895; $p < 0.01$). In addition, we note that our estimation does not suffer from either a weak identification test or an over-identification problem.

Overall, results from the above analyses provide strong evidence that our reported positive relationship between CIDHs and credit rating is not driven by endogeneity problems.

3.6.3. Propensity score matched sample analysis

There may be a concern that firms with higher levels of CEO inside debt may be systematically different from those with lower levels of CEO inside debt, thus introducing bias into our estimates. To alleviate this endogeneity concern, we employ a PSM sample analysis. To conduct PSM analysis, we divide our sample into two groups based on the median value of *CIDH*. We consider firm-year observation with above (below) median *CIDH* as the treated (control) group. To create our matched sample, we estimate the propensity scores with a logistic regression that predicts *High CIDH* (i.e., an indicator variable that equals one (zero) if *CIDH* is above (below) median level). We use all controls and fixed effects for this regression. We choose one-to-

[9] We acknowledge that the coefficient for our second-stage regression result is considerably higher compared with the main regression result. However, a higher level of coefficient for the IV is common in corporate finance studies. For example, Jiang (2017) shows that IV estimates are larger than their corresponding uninstrumented estimates in about 80% of the studies. The author notes that "[t]he magnitude of the IV estimates is, on average, nine times of that of the uninstrumented estimates even when economic insights do not suggest a downward bias of the latter" (p. 127).

[10] In an additional robustness analysis, we use state-level median CEO inside debt (excluding the focal firm) as an instrument (Ertugrul et al., 2017; Hasan, 2020). Untabulated results show that inferences from both first-stage and second-stage regressions remain robust.

Table 7
Additional controls. This table repeats baseline regression after including additional controls. We control for *Discretionary Accruals* (column 1), *10-K File Size* (column 2), *Altman Z Score* (column 3), and all additional controls together (column 4). Robust *t*-statistics are reported in brackets below the coefficients. We correct standard errors by using two-way clustering at both firm and year levels (Cameron et al., 2011). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Appendix A.

Variables	(1)	(2)	(3)	(4)
CIDH	**0.214****	**0.219****	**0.219****	**0.238****
	(1.97)	**(2.05)**	**(2.00)**	**(2.23)**
Discretionary Accruals	−2.271***			−2.316***
	(−2.78)			(−2.64)
10-K File Size		−0.060		−0.085
		(−0.25)		(−0.35)
Altman Z Score			0.027	0.054
			(0.50)	(1.02)
Other baseline controls	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	4,406	4,609	4,576	4,306
Adjusted R^2	0.776	0.766	0.765	0.776

one matching without replacement and with a maximum caliper distance of 0.01. The resulting sample consists of 1,402 firm-year observations from the treated group, which are matched to 1,402 firm-year observations from the control group.

Panel A of Table 9 compares the means of matching variables between the treatment and control groups. We find that the firm characteristics between treatment and control groups are similar, and none of the matching variables is significantly different in the matched samples. Most importantly, we find that the firm-year observations in the treatment group have significantly higher credit ratings ($p < 0.01$) than their control counterparts. Overall, we find that our matching procedure is successful.

Panel B of Table 9 reports the multivariate regression results using the matched sample. The results show that *CIDH* are significantly and positively related to the credit ratings, after removing all observable differences between treatment and control groups. This finding remains robust, irrespective of the use of OLS, Fama–MacBeth, and ordered logit regression models. Overall, results from the PSM analysis indicate that our documented findings are unlikely to be driven by endogeneity problems stemming from observable firm characteristics.

3.6.4. Entropy balancing approach

Finally, following recent literature we use entropy balancing estimates to mitigate the endogeneity concern (McMullin and Schonberger, 2020). This estimation technique relies on a weighting approach that balances the covariates without requiring the adjustment of a propensity model (McMullin and Schonberger, 2020). Importantly, entropy balancing improves the balance quality without removing any unit from either the treatment or the control group (Hainmueller, 2012). By adjusting for random and systematic inequalities in the variable distributions between the treatment and control groups, this technique mitigates the concern that design choices could affect our results.

