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Firm complexity and credit ratings☆

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ABSTRACT

This paper examines the effect of firm complexity on credit ratings. Using a sample of U.S. non-financial firms and the state-of-the-art measure of firm complexity, we document a significantly negative relation between firm complexity and credit ratings, suggesting that rating agencies assign significantly lower credit score to more complex firms. Our results remain robust to alternative specifications and various endogeneity checks. Moreover, we find that the negative effect on credit ratings becomes weaker in more transparent and better-governed firms. Finally, we show that the effect is more pronounced during periods of high policy uncertainty. Overall, our paper provides a better understanding of complex firms and highlights the importance of transparency that enhances creditworthiness and mitigates credit risk.

1. Introduction

This paper investigates whether and to what extent credit ratings that reflect borrower's creditworthiness are associated with the complexity of the organization. We view complexity as an equilibrium outcome of corporate strategic and financial decisions observable in the data. As argued in Loughran and McDonald (2024), firm complexity is an important multifaceted concept, difficult to quantify with significant explanatory power for firm-level economic outcomes. Even though, generally speaking, firm complexity is positively associated with firm size, both differ in observable and time-varying characteristics as well as their impact on the dependent variable of interest. In our paper, we use state-of-the-art firm complexity metric developed in Loughran and McDonald (2024) and we relate it to various firm-based measures of creditworthiness.

Clearly, firm complexity should be inversely related to the easiness of assessing and projecting future operations of the firm, a fact that has profound implications for regulators and capital providers. On the other hand, firm complexity could yield tangible benefits to stakeholders in many aspects of corporate activity.

With this in mind, we develop two main competing research questions. First, we conjecture that more complex firms are more likely to have significantly lower credit ratings compared to the less complex ones, as complex firms are more likely to suffer from more severe information asymmetry problem (Byun, Choi, Hwang, & Kim, 2013; De la Fuente & Velasco, 2020; Larrain, Sertsios, & Urzúa, 2021; Maksimovic & Phillips, 2007). On the other hand, more complex firms benefit from the coinsurance effect – lower default risk that arises because business segments of complex firms have less correlated cash flows that tend to insure each other (Lewellen, 1971). It follows that a complex firm should have a lower default risk than a similar non-complex firm of the same size, and therefore, a complex firm is likely to receive a better credit

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rating, ceteris paribus. The coinsurance effect as mentioned above is reinforced by the "replicability" effect of large, complex, and successful corporations, as it is nearly infeasible to replicate the success of such organizations (Reeves, Levin, Fink, & Levina, 2020). It seems there can be only one Alphabet, Meta, or Nvidia. Given these conflicting predictions provided by theory and empirical evidence, our study attempts to answer the question of which of these two effects prevails.[1]

To test these predictions, we employ a sample of U.S. non-financial firms over the period 1994 through 2017 with 15,482 firm-year observations. Our main explanatory variable is a measure of firm complexity developed in Loughran and McDonald (2024) that uses machine learning techniques together with a lexicon. They document that their complexity measure used in tandem with the size of the 10 K report "dominates traditional measures" of firm complexity found in the corporate finance literature. Therefore, as suggested Loughran and McDonald (2024) in all regressions we use firm complexity proxy in tandem with the variable that captures the size of 10 K (in addition to all standard controls). Our response (dependent) variable is the measure of credit ratings provided by Standard and Poor's. More specifically, we use three alternative scales of credit ratings that reflect borrower's creditworthiness.

Our main empirical findings can be summarized as follows. First and foremost, we find a negative association between firm complexity and credit ratings implying that more complex firms, ceteris paribus, have higher borrowing costs. This result lends support to the argument that complex firms suffer from more severe information asymmetry problem as compared to less complex organizations. To put it differently, outsiders have access to less information about complex firms, more complex information, or have a higher cost of acquiring information than insiders and therefore debt's required rate of return is higher for these firms. This effect is statistically and economically significant and persists for each of our three distinct measures of credit ratings. Consequently, we do not find support for the coinsurance effect hypothesis.

Next, we conduct additional tests to corroborate our main findings. We demonstrate that the observed effect appears to be stronger in the three-year period after the enactment of the Sarbanes-Oxley Act (SOX) as compared to the pre-SOX period. This result could be explained by the increased amount of disclosure in 10 K reports in the post-SOX period mandated by stricter stock exchange listing rules that in turn may reflect enhanced corporate complexity that emerge from these reports. This result is generally consistent with the literature indicating that SOX mandates enhanced disclosure but at the same time the effect of this additional disclosure may be detrimental to shareholders leading to e.g., higher firm risk and greater cost of equity (e.g., Akhigbe, Martin, & Newman, 2008; Ashbaugh-Skaife, Collins, Kinney Jr, & LaFond, 2009). In separate tests, we show that our main evidence – that more complex firms exhibit significantly lower debt ratings – does not depend on the quality of firm's information environment, market liquidity of firm's publicly traded stock, corporate governance arrangements, percentage of institutional ownership in firms' ownership base, degree of economic policy uncertainty, and the incidence of the election year. Nevertheless, it should be emphasized that the effect is somewhat stronger for companies with weaker information environments, worse quality of corporate governance and during times of increased policy uncertainty.

We then turn to a series of further robustness checks. We start by including in the panel data model firm fixed effects (in addition to industry fixed effects). This econometric specification is highly demanding, as incorporating fixed effects requires estimating a substantial number of dummy variables (one for each firm), thereby reducing the degrees of freedom. As such, this process can increase the difficulty of detecting statistically significant effects and works against finding a significant relation between firm complexity and credit ratings. In the next test, we use lagged firm complexity. Using lagged explanatory variables addresses the issue of autocorrelation of the error term and captures the dynamic effect of firm complexity on credit ratings. In the following step, we use the propensity score matching (PSM) algorithm. This method is used in corporate finance research to address selection bias and improve causal inference. Finally, we use alternative measures of firm complexity and credit ratings. Overall, each of the above tests confirms our baseline results reinforcing our primary hypothesis that complex firms exhibit lower credit ratings.

To the best of our knowledge, our paper is the first to investigate a relationship between firm complexity and credit ratings. It should be stressed, however, that the literature that focuses on firm complexity as the central explanatory variable is very limited. For example, among more recent papers, firm complexity has been analyzed vis-à-vis voluntary disclosure (Farzamfar, Foroughi, Bahar, & Ng, 2024), post-earnings announcement drift (Barinov, Park, & Yıldızhan, 2024), information asymmetry (Clark, Palepu, & Siddique, 2024), board composition (Markarian & Parbonetti, 2007), and corporate social responsibility (Läger, Bouzzine, & Lueg, 2022). On the other hand, there are many studies that use firm complexity in a set of additional tests or robustness checks with the aim to gain further insights on the link between the firm-level economic outcome and their main explanatory variable. For example, Offenberg, Straska, and Waller (2014) find that value gains from acquisitions are affected by the target firm complexity, Bai and Mkrtchyan (2023) show that the association between CEO turnover and firm performance is moderated by complexity of the firm, further Bennett, Stulz, and Wang (2020) demonstrate that the impact of stock price informativeness on firm-level productivity is weaker among complex firms, whereas Duchin and Schmidt (2013) indicate that more complex organizations are more likely to divest pollutive plants in response to environmental pressures. We extend this literature by showing that, ceteris paribus, rating agencies assign lower debt ratings to more complex firms and the impact of firm complexity on credit ratings becomes weaker in firms, where information asymmetry is less extreme.

Second, our study adds to the broad literature on the determinants of credit ratings. To provide a few examples, this line of research examines the association between cost of corporate borrowing (reflected in credit ratings) and ownership structure (Lin et al., 2011); regulation (Dimitrov, Palia, & Tang, 2015); information reliability (Goel & Thakor, 2015); role of large shareholders (Kedia, Rajgopal, & Zhou, 2017); subjectivity of analyst ratings (Fracassi, Petry, & Tate, 2016); reputations (Baghai & Becker, 2020); policy uncertainty (Kaviani, Kryzanowski, Maleki, & Savor, 2020); and liquidity risk (Mian & Santos, 2018). Building on this line of literature, we demonstrate that firm complexity is an important but omitted factor in empirical econometric models that has an incremental ability to explain firm-specific heterogeneity in credit ratings.

The remainder of the study proceeds as follows. Section 2 provides an overview of the theoretical background and develops hypotheses. Section 3 describes the sample, variables, and summary statistics. Section 4 discusses the results from the baseline analysis and robustness checks. Section 5 provides results from the additional empirical tests and robustness checks. Section 6 concludes the paper.

2. Related literature and hypothesis development

2.1. Main hypotheses

In the corporate context, managers have access to more information about firm's cash flows and profitability vis-à-vis firm's outside investors. Ideally, managers should use 10-K reports to lower information asymmetry between investors and firms. Hence, when preparing 10-K filings, management has the choice of wording between less and more complicated terminology, which then allows investors to learn more about firms. On the other hand, complexity may also arise from asymmetry between internal and external business and economic factors, the

[1] More comprehensive discussion of the literature together with secondary hypotheses is provided in the next section.

multi-national corporate structure, and different quality of firm's information environment.

Complex firms are likely to receive lower ratings for several reasons. First, the information asymmetry between management and external stakeholders in relation to the firm's cash flows and risks might be related to firm complexity (Dolde & Mishra, 2007; Liu & Lai, 2012). Moreover, Jennings, Seo, and Tanlu (2014) show that information sharing among business segments in a multi-segment firm is inherently problematic. They also argue that managers struggle to separate information based on relevance, which makes it difficult for them to disclose accurate and relevant information to shareholders. As a result, external stakeholders face lower quality-information about the firm's future cash flows compared to the management.

Further, excess corporate complexity comes with a slew of costs for complex firms and their investors. The complexity of the firm is costly not only for internal operations but also for external growth. Furthermore, excess complexity might have a negative effect on customer satisfaction and competitiveness. Also, more complex firms require better and more specialized managers, resulting in higher monitoring costs (Coles, Daniel, & Naveen, 2008; Linck, Netter, & Yang, 2008). Finally, monitoring costs of the debtholders are higher for complex firms, since debtholders might demand higher returns to compensate for greater risk taking (Becker & Milbourn, 2011; Kedia, Rajgopal, & Zhou, 2014).