To conduct entropy balancing estimates, we divide our sample into two groups using the same methodology as in the PSM analysis. Panel A of Table 10 shows that the means of our entropy balanced sample achieve a desirable covariate balance. Using the entropy balanced sample, we combine the matched pairs into a pooled sample and re-estimate our baseline regression analysis. In Panel B of Table 10, we continue to find a positive and significant relation between *CIDH* and credit ratings, and this result holds irrespective of the regression model used in the analysis. This empirical finding further confirms that our results are not driven by an endogeneity problem.

3.7. Cross-sectional analysis

3.7.1. CEO inside debt and credit ratings: The role of incentive alignment (i.e., corporate governance mechanism)

In this section, we investigate whether the incentive alignment moderates the relationship between CIDHs and credit ratings. While developing the hypothesis, we argue that CIDHs curb managerial opportunism and risk-seeking behavior. It also mitigates unethical and even illegal managerial misconduct. Therefore, CIDHs tend to reduce a firm's cash flow risk and probability of default, which in turn results in a favorable credit rating. This argument thus suggests that our documented positive relationship between CIDHs and credit ratings is more pronounced for the subsample of firms with less incentive alignment (i.e., more agency problems). To empirically test this conjecture, we use CEO power as a moderating variable. Prior studies show that powerful CEOs have more decision-making power, are difficult to monitor, and exhibit more perquisite consumption or overcompensation, all issues that harm both shareholders and bondholders (Core et al., 1999; Liu and Jiraporn, 2010). Therefore, we argue that CEO power is the manifestation of incentive misalignment.

We develop a comprehensive CEO Power Index that consists of five different components, namely, CEO/chair duality, CEO equity ownership, board cooption, CEO tenure, and CEO pay slice. The CEO Power Index score ranges from 0 to 5 with a

Table 8
Instrumental variable approach. This table presents two-stage least squares regression results. In column (1) we use State Wage Tax and State Mortgage Subsidy as instruments. In column (2), we report second stage regression results. Column (3) reports the instrumental variable (IV) regression estimation using heteroskedasticity-based instruments (Lewbel, 2012). We correct standard errors by using two-way clustering at both firm and year levels (Cameron et al., 2011). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Appendix A.

Variables	DV = *CIDH*	DV = *Rating*	DV = *Rating*
	First Stage IV = State Wage Tax and State Mortgage Subsidy	Second Stage	Second Stage (Lewbel, 2012)
	(1)	**(2)**	**(3)**
***CIDH* (instrumented)**		**4.426****	**0.895*****
		(2.10)	**(2.59)**
CEO Age	0.005***	−0.021	−0.004
	(3.36)	(−1.57)	(−0.82)
CEO Tenure	−0.004***	0.023*	0.007
	(−3.22)	(1.95)	(1.53)
Total Pay	0.010	−0.198**	−0.166***
	(1.06)	(−2.32)	(−3.84)
INST Total Ownership	−0.071	−0.601	−0.820***
	(−0.84)	(−1.02)	(−3.49)
Board Independence	0.236**	−0.811	0.048
	(2.12)	(−0.85)	(0.13)
Firm Size	0.012	1.372***	1.418***
	(1.28)	(20.28)	(51.41)
Leverage	0.095	−1.425**	−1.052***
	(1.36)	(−2.04)	(−3.99)
ROA	−0.389***	7.286***	5.812***
	(−2.58)	(5.33)	(11.72)
LOSS	0.032	−0.385**	−0.282***
	(1.06)	(−2.12)	(−3.20)
Tangibility	0.130**	−1.335**	−0.903***
	(2.03)	(−2.40)	(−5.17)
Interest Coverage Ratio	−0.024	−1.073***	−1.130***
	(−0.57)	(−3.64)	(−8.95)
SUBORD	0.006	−0.261	−0.217***
	(0.18)	(−1.32)	(−2.65)
Cash Flow Volatility	−0.528**	−9.558***	−11.854***
	(−2.09)	(−3.02)	(−6.42)
KZ	−0.051***	−0.258*	−0.434***
	(−3.69)	(−1.86)	(−8.80)
State Wage Tax	**0.008***		
	(1.91)		
State Mortgage Subsidy	**−0.018*****		
	(−3.76)		
Industry dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	4,646	4,646	4,646
Adjusted R^2	0.143	0.470	0.760
Kleibergen–Paap (*p*-value)	0.04		0.00
Cragg–Donald Wald F statistics	19.35		58.19
Hansen J-test p-value	0.38		0.13