Putting it all together, we conjecture that complex firms are likely to have greater information asymmetry, higher costs of operations, and higher costs of managerial monitoring. All of the above increase the agency risk faced by external stakeholders and lower the expected value of the cash flows to the firm and its external stakeholders. Higher risks associated with firm's operations and multi-segment organizational structure should lead to lower credit ratings in the complex organization. Accordingly, we propose our first hypothesis:

H1. : All else being equal, firm complexity has a negative effect on corporate debt ratings.

A competing view is that firm complexity might be beneficial to firms. In the classic paper, Lewellen (1971) argues that since complex firms operate many different businesses from different industries, they produce cash flows that are not perfectly correlated with each other. Consequently, these segments tend to co-insure each other in business cycles in a sense that during economic downturns higher cash flows of one segment can make up for lower cash flows of the other segment, and vice versa. In this situation, the multi-segment company has higher cash flows, on average, as compared to the pure-play company that operates only one business segment in a single industry. This further implies that multi-segment complex firms have higher debt capacity compared to a single-segment firm. To put it differently, the marginal cost of an additional unit of debt for a multi-segment complex firm should be lower than for a single-segment firm because of the lower business risk tied to coinsured cash-flows as opposed to cash flows that are not co-insured and thus more volatile. Furthermore, it is argued that organizational complexity may lead to greater resilience and adaptability. What is more, complexity of corporate strategy could make it harder to replicate by the company's peers and yield long-term competitive advantage over rivals (Reeves et al., 2020). This leads us to our alternative competing hypothesis:

H2. : All else being equal, firm complexity has a positive effect on corporate debt ratings.

2.2. Secondary hypotheses

In the sections below, we develop secondary hypotheses that are complimentary to the main hypotheses discussed above.

2.2.1. The role of information environment

The information environment within the realm of corporate finance refers to the quality, transparency, and accessibility of information that firms provide to stakeholders, including investors, analysts, and regulators. A well-structured firm's information environment reduces information asymmetry, thereby enhancing decision-making processes and contributing to the efficiency of capital markets.

It appears that in the existing finance literature, the quality of information environment is an important conditional variable used both in corporate and market finance research. For example, Bae, Stulz, and Tan (2008) find that analysist domiciled in proximity to firms are particularly important for firms with more opaque information environment. Further, Fernandes & Ferreira (2008) show that the impact of the stock cross-listing on the strength of the information environment is not homogenous and varies across countries, whereas Tsang, Yang, and Zheng (2022) document that the higher quality of information environment, the greater the chance that the firm has secondary security actively listed and traded in a foreign country.

In light of the above, we are particularly interested in the question of the interplay between firm complexity (our main explanatory variable) and credit ratings, when the degree of strength of the information environment varies. The existing literature provides some guidance in this regard. For example, Cheng, Jin, and Ma (2023) find that managers engage in tone management of mandatory disclosure reports to benefit from insider trading and more opaque information environment amplifies the self-serving behavior of managers. From a somewhat different angle, Feldman, Govindaraj, Livnat, and Segal (2010) show that manager tone is incrementally more informative when the information environment surrounding the firm is weaker. Similarly, we conjecture that the strength of the information environment can play an important role in mitigating the negative relationship between firm complexity and debt ratings. A transparent and high-quality information environment can provide creditors with greater visibility into firm's operations, reducing the uncertainty and perceived risks associated with complex firms. Our next hypothesis is therefore:

H3. : The potential negative effect of firm complexity on corporate debt ratings becomes weaker if firm's information environment is stronger.

2.2.2. The role of corporate governance

Corporate governance is an important economic factor that appears to determine corporate behavior, organizational structure, and performance (e.g., Bae, Baek, Kang, & Liu, 2012; Chattopadhyay, Shaffer, & Wang, 2020). A survey of literature reveals that corporate governance arrangements can be associated with firm complexity. For example, weak managerial monitoring may lead to external growth through cross-industry and cross-border mergers and acquisitions that render firms more complex (e.g., Duchin & Schmidt, 2013; Ishii & Xuan, 2014). Similarly, a classic and widely cited paper on corporate governance by Gompers, Ishii, and Metrick (2003) demonstrates that weaker shareholder rights lead to more corporate acquisitions, which make companies bigger and more complicated.

An interesting avenue in the corporate governance research is the role of institutional investors as external monitors. Interestingly, recent papers document that passive institutional investors (e.g., BlackRock, Vanguard, and State Street) engage directly with the management with the aim to pressure management to shape corporate strategies and policies (e.g., Croci, Mazur, & Salganik-Shoshan, 2024; Dimson, Karakaş, & Li, 2015; Kakhbod, Loginova, Malenko, & Malenko, 2023; Karolyi, Andrew, & Liao, 2020; McCahery, Sautner, & Starks, 2016). Taken together, corporate governance literature implies that good corporate governance should mitigate negative effect of firm complexity on credit ratings either through internal governance mechanisms such as board of directors, or alternatively through external corporate governance monitoring activities by institutional investors. Consequently, our

Table 1
Descriptive Statistics.

Descriptive statistics for entire sample								
Variables	Sample	Mean	Median	Min	P25	P75	Max	SD
S&P24	15,482	18.34	18.00	1.00	16.00	20.00	24.00	2.54
S&P22	15,482	12.05	12.00	3.00	10.00	15.00	22.00	2.87
S&P17	15,482	9.42	9.00	1.00	6.00	9.00	17.00	1.21
COMPLEX	15,482	8.78	8.65	3.24	7.45	9.87	12.86	0.90
FILE	15,482	3598.32	987.54	119.74	313.87	4618.67	5174.98	7844.11
SIZE	15,482	8.40	8.34	4.27	7.49	9.29	10.64	1.25
LEV	15,482	0.35	0.32	0.00	0.22	0.44	0.61	0.19
NI/TA	15,482	0.03	0.03	−1.36	0.01	0.07	0.29	0.10
MB	15,482	2.98	1.97	0.18	2.79	5.95	7.04	0.43
LOSS	15,482	0.19	0.00	0.00	0.00	0.00	1.00	0.39
TANG	15,482	0.63	0.57	0.00	0.26	0.93	2.01	0.43
INTCOV	15,482	4.18	3.61	−4.09	2.76	6.46	7.45	1.50
SDRET	15,482	0.10	0.08	0.03	0.06	0.12	0.51	0.06
IO	15,482	0.75	0.79	0.01	0.65	0.89	1.00	0.18

This table reports the descriptive statistics for our sample. Appendix A provides a detailed description of the variables used in the regression analysis. We winsorize continuous variables at the 1 % and 99 % levels.

next testable hypothesis is as follows:

H4. : The negative effect of firm complexity on corporate debt ratings is mitigated by better quality of corporate governance.

2.2.3. The effect of policy uncertainty

Clearly, firms do not exist in a vacuum and are influenced by economic, social, and political factors. Unforeseen changes in macroeconomic conditions such as inflation, interest rates, national budget deficits, and elections can result in policy amendments that in turn affect firms (Bordo, John, & Christoffer, 2016; Ng, Saffar, & Zhang, 2020; Danisman, Demir, & Ozili, 2021). Policy uncertainty, which refers to unpredictable government policies and changes in regulatory frameworks, has been shown to impede firm efficiency (Boutchkova, Doshi, Durnev, & Molchanov, 2012), profitability (Kahle & Stulz, 2013; Mian & Sufi, 2010), and increase stock return volatility (Shahzad, Raza, Balcilar, Ali, & Shahbaz, 2017). Moreover, Pástor and Veronesi (2012) argue that policy uncertainty should be considered as one of the risk factor for firm's operations.

When policy uncertainty is high, firms may be hesitant to invest in complex projects or engage in activities that could result in higher debt ratings. This could be because uncertainty creates riskier economic environment, which may make investors less willing to invest in firms with complex business models (Dang et al., 2022). Uncertainty around government policies could lead to changes in interest rates, inflation, and economic growth, which consequently could affect firm's ability to pay back its debts. The above implies that greater (lower) policy uncertainty can exacerbate (mitigate) the negative relationship between firm complexity and debt ratings on the condition that the relationship is negative. This is because policy uncertainty creates additional risks for firms with complex business models, which can further reduce their creditworthiness and increase the likelihood of a default. We thus hypothesize that greater policy uncertainty increases incremental risks for complex firms and consequently result in lower credit ratings. This leads to our final hypothesis:

H5. : High policy uncertainty aggravates negative association between firm complexity and corporate debt ratings.

3. Data, sample, and econometric specification

3.1. Data and sample

To explore how a firm's complexity affects its credit ratings, we utilize data from various sources including Compustat (S&P credit ratings and accounting measures), CRSP (stock price), I/B/E/S (analyst-following), Thomson Reuters (institutional ownership), and BoardEx (board of directors). We exclude financial firms due to their unique regulatory and reporting requirements. In additional analyses (Tables A2–3) we use M&A and divestiture data downloaded from LSEG (formerly Refinitiv), as well as voting and corporate governance data from ISS (Table A4). In our final tests, we construct economy-wide variables based on the data obtained from the US Census Bureau (Table A6).

Our final sample is an unbalanced panel consisting of 15,482 observations spanning the period from 1994 to 2017. We end the sample in the year 2017 because credit ratings variable available on Compustat has been updated for the last time in 2017, therefore it is not feasible to expand our dataset beyond 2017. In any case, our sample spans over a 20 year-period with many boom and bust cycles for the US economy.

3.2. Variables

We measure the S&P debt ratings by examining the letters assigned to S&P's long-term credit ratings, which range from AAA to D or SD, indicating descending credit quality. To be in line with previous research (Ashbaugh-Skaife, Collins, & LaFond, 2006; Cornaggia, Krishnan, & Wang, 2017; DeHaan, 2017; Ham & Koharki, 2016; Kim, Kraft, & Ryan, 2013), we translate these letter ratings into ordinal values using three scales: the S&P 24-point scale (S&P24), the S&P 22-point scale (S&P22), and the S&P 17-point scale (S&P17). These scales assign values from highest to lowest credit quality for each rating, ranging from 24 to 1 for S&P24, 22 to 1 for S&P22, and 17 to 1 for S&P17. Consequently, these ordinal measures (S&P24, S&P22, and S&P17) display a positive correlation with S&P letter ratings.[2]

For our main measure of firm complexity, we follow Loughran and McDonald (2024). This measure has been developed using machine learning techniques as well as a lexicon and has been made available on the website of the authors. They state that their firm complexity variable *"used in tandem with 10-K file size, provides a useful proxy that dominates traditional measures"*. Thus, we also download the variable that captures the size of the 10 K file available on the same website and we include it in our econometric specification as one of our controls.