higher score indicating more power.[11] We report results from this analysis in Panel A of Table 11. In columns (1) and (2), we define the CEO Power Index as high if the score is 4 or 5. We find that the coefficient on *CIDH* is positive, significant, and more pronounced only for the high-power subsample. In addition, in columns (3) and (4) we define the CEO Power Index as high if the score is greater than the median (i.e., 3). Again, we find that the coefficient of *CIDH* is positive, significant, and more pronounced only for the high-power subsample. An F-test confirms that the difference in coefficients for the *CIDH* between the high- and low-power subsamples is significant at the conventional level.

In columns (5) and (6) we employ leverage as a proxy for monitoring. Prior studies suggest that leverage can serve as a monitoring device. Therefore, a high (low) level of leverage indicates stronger (weaker) external monitoring (Ang et al., 2000; Stulz, 1990). We divide the sample into high- and low-leverage subsamples based on the median value of *Leverage*. Not surprisingly, we find that the relationship between CIDHs and credit ratings is positive, significant, and more pronounced only

[11] For example, we assign a score of 1 if there is a CEO/chair duality; if the CEO's equity holding is above the median; if the percentage of coopted directors on the board is above the median; if the CEO tenure is above the median; or if the CEO's total pay as a percentage of the total pay of the top five executives is above the median.

Table 9

Propensity score matched (PSM) sample. This table reports regression results based on PSM samples. Panel A presents the univariate comparison of means between treatment and control groups. Panel B presents the regression results. Robust *t*-statistics are reported in parentheses below the coefficients. We correct standard errors by using two-way clustering at both firm and year levels (Cameron et al., 2011). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Appendix A.

Panel A. Univariate tests of means between treatment and control groups.

Variables	**High Debt Incentive (treatment group)**	**Low Debt Incentive (control group)**	**Difference of mean (High − Low)**	
	Mean	***Mean***	***Diff.***	***t-stat***
Rating Score	12.459	12.049	0.410	3.62***
CEO Age	64.546	64.678	−0.132	−0.51
CEO Tenure	6.848	6.802	0.046	0.20
Total Pay	8.538	8.541	−0.003	−0.09
INST Total Ownership	0.817	0.814	0.003	0.61
Board Independence	0.868	0.869	−0.001	−0.40
Firm Size	8.689	8.676	0.013	0.24
Leverage	0.283	0.282	0.001	0.07
ROA	0.145	0.143	0.002	0.62
LOSS	0.105	0.110	−0.005	−0.43
Tangibility	0.287	0.284	0.003	0.28
Interest Coverage Ratio	0.141	0.147	−0.006	−0.67
SUBORD	0.093	0.088	0.005	0.46
Cash Flow Volatility	0.026	0.025	0.001	0.20
KZ	0.610	0.623	−0.013	−0.40

Panel B. Regressions results using PSM sample.

Variables	Main Model with all controls and fixed effects	Main Model Fama–MacBeth specification	Main Model Ordered Probit specification
	(1)	**(2)**	**(3)**
CIDH	**0.321****	**0.342*****	**0.218****
	(2.41)	**(4.03)**	**(2.49)**
Other controls	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
Year dummies	Yes	No	Yes
Observations	2,804	2,804	2,804
Adjusted/Pseudo R^2	0.754	0.803	0.290

for the low-leverage (low monitoring) subsample. An F-test suggests that the difference in coefficient of *CIDH* is significantly more pronounced for the subsample of firms with a low level of leverage (χ^2 = 12.07; p = 0.001).

Taken together, results from this analysis provide strong evidence that CIDHs have a more pronounced effect on credit ratings when there is a poor incentive alignment (i.e., more agency problems), lending support to our incentive alignment-based argument.

3.7.2. CEO inside debt and credit ratings: The role of corporate information environment

Prior studies show that CIDHs improve the corporate information environment and transparency as reflected by lower abnormal accruals, a lower probability of earnings misstatements, a lower prevalence of earnings benchmark beating, and better accruals quality (He, 2015). Therefore, we predict a better information environment stemming from CIDHs to reduce information risk and default risk, which in turn results in better credit ratings. If this argument holds, the positive relationship between CIDHs and credit ratings would be stronger for firms that are exposed to more information asymmetry. To test this prediction empirically, we use three measures of information asymmetry: (i) discretionary accruals estimated from the modified Jones model; (ii) 10-K file size; and (iii) the percentage of weak modal words in the 10-K file.[12] For each of the information asymmetry measures, we split the sample into two subgroups based on the median value of the information asymmetry proxy. Therefore, the subsample of firms with more (less) than the median discretionary accruals, 10-K file size, and weak modal are subject to more (less) information asymmetry.

Panel B of Table 11 presents results from this analysis. In columns (1) to (6), we find that the relationship between *CIDH* and credit ratings is positive, significant, and more pronounced for the subsample of firms with more discretionary accruals (discretionary accruals > median) (χ^2 = 3.08; p = 0.079), larger 10-K file size (10-K file size > median) (χ^2 = 4.36; p = 0.037),

[12] These measures have been extensively used in prior literature to proxy for information asymmetry (Callen et al., 2013; Ertugrul et al., 2017; Hasan and Habib, 2020; Lee, 2012; Loughran and McDonald, 2011).

Table 10

Entropy balanced sample. This table reports regression results based on an entropy balanced sample. Panel A shows proof that the means of our treatment and control groups converge when entropy balancing estimates are implemented. Panel B presents the regression results. Robust *t*-statistics are reported in parentheses below the coefficients. We correct standard errors by using two-way clustering at both firm and year levels (Cameron et al., 2011). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Appendix A. Detailed discussion is presented in Section 3.6.2 of the main text.

Panel A. Proof that treatment and control group means converge after entropy balancing.

	High Debt Incentive (treatment group)	***Low Debt Incentive (control group)***	***High Debt Incentive (treatment group)***	***Low Debt Incentive (control group)***
Variables	*Before Balancing*		*After Balancing*	
CEO Age	64.890	63.970	64.890	64.890
CEO Tenure	6.304	7.573	6.304	6.304
Total Pay	8.638	8.414	8.638	8.638
INST Total Ownership	0.806	0.814	0.806	0.806
Board Independence	0.879	0.853	0.879	0.879
Firm Size	8.947	8.502	8.947	8.947
Leverage	0.278	0.282	0.278	0.278
ROA	0.145	0.144	0.145	0.145
LOSS	0.094	0.127	0.094	0.094
Tangibility	0.290	0.271	0.290	0.290
Interest Coverage Ratio	0.121	0.165	0.121	0.121
SUBORD	0.080	0.102	0.080	0.080
Cash Flow Volatility	0.025	0.028	0.025	0.025
KZ	0.468	0.744	0.468	0.468

Panel B. Regressions results using entropy balanced sample.