An important strand of research uses textual analysis that examines tone and sentiment of mandatory SEC filings including 10 K reports (see e.g., Bae, Belo, Li, Lin, & Zhao, 2023; Loughran & McDonald, 2011; Loughran & McDonald, 2014) and relate it to different firm-level variables including performance, earnings management, and volatility. Alternative methods of reporting complexity use Accounting Reporting Complexity (ARC) method that employs XBRL tags (see e.g., Hoitash &

[2] See, for example, Appendix A for a detailed definition of variables.

Table 2
The impact of complexity disclosure on firm debt ratings.

Variables	S&P24	S&P22	S&P17
	(1)	(2)	(3)
COMPLEX	−0.4423	−0.4373	−0.4503
	(−12.58)***	(−12.54)***	(−11.89)***
LNFILE	0.0181	0.0158	0.0112
	(3.63)***	(2.81)***	(2.43)**
SIZE	0.9832	0.9871	0.8965
	(43.29)***	(43.22)***	(43.22)***
LEV	−3.0889	−3.0971	−2.9582
	(−20.18)***	(−20.16)***	(−20.82)***
NI/TA	1.8299	1.8284	1.6546
	(3.76)***	(3.75)***	(3.71)***
MB	0.0049	0.0046	0.0053
	(2.07)**	(2.00)**	(2.15)**
LOSS	−0.8687	−0.8681	−0.8176
	(−10.17)***	(−10.14)***	(−10.31)***
TANG	0.3484	0.3525	0.3026
	(4.53)***	(4.57)***	(4.18)***
INTCOV	0.0048	0.0050	0.0032
	(4.18)***	(4.19)***	(3.71)***
SDRET	−1.6108	−1.6288	−1.4099
	(−22.22)***	(−22.20)***	(−21.36)***
IO	1.7696	1.7866	1.5139
	(12.00)***	(12.06)***	(11.08)***
Constant	6.7553	5.7687	1.1945
	(9.77)***	(8.36)***	(1.93)*
Industry and Year effects	Yes	Yes	Yes
Adj R^2	0.6467	0.6460	0.6422
Nobs	15,482	15,482	15,482

This table reports the panel regression of firm debt credit ratings on complexity disclosure. The regression model is as follows:
$RATINGS_{i,t} = \alpha + \beta COMPLEX_{i,t-1} + CONTROLS_{i,t-1} + \varepsilon_{i,t}$ *(1)*
The dependent variable of interest, *RATINGSi,t,* indicates the numeric translation of S&P debt ratings (either S&P24, S&P22, or S&P17). In Column 1, S&P24 takes an ordinal value of 24 (1) for better (worse) letter ratings (e.g., AAA = 24, …. D or SD = 1). In Column 2, S&P22 takes an ordinal value of 22 (1) for better (worse) letter ratings (e.g., AAA = 22, …. D = 1). In Column 3, S&P17 takes an ordinal value of 17 (1) for better (worse) letter ratings (e.g., AAA = 17, …. CCC+ and lower grades = 1). *COMPLEX* is defined as the logarithm of the total number of Complex words in the 10-K filing. *CONTROLS* is the set of control variables with a one-year lag, including 10 K File size (*LNFILE*), firm size (*SIZE*), leverage (*LEV*), net income to total assets (*NI/TA*), market-to-book ratio (*MB*), operating loss (*LOSS*), tangibility (*TANG*), interest coverage (*INTCOV*), stock return volatility (*SDRET*), and institutional ownership (*IO*). Unless otherwise specified, all specifications include industry and year fixed effects. Detailed definitions of the variables are provided in Appendix A. The *t*-statistics shown in parentheses are based on standard errors that are adjusted for heteroscedasticity and are clustered at the firm level. We winsorize continuous variables at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

Hoitash, 2018, 2022). Nevertheless, the variable developed in Loughran and McDonald (2024) seem more appealing, as it uses full information contained in mandatory filings for a long time series since 1996 as opposed to the e.g., ARC approach that can only be used as of 2011.

3.3. Empirical model

To explore the relation between the firm complexity and its credit ratings, we use the specification model for panel data as in Eq. (1):

$$\mathrm{RATINGS}_{i,t} = \alpha + \beta \mathrm{COMPLEX}_{i,t-1} + \mathrm{CONTROLS}_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

where, the dependent variable, $RATINGS_{i,t}$, indicates the S&P debt ratings using different scales (i.e. *S&P24*, *S&P22*, and *S&P17*) for firm *i* in year *t* (as defined above). Our main variable of interest, $COMPLEX_{i,t-1}$, *is* the firm complexity variable developed in Loughran and McDonald (2024) based on textual analysis of 10 K reports using machine learning techniques and a lexicon. Following prior studies (Ashbaugh-Skaife et al., 2006; Cornaggia et al., 2017; DeHaan, 2017; Ham & Koharki, 2016), we use various controls that have been shown in the literature to affect firm's credit ratings (measured in year *t-1*) including 10-K file size (*LNFILE*), firm size (*SIZE*), market-to-book (*MB*), leverage (*LEV*), profitability (*NI/TA*), operating loss (*LOSS*), asset tangibility (*TANG*), interest coverage (*INTCOV*), stock return volatility (*SDRET*), and institutional ownership (*IO*). In all specifications, we control industry and year fixed effects. Industries are classified based on the two-digit SIC codes. In all regressions we use robust standard errors clustered by firm.+.

3.4. Summary statistics

Table 1 presents the descriptive statistics for our main variables. The S&P debt ratings are using three different scales: S&P 24-point scale (S&P24), S&P 22-point scale (S&P22), and S&P 17-point scale (S&P17). The scales assign ordinal values to each credit rating, with higher values indicating better credit quality. The mean credit rating for S&P24 is 18.43, for S&P22 is 12.32, and for S&P17 is 9.37, which are consistent with the findings of prior studies such as Park, Nam, Tsang, and Lee (2022), Griffin, Hong, and Ryou (2018), Cornaggia et al. (2017), and Ashbaugh-Skaife et al. (2006). The results suggest that the credit quality of the firms in the study tends to be relatively high, as evidenced by the mean credit ratings above 9.0 for all three scales. The use of multiple scales may allow for greater flexibility in analyzing the relationship between credit quality and firm complexity. The range of firm complexity scores falls between 7.63 and 10.65, with a median of 9.21. The range of firm complexity scores is relatively narrow, with a difference of only 2.02 between the highest and lowest scores. This suggests that the sample is relatively homogeneous in terms of firm complexity but still displays variability. The median value of 9.21 is closer to the lower end of the range, which may indicate that the majority of firms in the sample have relatively low complexity scores. The control variables exhibit standard characteristics, with mean and median values that are quite similar to each other indicating that the distributions of these variables are fairly symmetric.

3.5. Unit root test

Before we begin a full-fledge panel data analysis, we perform a unit root test. Running a unit root test on panel data is important particularly when analyzing data across different cross-sectional units (e.g., firms). We perform Hadri unit root test on the set of our main variables (se Table A5). As seen it the table, the obtained *p*-values from this analysis signify non-unit characteristics in the data and confirms stationarity of our dataset that helps avoid spurious results and ensures valid inference.

4. Empirical results

4.1. Main results

Table 2 reports the regression results of firm's debt ratings (measured by different translation of S&P debt ratings - S&P24, S&P22, and S&P17) on firm complexity measure, and a set of control variables as identified in Eq. (1). Year and industry-fixed effects are included in all specifications.

Table 2 shows that coefficient estimates on *COMPLEX* are negative and significant at the 1 % level in all specifications, suggesting a significant negative relation between firm complexity and S&P debt ratings. This results appears to be consistent with the Hypothesis H1, and therefore we reject Hypothesis H2. As conjectured, the effect is most likely due to lower quality of information about the firm's cash flows disclosed to external stakeholders that bear higher risks for holding firm's debt (Jennings et al., 2014). Another possibility is that the increase in operating costs (Harvard Business Review Analytic Services report, 2015), and monitoring costs of debtholders in complex firms

Table 3
The impact of complexity disclosure on firm debt ratings – Robustness checks.

Variables	Panel A: Firm and year fixed effects			Panel B: 5-year lagged independent variable		
	S&P24	S&P22	S&P17	S&P24	S&P22	S&P17
	(1)	(2)	(3)	(4)	(5)	(6)
COMPLEX	−0.2675	−0.2597	−0.3014			
	(−9.05)***	(−8.96)***	(−8.17)***			
$COMPLEX_{t-5}$				−0.2082	−0.2058	−0.2196
				(−2.34)**	(−2.32)**	(−2.54)**
LNFILE	0.0163	0.0127	0.0076	0.0146	0.0134	0.0101
	(2.78)***	(2.23)**	(2.07)**	(2.46)**	(2.29)**	(2.11)**
SIZE	0.6268	0.6287	0.5658	0.9555	0.9590	0.8791
	(9.89)***	(9.91)***	(9.15)***	(42.94)***	(42.88)***	(42.98)***
LEV	−1.9694	−1.9732	−1.7759	−3.5219	−3.5303	−3.3291
	(−11.94)***	(−11.95)***	(−11.26)***	(−24.66)***	(−24.61)***	(−25.03)***
NI/TA	0.0156	0.0122	0.0700	1.6734	1.6768	1.4568
	(0.19)	(0.17)	(0.42)	(3.53)***	(3.53)***	(3.37)***
MB	0.0017	0.0019	0.0020	0.0034	0.0045	0.0052
	(1.54)	(1.56)	(1.64)	(1.54)	(1.59)	(1.71)*
LOSS	−0.2429	−0.2425	−0.2291	−0.9101	−0.9080	−0.8737
	(−6.25)***	(−6.24)***	(−6.27)***	(−10.55)***	(−10.51)***	(−10.93)***
TANG	0.3452	0.3507	0.3432	0.0102	0.0099	0.0473
	(2.25)**	(2.29)**	(2.33)**	(0.18)	(0.16)	(0.92)
INTCOV	0.0001	0.0001	0.0001	0.0044	0.0046	0.0027
	(0.21)	(0.25)	(0.02)	(3.99)***	(4.00)***	(3.38)***
SDRET	−3.2264	−3.2283	−2.6955	−1.0660	−1.0767	−1.8675
	(−11.57)***	(−11.59)***	(−10.82)***	(−26.30)***	(−26.28)***	(−25.63)***
IO	0.2813	0.2809	0.1693	2.0555	2.0724	1.8526
	(2.13)**	(2.10)**	(1.34)	(14.08)***	(14.13)***	(13.51)***
Constant	7.2159	6.2248	1.8405	7.8748	6.8963	2.3204
	(12.03)***	(10.38)***	(3.15)***	(27.88)***	(24.39)***	(8.64)***
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.9568	0.9566	0.9551	0.5989	0.5983	0.5925
Nobs	15,482	15,482	15,482	7276	7276	7276

This table reports the panel regression of firm debt ratings on complexity disclosure (i) controlling for firm and year fixed effects, and (ii) use of using lagged independent variable. To measure S&P debt ratings, we translate letters assigned to S&P debt ratings into three ordinal scales: the S&P 24-point scale (S&P24) takes an ordinal value of 24 (1) for better (worse) letter ratings (e.g., AAA = 24, …. SD = 1); the S&P 22-point scale (S&P22) takes an ordinal value of 22 (1) for better (worse) letter ratings (e.g., AAA = 22, …. D or SD = 1); and the S&P 17-point scale (S&P17) takes an ordinal value of 11 (1) for better (worse) letter ratings (e.g., AAA =17, …. CCC+ and lower grades = 1). *COMPLEX* is defined as the logarithm of the total number of Complex words in the 10-K filing. *CONTROLS* is the set of control variables with a one-year lag, including 10 K File size (*LNFILE*), firm size (*SIZE*), leverage (*LEV*), net income to total assets (*NI/TA*), market-to-book ratio (*MB*), operating loss (*LOSS*), tangibility (*TANG*), interest coverage (*INTCOV*), stock return volatility (*SDRET*), and institutional ownership (*IO*). Detailed definitions of the variables are provided in Appendix A. The *t*-statistics shown in parentheses are based on standard errors that are adjusted for heteroscedasticity and are clustered at the firm level. We winsorize continuous variables at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

(Bushman, Piotroski, & Smith, 2004) can reduce firm's expected cash flows and increase the default risk of bondholders (Ashbaugh-Skaife et al., 2006).

The effects of the control variables are consistent with previous studies. More specifically, coefficients on firm size, net income to total assets, asset tangibility, interest coverage, and institutional ownership are all positive and significant at 1 % level, suggesting the positive impact of these factors on firms' debt ratings. On firm's debt is rated lower, if the firm has higher leverage, operating loss, and higher stock return volatility (these coefficient estimates are negative and significant at 1 % level).

To further reinforce our baseline findings, we investigate the potential effect of macroeconomic variables on credit ratings. Consistent with the previous studies (e.g., Ali & Daly, 2010; Figlewski, Frydman, & Liang, 2012), we incorporate several macroeconomic variables sourced from the U.S. Census Bureau as additional controls in our main econometric specification. These variables include the educational attainment of a state's population (*STATE_EDU*), the median household income at the state level (*STATE_INCOME*), the educational attainment of a county's population (*COUNTY_EDU*), and the median household income at the county level (*COUNTY_INCOME*). The results are presented in Table A6. As expected, the coefficient estimates on *COMPLEX* continue to exhibit significant negative association with credit ratings at the 1 % level, which consistent with our main findings.

4.2. Robustness checks

4.2.1. Firm fixed effects (FFE) and lagged variables

Despite considering various firm characteristics found in previous studies that can affect firm's debt ratings, it is possible that there are still unobservable firm factors omitted from the model. This may lead to endogeneity issues that bias our estimates. Therefore, we re-estimate Eq. (1) with inclusion of both firms and year fixed effects. The inclusion of fixed effects helps to control for time-invariant factors that may be correlated with both firm complexity and debt ratings. By including firm fixed effects, we account for unobservable characteristics that are specific to each firm, such as its business model, management quality, and financial health. Year fixed effects control for macroeconomic conditions and regulatory changes that affect all firms in a given year.

The regression results reported in Panel A of Table 3 suggest that the negative relationship between firm complexity and debt ratings persists even after controlling for firm and year fixed effects. The complexity coefficient estimates are negative and statistically significant at the 1 % level for all measures of debt ratings - S&P24, S&P22, and S&P17. This findings continue to support *Hypothesis H1* that higher firm complexity is associated with lower credit quality due to information asymmetries.

Further, to take into account unobserved effects that can affect concurrent firm complexity and credit ratings, we estimate Eq. (1) replacing the current firm complexity level with its five-year lag (*$COMPLEX_{t-5}$*). In other words, the use of a five-year lag for firm complexity helps address potential reverse causality issues, where

Table 4
Propensity score matching analysis.

Variables	Panel A: Propensity score matching		
	Treatment	Control	t-test
FILE	2899.32	2896.54	0.54
SIZE	8.1147	8.1116	0.38
LEV	0.4077	0.3854	0.87
NI/TA	0.0662	0.0689	1.17
MB	2.8744	2.9343	0.43
LOSS	0.1744	0.1732	0.28
TANG	0.5028	0.5079	0.56
INTCOV	14.8777	15.8068	0.67
SDRET	0.0978	0.0970	0.40
IO	0.7542	0.7552	0.28
	Panel B: Complexity disclosure and credit ratings		
	S&P24	S&P22	S&P17
COMPLEX	−0.1684	−0.1581	−0.1982
	(−5.95)***	(−5.88)***	(−5.10)***
Constant	6.0929	6.0654	1.7141
	(10.10)***	(9.54)***	(2.37)**
Control variables	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
Adj R^2	0.4882	0.4869	0.4715
Nobs	1036	1036	1036

This table reports panel regression results of S&P debt ratings on firm complexity and controls using PSM analysis. Panel A reports the mean values of the matched variables for treated and control firms along with the corresponding *t*-statistics. Panel B reports the results of the regression-based on a PSM framework. To measure S&P debt ratings, we translate letters assigned to S&P debt ratings into three ordinal scales: the S&P 24-point scale (*S&P24*) takes an ordinal value of 24 (1) for better (worse) letter ratings (e.g., AAA = 24, …. SD = 1); the S&P 22-point scale (*S&P22*) takes an ordinal value of 22 (1) for better (worse) letter ratings (e.g., AAA = 22, …. D or SD = 1); and the S&P 17-point scale (*S&P17*) takes an ordinal value of 17 (1) for better (worse) letter ratings (e.g., AAA = 17, …. CCC+ and lower grades = 1). *COMPLEX* is defined as the logarithm of the total number of Complex words in the 10-K filing. *CONTROLS* is the set of control variables with a one-year lag, including firm 10 K File size (*LNFILE*), size (*SIZE*), leverage (*LEV*), net income to total assets (*NI/TA*), market-to-book ratio (*MB*), operating loss (*LOSS*), tangibility (*TANG*), interest coverage (*INTCOV*), stock return volatility (*SDRET*), and institutional ownership (*IO*). Unless otherwise specified, all specifications include industry and year fixed effects. Detailed definitions of the variables are provided in Appendix A. The *t*-statistics shown in parentheses are based on standard errors that are adjusted for heteroscedasticity and are clustered at the firm level. We winsorize continuous variables at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

Table 5
Alternative proxies for firm-level debt ratings.

Variables	*DEFAULT1*	*DEFAULT2*
	(1)	(2)
COMPLEX	−0.1167	−0.1519
	(−3.55)***	(−3.62)***
LNFILE	0.0066	0.0059
	(2.17)**	(2.05)**
SIZE	0.0331	0.0219
	(6.90)***	(4.40)***
LEV	−0.6065	−0.7049
	(−16.78)***	(−18.8)***
NI/TA	0.3508	0.5024
	(4.19)***	(5.17)***
MB	0.0010	0.0014
	(1.60)	(2.19)**
LOSS	−0.2146	−0.2327
	(−10.59)***	(−10.93)***
TANG	0.0711	0.1312
	(3.88)***	(7.10)***
INTCOV	0.0001	0.0002
	(1.23)	(2.38)**
SDRET	−1.0274	−1.5795
	(−9.06)***	(−13.25)***
IO	0.0372	0.0908
	(1.11)	(2.73)***
Constant	1.4484	1.1082
	(16.12)***	(10.27)***
Industry and Year effects	Yes	Yes
Adj R^2	0.4348	0.4517
Nobs	15,276	15,276

This table reports the panel regression of firm debt ratings on complexity disclosure using alternative proxies for firm debt ratings. *DEFAULT1* is a binary measure equal to one (zero) if the original Altman *Z*-Score falls in the bankruptcy level above (below) 1.81. *DEFAULT2* is a binary measure equal to one (zero) if the modified Altman Z-Score falls in the bankruptcy level above (below) 1.1. *COMPLEX* is defined as the logarithm of the total number of Complex words in the 10-K filing. *CONTROLS* is the set of control variables with a one-year lag, including 10 K File size (*LNFILE*), firm size (*SIZE*), leverage (*LEV*), net income to total assets (*NI/TA*), market-to-book ratio (*MB*), operating loss (*LOSS*), tangibility (*TANG*), interest coverage (*INTCOV*), stock return volatility (*SDRET*), and institutional ownership (*IO*). Unless otherwise specified, all specifications include industry and year fixed effects. Detailed definitions of the variables are provided in Appendix A. The *t*-statistics shown in parentheses are based on standard errors that are adjusted for heteroscedasticity and are clustered at the firm level. We winsorize continuous variables at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

current debt ratings could impact current firm complexity levels. The results shown in Panel B of Table 4 confirm our earlier findings. The coefficient estimate on the lagged firm complexity variable is negative and statistically significant at the 1 % level. Collectively, the above results suggest that our estimations are robust to time-invariant unobservable firm characteristics as well as any other unobserved contemporaneous factors.

4.2.2. *Propensity score matching (PSM) analysis*

The effect of firm complexity on its debt ratings may stem from uncontrolled inherent differences in firm characteristics. To address this issue, we employ propensity score matching (PSM) analysis, as suggested by Smith (2016), to mitigate systematic differences between complex and non-complex firms and identify unobserved factors. PSM analysis also proves valuable in mitigating any potential selection bias in categorizing firms into two groups, as shown in Guindy (2021).