Variables	Main Model with all controls and fixed effects	Main Model Fama MacBeth specification	Main Model Ordered Probit specification
	(1)	**(2)**	**(3)**
CIDH	**0.226****	**0.186*****	**0.155****
	(2.03)	**(3.64)**	**(2.09)**
Other controls	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
Year dummies	Yes	No	Yes
Observations	4,646	4,646	4,646
Adjusted/Pseudo R^2	0.756	0.794	0.287

and a higher percentage of weak modal words (weak modal > median) (χ^2 = 12.07; p = 0.001). These results thus support our information environment-based argument for a positive relationship between CIDHs and credit ratings.

3.8. Disentangling the direct and indirect effects of CIDHs

Prior literature shows that CIDHs are associated with fewer abnormal accruals and better accruals quality (Dhole et al., 2016; He, 2015). Studies also show that better reporting quality is associated with less uncertainty about credit risk for CRAs (Akins, 2018). Given these findings, it is important to understand the extent to which CIDHs affect credit ratings directly (without mediation by accruals quality in the model) and indirectly through their effect on a firm's accruals quality, the so-called mediation effect. We use a simultaneous equation model for estimating such effects.

We specify the following model to isolate the direct and indirect effect of CIDHs:

$$RATING_{t+1} = \psi_0 + \psi_1 CIDH_t + \psi_2 DiscretionaryAccruals_t + \psi' Controls_t + INDFE + YEARFE + \varepsilon \tag{2.1}$$

$$DiscretionaryAccruals_t = \gamma_0 + \gamma_1 CIDH_t + \gamma' Controls_t + INDFE + YEARFE + \varepsilon \tag{2.2}$$

The model consists of two equations. Equation (2.1) exhibits how the discretionary accruals (*DAC*) channel influences *RATING*. The presence of *CIDH* in Equation (2.1) allows for the possibility that CIDHs may have a direct effect on credit ratings. Equation (2.2) shows how *CIDH* affect credit ratings through the *DAC* channel (indirect effect). In summary, the direct effect of *CIDH* on *RATING* is captured by ψ_1 and the indirect effect is captured by $\gamma_1\psi_2$ in Equations (2.1) and (2.2), respectively. In Equation (2.2), following prior studies (e.g., Fang et al., 2021; Li et al., 2020; Ng et al., 2021; Ramalingegowda et al., 2021), we additionally control for market-to-book ratio (*MTB*) and an indicator variable (*Big4*), set to one if a firm is audited by one of the Big 4 accounting firms, and to zero otherwise. Inclusion of these additional controls ensure that our two-equation simultaneous equations model is identified (Wooldridge, 2015).

Table 12 presents the results from channel analysis. In column (1) we find that the coefficient of *CIDH* is positive and significant (p < 0.01), while that of discretionary accruals is negative and significant (p < 0.01). These results suggest that CIDHs

Table 11

Cross-sectional regressions. This table reports results of cross-sectional regression analysis. Panel A tests whether the relationship between CEO inside debt and credit ratings is moderated by the incentive alignment, and Panel B tests whether the relationship between CEO inside debt and credit ratings is moderated by information environment. Robust *t*-statistics are reported in parentheses. We correct standard errors by using two-way clustering at both firm and year levels (Cameron et al., 2011). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Chi-square test statistics and *p*-values are provided if the null hypothesis is that the coefficients for *CIDH* for both subsamples are the same. Variable definitions are provided in Appendix A.

Panel A: CEO inside debt and credit ratings: The role of incentives alignment (i.e., corporate governance mechanism)

	CEO Power Index		CEO Power Index		Leverage	
Variables	High Power (score $\geq$ 4)	Low Power	High Power (score $\geq$ 3)	Low Power	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
CIDH	**0.517****	**0.152**	**0.367****	**0.149**	**−0.008**	**0.439*****
	(2.52)	**(1.50)**	**(2.18)**	**(1.35)**	**(−0.06)**	**(3.18)**
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,483	3,163	2,405	2,241	2,323	2,323
Adjusted R^2	0.776	0.775	0.781	0.769	0.766	0.753
Chi(2) Stat	6.71***		3.12*		12.07***	
Chi(2) *p*-value	0.009		0.077		0.001	