The PSM approach involves pairing treated units (in the treatment group) with non-treated units (in the control group) possessing similar characteristics based on propensity scores. These scores are calculated using our base set of controls. We define "Treatment" as firms with complexity measures above the median and "Control" as firms with complexity measures below the median. To establish a robust control group for treated firms, we estimate propensity scores using base controls and match on year, 2-digit SIC-industry classification, and the closest propensity score with a maximum distance of 0.1 % absolute value and no replacement. Consequently, we have identified 1628 treatment-control pairs.

The results in Panel A of Table 4 indicate that there are no significant differences in observable characteristics between the treatment and control groups, implying that all firm characteristics are closely matched. As the next step, we re-estimate Eq.(1) for the matched treatment-control pairs. The results in Panel B of Table 4 show a negative relation between firm complexity and debt ratings similar to our baseline results presented in Table 2. This result suggests that the significant relationship between firm complexity and debt ratings is not due to the inherent and unaccounted for differences in firm characteristics between complex and non-complex firms.

4.2.3. *Alternative measures of credit ratings*

Our results might potentially be sensitive to the choice of the proxy for debt ratings. Consequently, we consider two alternative measures of

Table 6
Test of causal relation between complexity disclosure and firm debt ratings.

	COMPLEX		S&P24		S&P22		S&P17	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Pre-SOX (2000–2002)	6.26	6.03	19.38	19.00	12.89	12.00	8.74	8.00
Post-SOX (2004–2006)	7.65	7.18	17.24	17.00	11.23	11.00	7.43	7.00
Diff - Pre VS Post	1.39	1.15	2.14	2.00	1.66	1.00	1.11	1.00
T-test / MW test	(2.23)**	(3.54)***	(3.65)***	(5.34)***	(2.43)**	(3.10)***	(2.05)**	(2.38)**

	S&P24			S&P22			S&P17		
	Pre-SOX (2000–2002)	Post-SOX (2004–2006)	Diff in coeff. and Chi^2 Column (1) vs (2)	Pre-SOX (2000–2002)	Post-SOX (2004–2006)	Diff in coeff. and Chi^2 Column (1) vs (2)	Pre-SOX (2000–2002)	Post-SOX (2004–2006)	Diff in coeff. and Chi^2 Column (1) vs (2)
	(1)	(2)		(1)	(2)		(1)	(2)	
COMPLEX	−0.2303	−0.3348	0.1045	−0.2117	−0.3215	0.1098	−0.2197	−0.3304	0.1107
	(−5.55)***	(−9.34)***	[21.47]***	(−5.42)***	(−8.57)***	[22.76]***	(−4.87)***	(−7.30)***	[23.13]***
Constant	5.4309	7.3241		5.3221	6.3374		4.3818	5.3213	
	(6.29)***	(11.39)***		(4.83)***	(10.33)***		(3.22)***	(9.73)***	
Control variables	Yes	Yes		Yes	Yes		Yes	Yes	
Fixed effects	Yes	Yes		Yes	Yes		Yes	Yes	
Adj R^2	0.6323	0.6438		0.6261	0.6284		0.6179	0.6238	
Nobs	1814	2644		1814	2644		1814	2644	

Panel A of the table reports the mean and median values of the Complexity Score and Firm Debt Ratings before and after the enactment of SOX 2002. It also presents the results of a t-test for mean differences and a Mann-Whitney test for median differences, comparing each variable between the pre- and post-SOX periods. The Panel B of the table reports the results of tests of the causal relation between complexity disclosure and firm debt ratings using the Sarbanes-Oxley Act of 2002 (SOX) as the exogenous shock to complexity disclosure. To measure S&P debt ratings, we translate letters assigned to S&P debt ratings into three ordinal scales: the S&P 24-point scale (S&P24) takes an ordinal value of 24 (1) for better (worse) letter ratings (e.g., AAA = 24, …. SD = 1); the S&P 22-point scale (S&P22) takes an ordinal value of 22 (1) for better (worse) letter ratings (e.g., AAA = 22, …. D or SD = 1); and the S&P 17-point scale (S&P17) takes an ordinal value of 11 (1) for better (worse) letter ratings (e.g., AAA =17, …. CCC+ and lower grades = 1). *COMPLEX* is defined as the logarithm of the total number of Complex words in the 10-K filing. *CONTROLS* is the set of control variables with a one-year lag, including 10 K File size (*LNFILE*), firm size (*SIZE*), leverage (*LEV*), net income to total assets (*NI/TA*), market-to-book ratio (*MB*), operating loss (*LOSS*), tangibility (*TANG*), interest coverage (*INTCOV*), stock return volatility (*SDRET*), and institutional ownership (*IO*). Detailed definitions of the variables are provided in Appendix A. The *t*-statistics shown in parentheses are based on standard errors that are adjusted for heteroscedasticity and are clustered at the firm level. We winsorize continuous variables at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

Table 7
Alternative proxy for firm complexity.

Variables	Panel A: GIC								
	GIC5			GIC20			GIC50		
	S&P24	S&P22	S&P17	S&P24	S&P22	S&P17	S&P24	S&P22	S&P17
GIC	−0.0056	−0.0052	−0.0100	−0.0044	−0.0047	−0.0076	−0.0041	−0.0037	−0.0067
	(−2.85)***	(−2.70)***	(−2.55)**	(−2.84)***	(−2.68)***	(−2.46)**	(−2.65)**	(−2.57)**	(−2.46)**
Constant	6.8789	6.7850	1.0193	6.8848	6.7888	1.0150	7.3386	6.9506	1.4975
	(9.18)***	(8.91)***	(1.00)	(9.55)***	(9.25)***	(0.96)	(8.42)***	(8.23)***	(2.02)**
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.6382	0.6274	0.6362	0.6259	0.6254	0.6181	0.6248	0.6182	0.6150
Nobs	2984	2984	2984	2984	2984	2984	2984	2984	2984

This table reports the panel regression of firm debt ratings on complexity disclosure using alternative proxy for firm complexity. The dependent variable, RATINGSi,t denotes a set of alternative proxy for complexity of firm i in year t. GIC is Business Group Index of Complexity and calculated as a function of the number of affiliates on a given hierarchical level, of the total number of affiliates belonging to the group and of the total number of levels. CONTROLS is the set of control variables with a one-year lag, including 10 K File size (LNFILE), firm size (SIZE), leverage (LEV), net income to total assets (NI/TA), market-to-book ratio (MB), operating loss (LOSS), tangibility (TANG), interest coverage (INTCOV), stock return volatility (SDRET), and institutional ownership (IO). Unless otherwise specified, all specifications include industry and year fixed effects. Detailed definitions of the variables are provided in Appendix A. The t-statistics shown in parentheses are based on standard errors that are adjusted for heteroscedasticity and are clustered at the firm level. We winsorize continuous variables at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

credit ratings: $DEFAULT_1$ and $DEFAULT_2$, which are dummy variables based on the Altman *Z*-score and the modified Altman Z-score, respectively (e.g., Gredil, Kapadia, & Lee, 2022). More specifically, $DEFAULT_1$ is defined as a dummy variable that take a value of 1, if Altman Z-Score is higher than 1.81 in year *t*, indicating a greater likelihood of bankruptcy in the near future, and 0 otherwise; $DEFAULT_2$ is defined as a dummy variable that take a value of 1, if the modified Altman Z-score is higher than 1.1 in year *t*, and 0 otherwise. The results reported in Table 5 reveal a negative coefficient estimate on *COMPLEX* that is statistically significant at the 1 % level and are in line with our main results presented in Table 2. The two alternative proxies of credit ratings shown in the table provide further evidence on the negative relationship between the degree of firm complexity and the level of credit ratings. As already mentioned above, these results suggest that due to the information asymmetries of more complex firms that are more difficult to assess, organizations that are considered more complex are assigned lower credit ratings by independent rating agencies. Thus, this result is consistent with the Hypothesis H1.

Table 8
Audit fees as an alternative proxy for firm complexity.

COMPLEX	0.0889
	(11.50)***
SIZE	0.3286
	(48.88)***
LNFILE	−0.0488
	(−4.53)***
NONAFEE	0.0277
	(23.60)***
LOSS	0.0680
	(6.65)***
BUSY	0.0902
	(5.36)***
ROA	−0.1072
	(−6.05)***
AUOP	0.1729
	(2.91)***
BIG4	0.0548
	(2.77)***
GEOSEGMENT	0.1043
	(8.28)***
BUSSEGMENT	0.0840
	(8.89)***
FORSALES	−0.4162
	(−0.78)
SPECIAL	0.1219
	(14.36)***
LEV	−0.0609
	(−2.53)**
AUCHANGE	0.1240
	(1.22)
MB	0.0510
	(7.16)***
LITIGATION	−0.0015
	(−0.12)
INHERENT	0.4055
	(11.14)***
M&A	0.1133
	(10.29)***
SEO	0.0067
	(0.50)
EMPLOYEE	0.0758
	(13.80)***
Constant	8.4854
	(21.87)***
Industry and Year effects	Yes
Adj R^2	0.8469
Nobs	15,482

This table reports the panel regression of auditor fee on firm complexity. Where $AUDFEE_{i,t}$ denotes the audit fee of client firm *i* in year *t*. *COMPLEX* is defined as the logarithm of the total number of Complex words in the 10-K filing *CONTROLS* is the set of control variables with a one-year lag, including firm size (*SIZE*), File Size (*LNFILE*),market-to-book ratio (*MB*), non-audit fee (*NONAFEE*), loss firms (*LOSS*), acquisition activity (*M&A*), big auditors (*BIG4*), operating performance (*ROA*), firm with reporting date in the period Dec-Mar (*BUSY*), leverage (*LEV*), geographic segments (*GEOSEGMENT*), business segments (*BUSSEGMENT*), firm reports foreign sales (*FORSALES*), firm reports special items (*SPECIAL*), change in the auditor (*AUCHANGE*), litigation industry (*LITIGATION*), inherent risk (*INHERENT*), seasoned equity offerings (*SEO*) and employees (*EMPLOYEE*). The *t*-statistics shown in parentheses. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