Panel B: CEO inside debt and credit ratings: The role of the corporate information environment

	Discretionary Accruals		10-K File Size		Weak Modal	
Variables	High	Low	Large	Small	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
CIDH	**0.352*****	**0.131**	**0.302*****	**0.132**	**0.440*****	**−0.008**
	(2.74)	**(0.94)**	**(2.69)**	**(1.11)**	**(2.61)**	**(−0.07)**
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,203	2,203	2,304	2,305	2,304	2,305
Adjusted R^2	0.762	0.782	0.778	0.750	0.769	0.760
Chi(2) Stat.	3.08*		4.36**		12.07***	
Chi(2) p-value	0.079		0.037		0.001	

Table 12

Direct and indirect effects of CIDHs. This table reports simultaneous equation regression results of estimating the direct and indirect effects (through discretionary accruals) of CIDHs on credit ratings. In column (2), we additionally control for market-to-book ratio (*MTB*) and an indicator variable (*Big4*), which is set to one if a firm is audited by one of the Big4 accounting firms, and to zero otherwise. Robust *t*-statistics are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Appendix A.

	(1)	(2)
Variables	*RATING*	*Discretionary Accruals*
CIDH	**0.199*****	**−0.002***
	(3.04)	**(−1.83)**
Discretionary Accruals	**−2.320*****	
	(−3.15)	
CEO Age	0.002	−0.000*
	(0.62)	(−1.68)
CEO Tenure	−0.001	0.000
	(−0.34)	(0.55)
Total Pay	−0.140***	−0.001
	(−3.78)	(−1.09)
INST Total Ownership	−0.734***	0.002
	(−3.86)	(0.63)
Board Independence	−0.012	0.013*
	(−0.03)	(1.79)
Firm Size	1.372***	−0.002***
	(57.08)	(−3.89)
Leverage	−1.685***	0.003
	(−8.00)	(0.77)
ROA	5.956***	0.004
	(14.27)	(0.43)
LOSS	−0.147*	0.002
	(−1.78)	(1.04)
Tangibility	−0.836***	−0.012***
	(−5.07)	(−3.51)

Table 12 (*continued*)

	(1)	(2)
Variables	*RATING*	*Discretionary Accruals*
Interest Coverage Ratio	−1.321***	
	(−10.36)	
SUBORD	−0.311***	
	(−3.73)	
Cash Flow Volatility	−11.932***	0.114***
	(−13.69)	(6.35)
KZ	−0.465***	
	(−13.80)	
MTB		0.000
		(0.16)
Big4		0.001
		(0.29)
Constant	2.300***	0.087***
	(3.19)	(5.84)
Industry dummies	Yes	Yes
Year dummies	Yes	Yes
Observations	4,284	4,284
R^2	0.78	0.08
Direct effect		
CIDH	0.199***	
	(3.04)	
Indirect effect		
Discretionary Accruals	0.006	
	(1.58)	
Total effect	0.205***	
	(3.13)	

(and discretionary accruals) increase (and decrease) *RATING* directly (i.e., independently). In column (2), we find that *CIDH* is negatively associated with discretionary accruals ($p < 0.10$), suggesting that CIDHs reduce discretionary accruals. This finding is consistent with that of He (2015). When we estimate the effect of *CIDH* on credit ratings through its effect on a firm's discretionary accruals (indirect effect), we find that this effect is statistically insignificant. However, the total effect (i.e., the sum of direct and indirect effects) of *CIDH* on credit ratings is positive and significant (coefficient = 0.205; $p < 0.01$). Overall, findings from this analysis signify that CIDHs have a direct effect on credit ratings, lending support to our main finding.

4. Concluding remarks

In this study, we have investigated the relationship between CIDHs and credit ratings of firms in the United States. Prior literature shows that CIDHs reduce managerial opportunistic and risk-seeking behaviors, which results in less cash flow risk, information risk, and default risk. Therefore, we predict that CIDHs are related to favorable credit ratings. Our empirical analysis provides support for this hypothesis. We show that our findings are both statistically and economically significant and that they remain robust in a battery of tests, implying that the association is unlikely to be spurious. To alleviate the concern with endogeneity, we use IV-based 2SLS and IV regression estimations using heteroskedasticity-based instruments. In addition, we employ propensity score matching and entropy balancing estimates. In all cases, findings from our analysis remain robust. In the cross-sectional analyses, we find that the relationship between CIDHs and credit ratings is more pronounced when agency problems are high and firms are exposed to more information asymmetry.

Our findings contribute to the emerging literature on CIDHs. Prior studies show that CIDHs reduce the cost of equity (Shen and Zhang, 2020), the cost of debt (Anantharaman et al., 2014), debt covenants (Chava et al., 2010), and the agency cost of debt (Edmans and Liu, 2011). We extend this literature by demonstrating that CIDHs help improve a firm's credit ratings. Finally, our finding that CRAs incorporate CIDHs in evaluating the creditworthiness of a firm contributes to credit rating literature.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Variable definitions

Variable Name	Definition
RATING	Long-term credit rating issued by Standard & Poor's (S&P). We assign numeric scores to the alphanumeric values with C = 1 and AAA = 21.
CIDH	The natural logarithm of one plus the debt-to-equity ratio of CEO compensation.
CIDH_ALT1	The natural logarithm of one plus the ratio of CEO-to-firm debt-to-equity.
CIDH_ALT2	A binary variable that takes a value of 1 if the ratio of CEO's debt-to-equity to firm's debt-to-equity is greater than 1, and 0 otherwise.
CIDH_ALT3	CEO debt compensation divided by a firm's lagged total assets.
CEO Age	CEO age, measured as the natural logarithm of the age of the CEO in year *t*.
CEO Tenure	Number of years the current CEO has been in the role.
Total Pay	Natural logarithm of one plus total CEO compensation as reported in ExecuComp.
INST Total Ownership	The percentage of total institutional ownership.
Board Independence	The number of independent directors scaled by board size.
Firm Size	The natural logarithm of market capitalization of the firm (PECC_F*CSHO).
Leverage	The ratio of total liabilities (DLC + DLTT) to total assets (AT).
ROA	Firm profitability, measured as the operating income (OIBDP) scaled by total assets (AT)
LOSS	A dummy variable that takes a value of 1 if income before extraordinary items (IB) is negative, and 0 otherwise.
Tangibility	Property, plant and equipment (PPENT) scaled by total assets.
Interest Coverage Ratio	Operating income (OIBDP) divided by interest expense (XINT).
SUBORD	A dummy variable that takes a value of 1 if the firm has subordinated debt, 0 otherwise
Cash Flow Volatility	Standard deviation of cash flow (OANCF/AT) for years $t-4$ to t.
KZ	A measure of financing constraints. Following Jha and Cox (2015), we measure this as: −1.002*(OIBDP/AT) − 39.368*(DV/AT) − 1.315*(CHE/AT) + 3.139*Leverage + 0.283*Tobin Q
Discretionary Accruals	The absolute value of discretionary accruals calculated by using the modified Jones (1991) model.
10-K File Size	A measure of readability of financial statements. We measure this as the natural logarithm of one plus gross file size (Loughran and McDonald, 2016).
Weak Modal	The count of weak modal words scaled by total words in the 10-K file (Loughran and McDonald, 2016).
CEO Power Index	This index is based on five components:(a) CEO/chair duality: if yes, we assign 1 point, 0 otherwise; (b) equity ownership: if this is above the sample median, we assign 1 point, 0 otherwise;(c) board co-option: if this is above the median then we assign 1 point, 0 otherwise;(d) CEO tenure: if this is above the sample median then we assign 1 point, 0 otherwise; and (e) CEO pay slice: if this is above the sample median then we assign 1 point, 0 otherwise. The CEO Power Index score ranges from 0 to 5.

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