4.2.4. Addressing endogeneity with SOX

In this section, we employ the enactment of the Sarbanes-Oxley Act (2002) (SOX), as a natural experiment to mitigate the potential problem of endogeneity and examine whether firm complexity and debt ratings might be causally related to each other. We first examine the relations between complexity disclosure and firm debt ratings across the pre- versus post-SOX periods, controlling for a standard set of explanatory variables used in our baseline specification presented in Table 2. Given that several SOX requirements were implemented in annual reports due on or after August 14, 2003, we exclude the 2003 fiscal year and treat years 2000–2002 as the pre-SOX period and 2004–2006 as the post-SOX period. We rerun the baseline model for both pre- and post-SOX periods separately and present the results in Table 6. As seen in the table, we find that the coefficient estimate on *COMPLEX* is negative and highly significant (at the 1 % level) for both pre- and post-SOX periods. Moreover, the difference in coefficients between the pre-SOX versus post-sox periods is also negative and significant indicating that the negative relationship between firm complexity and credit ratings is stronger in the post-SOX period as measured in our analysis. This result could be explained by the increased amount of disclosure in 10 K reports in the post-SOX period mandated by stricter stock exchange listing rules that in turn may reflect enhanced corporate complexity and opaqueness that emerge from this disclosure. This result is generally consistent with the literature indicating that SOX mandates enhanced disclosure but at the same time the effect of this additional disclosure may be detrimental to shareholders leading to e.g., higher firm risk and greater cost of equity (e.g., Akhigbe et al., 2008; Ashbaugh-Skaife et al., 2009). In our case, the additional disclosure triggered by SOX leads to a stronger relationship between firm complexity and credit rating suggestion that (at least in the short run) SOX does not reduce the opaqueness of complex firms that could have a positive effect on credit ratings.

4.2.5. Alternative proxies for firm complexity

The concept of firm complexity is multi-dimensional and intricate. Therefore, capturing the full extent of firm complexity requires a comprehensive and nuanced approach that takes into account multiple dimensions and factors (Loughran & McDonald, 2024). To ensure that our results are not driven by a selection of a specific proxy for firm complexity, we investigate two alternative variables that have been shown in the literature to affect firm complexity. The first one is Business Group Index of Complexity (GIC) used in Altomonte and Rungi (2013). This index is calculated as a function of the number of affiliates on a given hierarchical level, the number of affiliates belonging to the group, and the total number of levels. The index captures both hierarchical density and distance. Similar to the baseline results in Table 2, reported coefficient estimates of *GIC* in Table 7 are all negative and significant at the 5 % level in all specifications and suggest that firm complexity depresses debt ratings.

The second alternative proxy we use is the measure of audit fees. Audit fees have been shown to be highly correlated with firm complexity (Loughran & McDonald, 2024). As seen in Table 8, the coefficient estimate on *COMPLEX* is positive and significant at the 1 % level which implies that audit fees are a good proxy for firm complexity. Overall, taken together these findings further reinforce our main findings.

4.3. Additional analyses

4.3.1. The role of information environment and corporate governance

In this section, we examine further how firm complexity can affect debt ratings. The literature has shown that complex firms suffer from greater information asymmetry (Demirkan, Radhakrishnan, & Urcan, 2012; Farooqi, Harris, & Ngo, 2014; Jennings et al., 2014; Liu & Lai, 2012). and higher costs (Bushman et al., 2004; Coles et al., 2008; Linck et al., 2008). Therefore, we expect the negative effect of firm complexity on corporate debt ratings to become weaker in more transparent environment (*Hypothesis H3*) and in better-governed firms (*Hypothesis H4*).

Following extant literature, we employ financial analyst coverage (*ANALYST*) (e.g., Frankel & Li, 2004) as a proxy for information environment. Greater financial analyst coverage provides more information, leading to a better information environment. Financial analyst coverage can mitigate the negative relationship between firm complexity and debt ratings by providing greater transparency and reducing information asymmetry for investors. According to Dang et al. (2022), this coverage

Table 9
Information environment, complexity disclosure and debt ratings.

Variables	Panel A: Financial analyst coverage					
	Low ANALYST			*High ANALYST*		
	S&P24	S&P22	S&P17	S&P24	S&P22	S&P17
COMPLEX	−0.3737	−0.3651	−0.3814	−0.1626	−0.1509	−0.1624
	(−11.12)***	(−10.99)***	(−11.25)***	(−8.48)***	(−8.42)***	(−7.62)***
Constant	8.4786	7.5099	2.4966	7.0729	6.0793	1.8808
	(16.43)***	(14.31)***	(4.64)***	(11.42)***	(10.05)***	(4.46)***
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.6576	0.6563	0.6612	0.6032	0.6041	0.6169
Nobs	7749	7749	7749	7733	7733	7733

Variables	Panel B: Stock liquidity					
	High ILLIQUID			*Low ILLIQUID*		
	S&P24	S&P22	S&P17	S&P24	S&P22	S&P17
COMPLEX	−0.2668	−0.2652	−0.3196	−0.1443	−0.1371	−0.1487
	(−9.69)***	(−9.63)***	(−9.09)***	(−5.56)***	(−5.42)***	(−4.72)***
Constant	10.7806	9.7870	5.0064	5.0077	4.0290	0.4764
	(13.94)***	(12.65)***	(7.92)***	(6.93)***	(5.58)***	(0.73)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.6082	0.6078	0.5997	0.5990	0.5996	0.5820
Nobs	7742	7742	7742	7740	7740	3740

This table reports panel regression results on how the corporate information environment affects the relationship between firm complexity disclosure and debt ratings. We use financial analyst coverage (*ANALYST*) and Amihud's illiquidity estimate (*ILLIQUID*). For each fiscal year, we sort the firms into High groups (vs. Low) based on above (below) the median value of *ANALYST* in year *t*-1 and *ILLIQUID* in year *t*-1. Panel A (B) regresses S&P debt ratings on corporate business strategy and controls when conditional on financial analyst coverage (stock liquidity). To measure S&P debt ratings, we translate letters assigned to S&P debt ratings into three ordinal scales: the S&P 24-point scale (*S&P24*) takes an ordinal value of 24 (1) for better (worse) letter ratings (e.g., AAA = 24, ….SD = 1); the S&P 22-point scale (*S&P22*) takes an ordinal value of 22 (1) for better (worse) letter ratings (e.g., AAA = 22, …. D or SD = 1); and the S&P 17-point scale (*S&P17*) takes an ordinal value of 17 (1) for better (worse) letter ratings (e.g., AAA = 17, …. CCC+ and lower grades =1). *COMPLEX* is defined as the logarithm of the total number of Complex words in the 10-K filing. *CONTROLS* is the set of control variables with a one-year lag, including 10 K File size (*LNFILE*), firm size (*SIZE*), leverage (*LEV*), net income to total assets (*NI/TA*), market-to-book ratio (*MB*), operating loss (*LOSS*), tangibility (*TANG*), interest coverage (*INTCOV*), stock return volatility (*SDRET*), and institutional ownership (*IO*). Unless otherwise specified, all specifications include industry and year fixed effects. Detailed definitions of the variables are provided in Appendix A. The *t*-statistics shown in parentheses are based on standard errors that are adjusted for heteroscedasticity and are clustered at the firm level. We winsorize continuous variables at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

can help investors better understand firm's complexity, risks, and opportunities, which can increase their confidence in the firm's ability to generate cash flows and repay its debts. Financial analysts can also help complex firms to communicate their strategies, risks, and performance to investors in a clear and consistent manner. By doing so, they can help reduce information asymmetry and uncertainty, which can increase the firm's creditworthiness and debt ratings (Ferrer, Santamaría, & Suárez, 2019). We also employ stock illiquidity (*ILLIQUID*) (e.g., Welker, 1995; Attig et al., 2006) developed in Amihud (2002) to proxy for corporate information environment. High levels of information asymmetry can decrease stock market liquidity, resulting in greater illiquidity ratios (Kale & Loon, 2011). Stock liquidity can provide greater visibility and transparency for investors, which can help reduce information asymmetry and uncertainty. When a stock is highly liquid, investors can buy and sell it more easily, which allows them to react quickly to new information and adjust their portfolios accordingly (Lee, Sapriza, & Wu, 2016). This can lead to a more efficient market for the firm's stock and reduce the impact of negative news or events on its debt ratings.

To facilitate the estimation, we group firms into two categories (*High* vs. *Low*) based on the median values of *ANALYST* and *ILLIQUID* in the previous year (t-1). Companies that exceed the median value for *ANALYST* and *ILLIQUID* are placed in the "*High*" group, while the rest are placed in the "*Low*" group. We estimate Eq. (1) separately for each subgroup. As previous studies have shown (Aboody & Lev, 2000; Barth, Kasznik, & McNichols, 2001; Cheng & Subramanyam, 2008), low analyst coverage and high illiquidity ratios are indicative of weak information settings. Our results, presented in Table 9, confirm *Hypothesis H3* suggesting that a more transparent information environment, characterized by *High ANALYST* and *Low ILLIQUID*, is associated with lower negative coefficients on *COMPLEX*. This suggests that complex firms might be able to reduce information asymmetry and improve their debt ratings if placed within a more transparent information environment (Bonsall, Green, & Muller III, 2018; Cheng & Subramanyam, 2008).

To examine the effect of corporate governance on the relationship between firm complexity and debt ratings, we consider two different variables: institutional ownership and board independence. We conjecture that institutional ownership can help reduce the negative effect of firm complexity on debt ratings. More specifically, it can be argued that institutional investors should monitor the management and therefore reduce negative effect of firm complexity on the firm-level characteristics, if greater firm complexity is the result of self-serving behavior of the management (see Edmans, 2014 for an excellent review of the literature). Recent research shows that passive investors (e.g., BalckRock, Vanguard, State Street) engage with top managers of firms in order to shape corporate strategies and policies (e.g., Croci et al., 2024; Dimson et al., 2015; Kakhbod et al., 2023; Karolyi et al., 2020; McCahery et al., 2016). The expectation is that higher institutional ownerhsip should have a stronger mitigating effect on the relationship between firm complexity and debt ratings, on the condition that the association between these two variables is negative.

The second set of test employs board independence variable that captures internal monitoring function (versus external monitoring performed by institutional investors). Board independence is mandated by stock exchange listing requirements, however, the degree of board independence (above mandated threshold) varies firm by firm. In any case, greater board independence seems to be positively correlated with shareholder rights and therefore should deter self-daling and corporate misconduct (Neville et al., 2019). This in turns implies that companies

Table 10
Governance environment, complexity disclosure and debt ratings.

Variables	Panel A: Institutional ownership					
	Low IO			*High IO*		
	S&P24	S&P22	S&P17	S&P24	S&P22	S&P17
COMPLEX	−0.3387	−0.3366	−0.3422	−0.2349	−0.2285	−0.2475
	(−10.53)***	(−10.45)***	(−9.63)***	(−6.61)***	(−6.57)***	(−5.74)***
Constant	9.9901	9.0214	4.0732	7.0873	6.0932	1.5102
	(9.24)***	(8.35)***	(4.34)***	(7.47)***	(6.42)***	(1.71)*
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.6907	0.6894	0.6941	0.5903	0.5868	0.5978
Nobs	7737	7737	7737	7745	7745	7745

Variables	Panel B: Board independence					
	Low BIND			*High BIND*		
	S&P24	S&P22	S&P17	S&P24	S&P22	S&P17
COMPLEX	−0.2613	−0.2581	−0.2594	−0.1721	−0.1589	−0.1823
	(−7.83)***	(−7.79)***	(−8.22)***	(−5.62)***	(−5.58)***	(−4.80)***
Constant	14.4479	13.5030	7.8217	6.6448	5.6517	1.0035
	(15.37)***	(14.36)***	(9.39)***	(9.66)***	(8.19)***	(1.55)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.6595	0.6591	0.6688	0.6406	0.6403	0.6535
Nobs	2841	2841	2841	2920	2920	2920

Panel C: Shareholder activism						
	SHA			*NonSHA*		
	S&P24	S&P22	S&P17	S&P24	S&P22	S&P17
COMPLEX	−0.9759	−0.9842	−0.3359	−0.6032	−0.6079	−0.0941
	(−20.29)***	(−20.29)***	(−19.66)***	(−10.05)***	(−10.00)***	(−9.83)***
Constant	15.8315	13.8626	4.5459	15.4139	13.3837	4.6187
	(27.20)***	(23.74)***	(24.20)***	(12.84)***	(11.13)***	(12.61)***
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.6774	0.6758	0.6462	0.6528	0.6521	0.6096
Nobs	2080	2080	2080	2067	2067	2067

This table reports panel regression results on how corporate governance settings affect firm complexity disclosure and debt ratings. To capture corporate governance, we use institutional ownership (IO) board independence (BIND), Shareholder activism (SHA). For each fiscal year, we sort the firms into High group (vs. Low) based on above (below) the median value of IO in year t-1, BI in year t-1, SHA in year t-1 . In Panel A,B C, we regress S&P debt ratings on corporate business strategy and controls conditional on institutional ownership, board independence and shareholder activism in year t-1. To measure S&P debt ratings, we translate letters assigned to S&P debt ratings into three ordinal scales: the S&P 24-point scale (S&P24) takes an ordinal value of 24 (1) for better (worse) letter ratings (e.g., AAA = 24, …. SD = 1); the S&P 22-point scale (S&P22) takes an ordinal value of 22 (1) for better (worse) letter ratings (e.g., AAA = 22, …. D or SD = 1); and the S&P 17-point scale (S&P17) takes an ordinal value of 17 (1) for better (worse) letter ratings (e.g., AAA = 17, …. CCC+ and lower grades = 1). COMPLEX is defined as the logarithm of the total number of Complex words in the 10-K filing. CONTROLS is the set of control variables with a one-year lag, including 10 K File size (LNFILE), firm size (SIZE), leverage (LEV), net income to total assets (NI/TA), market-to-book ratio (MB), operating loss (LOSS), tangibility (TANG), interest coverage (INTCOV), stock return volatility (SDRET), and institutional ownership (IO). Unless otherwise specified, all specifications include industry and year fixed effects. Detailed definitions of the variables are provided in Appendix A. The t-statistics shown in parentheses are based on standard errors that are adjusted for heteroscedasticity and are clustered at the firm level. We winsorize continuous variables at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

with boards that are more independent should be managed in a better way from the perspective of firm stakeholders. Also, it seems that selecting specialists (business experts) versus generalists (non-experts) as independent directros to complex firms (Markarian & Parbonetti, 2007) should lead to higher quality of financial, operating, and investment decisions. Consequently, the above suggests that firms with a higher level of complexity may have higher debt ratings, if their boards of directors have a high level of independence and expertise. On the other hand, firms with a low level of board independence may face greater skepticism from credit rating agencies when it comes to overseeing complex operations, which could be reflected lower debt ratings.

In our study, institutional ownership (*IO*) is measured as the average percentage of shares outstanding held by institutional investors (e.g., Ashbaugh-Skaife et al., 2006). Board independence (*BIND*) is measured as the percentage of independent directors on the board. Similar to examination of information asymmetry effect, we also divide the sample into "*High*" (and "*Low*") group if firms have *IO* and *BIND* values in year *t*-1 above (below) the median level. The panel Eq. (1) is re-estimated separately for each subsample (i.e., *High* vs. *Low*). Results reported in Table 10 reveal lower negative coefficient estimates on *COMPLEX* in better governed firms (i.e. *High IO* and *High BIND*) for all debt ratings proxies. This suggests that the negative effect of complexity on debt ratings is diminished, if *firms have higher institutional ownership and enjoy greater board independence. These findings are consistent with Hypothesis H4.*

4.3.2. *The effect of policy uncertainty*

Given the importance of government policies in setting the firm's business environment, we examine the role of policy uncertainty in affecting the relationship between firm complexity and debt ratings (*Hypothesis H5*). We capture policy uncertainty, by employing Baker et al. (2016)'s economic policy uncertainty (*EPU*) index as well as the information on the U.S. presidential elections (*ELECTION*).

Firms are in high policy uncertainty environment if they have the

Table 11
Policy uncertainty, complexity disclosure, and debt ratings.

Variables	Panel A: Economic policy uncertainty (*EPU*)					
	High EPU			*Low EPU*		
	S&P24	S&P22	S&P17	S&P24	S&P22	S&P17
COMPLEX	−0.3204	−0.3047	−0.3369	−0.1689	−0.1613	−0.1911
	(−10.43)***	(−10.23)***	(−9.63)***	(−4.18)***	(−4.21)***	(−3.34)***
Constant	6.7034	6.6740	1.4611	5.7085	4.7360	1.3101
	(12.18)***	(12.04)***	(2.18)**	(6.86)***	(5.54)***	(1.64)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.6175	0.6154	0.6098	0.6047	0.60355	0.5988
Nobs	6687	6687	6687	6689	6689	6689

Variables	Panel B: Presidential elections (*ELECT*)					
	With presidential elections (ELECTION = 1)			*Without presidential elections (ELECTION = 0)*		
	S&P24	S&P22	S&P17	S&P24	S&P22	S&P17
COMPLEX	−0.2901	−0.2736	−0.1580	−0.1046	−0.1027	−0.1133
	(−8.26)***	(−8.19)***	(−5.75)***	(−5.89)***	(−5.84)***	(−4.48)***
Constant	4.9343	4.6638	2.3496	3.3704	3.2117	2.1489
	(7.62)***	(6.98)***	(2.43)**	(6.12)***	(5.83)***	(1.69)*
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.6840	0.6823	0.6488	0.6724	0.6711	0.6406
Nobs	3868	3868	3868	11,614	11,614	11,614

This table reports panel regression results on how the U.S. policy uncertainty affects the relationship between firm complexity disclosure and debt ratings. To capture policy uncertainty, we use the index of economic policy uncertainty (*EPU*) and the U.S. presidential election (*ELECTION*). For each fiscal year, we sort the firms into High group (vs. Low) based on above (below) the median value of *EPU* in year *t*-1. In Panel A (B), we regress S&P debt ratings on corporate business strategy and controls conditional on economic policy uncertainty (the U.S. presidential election). To measure S&P debt ratings, we translate letters assigned to S&P debt ratings into three ordinal scales: the S&P 24-point scale (*S&P24*) takes an ordinal value of 24 (1) for better (worse) letter ratings (e.g., AAA = 24, …. SD = 1); the S&P 22-point scale (*S&P22*) takes an ordinal value of 22 (1) for better (worse) letter ratings (e.g., AAA = 22, …. D or SD = 1); and the S&P 17-point scale (*S&P17*) takes an ordinal value of 17 (1) for better (worse) letter ratings (e.g., AAA =17, …. CCC+ and lower grades = 1). *COMPLEX* is defined as the logarithm of the total number of Complex words in the 10-K filing. *CONTROLS* is the set of control variables with a one-year lag, including 10 K File size (LNFILE), firm size (*SIZE*), leverage (*LEV*), net income to total assets (*NI/TA*), market-to-book ratio (*MB*), operating loss (*LOSS*), tangibility (*TANG*), interest coverage (*INTCOV*), stock return volatility (*SDRET*), and institutional ownership (*IO*). Unless otherwise specified, all specifications include industry and year fixed effects. Detailed definitions of the variables are provided in Appendix A. The *t*-statistics shown in parentheses are based on standard errors that are adjusted for heteroscedasticity and are clustered at the firm level. We winsorize continuous variables at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

EPU index in year *t-1* above the median value (*High EPU*) or if there is a presidential election in year *t-1 (ELECTION* = *1*). Otherwise, they are considered to be in the low policy uncertainty environment (i.e. *Low EPU* or *ELECTION* = *0)*. As in previous tests, we re-estimate Eq. (1) separately for each sub-sample. Results in Table 11 report higher negative coefficient estimates on *COMPLEX* for each proxy of debt ratings (i.e. *S&P24*, *S&P22*, and *S&P17*) for firms that experience increased policy uncertainty (*High EPU* and *ELECTION* = *1*). Coefficient estimates are all significant at the 1 % level. This finding confirms Pástor and Veronesi (2012) argument about the role of policy uncertainty in amplifying firm's risk. The issue is more pronounced in complex firms, which have been perceived as riskier by credit rating agencies. Therefore, our findings are consistent with *Hypothesis H5*.

4.3.3. Remaining tests

In the last section, we perform some additional tests to gain more insights on the interaction between firm complexity and credit ratings. These analyses focus mostly on dynamic aspect of firm complexity knowing that the degree of firm complexity may vary over time depending on the strategy of firms and corporate transactions companies undertake. For example, the rational expectation is that some corporate activities, for example, mergers and acquisitions increase firm complexity, ceteris paribus, whereas divestitures decrease firm complexity. Practically, companies make many acquisition, as well as acquisitions and divestitures at the same time, therefore the net effect of M&As and divestitures on firm complexity is not obvious.

In Table A2 (Panel A), we analyze companies who engage either in cross-industry M&A or divestitures and divide them into two separate groups. Then, we measure changes in complexity as the differences between averages and medians calculated over a two-year period around the year of the event. To be more specific, a two-year period before the event is called "Pre-Event" and a two-year period after the event is called "Post-Event". A change is calculated as the first difference between "Pre-Event" and "Post-Event". As seen in panel A, cross-industry M&As increase complexity, whereas divestitures tend to decrease complexity. The effects are significant at the 1 % and 5 % levels and they are economically larger for M&A as compared to divestitures. This result suggests that as companies grow more complex due to M&A their credit ratings are likely to diminish due to rising firm complexity. The reverse effect is observed for divestitures.

In the next tests, we use the same groups of companies divided between cross-industry M&A and divestitures and investigate whether M&As and divestitures affect credit rating and if so in which direction and to what extent. We use three different measures of credit rating (as in previous tests above) (see Panels B—D). As seen in all three panels, cross-industry M&As decrease credit ratings significantly. The economic effect is strongest for the first measure of credit rating (Panel B) and weakest for the third measure (Panel D). Statistical significance follows and the effect presented in Panel B (D) is statistically strongest (weakest). As for divestitures, we see a similar pattern but the effects are somewhat stronger in a statistical sense.

In the last test presented in Panel E, we run two separate Probit models, where the dependent variable equals to 1 if the firm engages in a cross-industry M&A (first regression) or undertakes a divestiture (second regression). As seen in the table, firm complexity decreases probably of undertaking an acquisition, however, it increases the probability of undertaking a divestiture.

Further, to capture the dynamic nature of changes in complexity and credit ratings, we run regressions using first differences in the measure of both firm complexity and credit ratings for companies that undertake an M&A or a divestiture. First differences are calculated between averages estimated over a two-year period before and after the event, where event is defined as either cross-industry M&A or a divestiture. The results are presented in Table A3. As seen in the table Panels A and B, there is a negative relationship between changes in firm complexity and changes in firm credit rating around corporate events. These findings imply that if the change in complexity is positive (a company becomes more complex) then the change in credit rating is negative (credit rating becomes lower). Therefore, the results of this test confirm our baseline results reported in Table 2.

Next, in Table A4 Panel A, we investigate the relationship between changes in corporate governance measured as the inverse of the anti-takeover index developed in Gompers et al. (2003) and firm complexity. As seen in the panel, the positive change in corporate governance is negatively related to firm complexity. This result implies that if shareholder rights become stronger, companies become less complex. This result is in line with our main finding presented in Table 2 as well as results reported in Table 10 where we examine static corporate governance factors. Further, in Panels B and C of Table A4, we investigate positive voting outcomes for large mergers (Panel B) as well as divestitures (Panel C) and relate them to firm complexity. As seen in Panel B of Table A4, the coefficient estimate on the variable that measures successful voting outcomes for large mergers (*VOTE_M&A*) is positive and significant at the 5 % level implying that large mergers significantly increase firm complexity. The coefficient estimate on divestitures (*VOTE_Divestitures*) is negative but insignificant implying that divestitures have no statistical effect on complexity of firms.

5. Conclusion

This paper investigates a potential relationship between firm complexity and credit ratings. We explore two competing predictions. On the one hand, the opaqueness of assets and strategies of complex firms might induce lower credit ratings. On the other hand, the coinsurance effect between business segments in the complex firm might reduce default risk, and therefore complex firms could be assigned higher credit ratings.

Our empirical analysis finds support for the negative relationship between firm complexity and credit ratings, implying that more complex firms tend to have higher default risks, and therefore they are assigned lower credit ratings. This effect is mitigated, if the firm is more transparent and has higher quality of corporate governance. We also show that during periods of increased policy uncertainty, negative relationship between firm complexity and credit ratings is aggravated. It should be stressed that we find no evidence for the competing hypothesis stating that firm complexity is beneficial for the firm and reduces credit ratings du e to the coinsurance effect.

The findings of our paper have important implications for both firms and investors. For firms, the negative relation between complexity and credit ratings suggests that they should strive to simplify their business operations and financial reporting in order to improve their creditworthiness. This may involve streamlining operations, reducing the number of business segments, or providing more transparent financial disclosures. Furthermore, the finding that the negative effect on credit ratings is weaker in more transparent and better-governed firms highlights the importance of good corporate governance practices and transparency in mitigating the negative effect of firm complexity.

For investors, our results imply that complexity is an important factor to consider when evaluating company's credit risk. Companies with higher levels of complexity may be more vulnerable to credit downgrades, particularly during periods of high policy uncertainty. Therefore, investors should carefully assess firm's level of complexity before making investment decisions. This may involve analyzing firm's business operations, financial reporting, and corporate governance practices.

Overall, our paper provides valuable insights into the relationship between firm complexity and credit ratings. As such, the findings of this paper should be of interest to academics, practitioners, and market regulators.

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Appendix A

Table A1
Variable definitions

Variables	Acronym	Description	Data sources
1. Dependent variables			
S&P Credit Ratings	*S&P24*	The S&P 24-point scale takes an ordinal value of 24 (1) for better (worse) letter ratings (e.g., AAA = 24, …. SD = 1).	Compustat
	S&P22	The S&P 22-point scale takes an ordinal value of 22 (0) for better (worse) letter ratings (e.g., AAA = 22, …. D or SD = 1).	Compustat
	S&P17	The S&P 17-point scale takes an ordinal value of 17 (1) for better (worse) letter ratings (e.g., AAA = 17, …. CCC+ and lower grades = 1).	Compustat
Altman Z-Score	*DEFAULT1*	A binary measure is equal to one (zero) if the original Altman Z-Score falls in the bankruptcy level above (below) 1.81.	Compustat
Modified Altman Z-Score	*DEFAULT2*	A binary measure is equal to one (zero) if the modified Altman Z-Score falls in the bankruptcy level above (below) 1.1.	Compustat
2. Firm-level variables			
Firm complexity	*COMPLEX*	Firm complexity measure as in Loughran and McDonald (2024)	Loughran and McDonald (2024)
File Size	*LNFILE*	-1 x the natural logarithm of file size (*FILE*) of the 10-K filing	WRDS SEC Analytics Suit

(*continued on next page*)

Table A1 (*continued*)

Variables	Acronym	Description	Data sources
Hierarchical Complexity	*GIC*	Business Group Index of Complexity and calculated as a function of the number of affiliates on a given hierarchical level, of the total number of affiliates belonging to the group and of the total number of levels.	Altomonte and Rungi (2013)
Firm size	*SIZE*	Firm size, defined as the natural logarithm of total assets.	Compustat
Market to book	*MB*	Market to book, defined as the ratio of the market value of equity to the book value of equity.	Compustat
Leverage	*LEV*	Leverage, defined as long-term debt plus debt in current liabilities divided by book assets.	Compustat
Profitability	*NI/TA*	Profitability, defined as the ratio of net income to total assets.	Compustat
Operating loss	*LOSS*	Operating loss, defined as a dummy measure equal to one (zero) if a firm's net income to total assets is negative (positive).	Compustat
Tangibility	*TANG*	Tangibility, defined as the ratio of gross property, plant, and equipment scaled by total assets.	Compustat
Interest coverage	*INTCOV*	Interest coverage, defined as the ratio of operating income before depreciation divided by interest expense.	Compustat
Stock return volatility	*SDRET*	Stock return volatility, defined as the annualized standard deviation of monthly stock returns in year t-1.	CRSP
Institutional ownership	*IO*	Institutional ownership, defined as the percentage of shares outstanding held by institutional investors, taking the average over the four quarters of the firm's fiscal year t. *IO* is set to zero if it is missing.	13F
Analyst coverage	*ANALYST*	Analyst coverage, defined as the natural logarithm of one plus the average of the monthly number of analysts following a firm.	I/B/E/S
Amihud's (2002) illiquidity estimate	*ILLIQUID*	Illiquidity estimate, defined as an average ratio of the absolute daily return to the (dollar) trading volume on that day, giving the absolute (percentage) price change per dollar of daily trading volume, or the daily price impact of the order flow (multiplied by100,000 for presentation).	CRSP
Board independence	*BIND*	Board independence, defined as the percentage of independent directors on the board. We first use the BoardEx database to obtain this variable. We then use the institutional shareholder services (ISS) database to obtain the missing *BI*.	BoardEx
Corporate governance	*CG*	Corporate governance score as in Gompers, P., Ishii, J., & Metrick, A. (2003)	ISS
Economic policy uncertainty	*EPU*	The monthly economic policy uncertainty index compiled by Baker et al. (2016). They constructed a monthly index of economic policy uncertainty using three different data sources. These sources include (i) a search of newspaper articles containing terms related to economic policy uncertainty, (ii) data from the Congressional Budget Office on the present value of future scheduled tax code expirations, and (iii) data from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters, which measures the level of disagreement among economists regarding consumer price index, state and local government purchases, and federal government purchases of goods and services.	Policy uncertainty
Presidential elections	*ELECTION*	A dummy variable taking the value 1 if the USA holds presidential election in year t, and zero otherwise	Database of Political Institutions
State education	*STATE_EDU*	The proportion of a state's population being at least 25 years old and having a bachelor's degree, master's degree, and/or professional degree.	U.S. Census Bureau
State income	*STATE_INCOME*	The median household income at the state level.	U.S. Census Bureau
County education	*COUNTY_EDU*	The proportion of a county's population being at least 25 years old and having a bachelor's degree, master's degree, and/or professional degree.	U.S. Census Bureau
County income	*COUNTY_INCOME*	The median household income at the county level.	U.S. Census Bureau

Table A2
The impact of Corporate Events.

	M&As		Divestures	
	Mean	Median	Mean	Median
Panel A: Effect of Firm Complexity Pre VS Post-Corporate Events				
Pre-Events	6.94	6.12	8.95	7.21
Post-Events	8.28	7.74	7.86	6.04
Diff - Pre VS Post	−1.34	−1.62	1.09	1.17
T-test / MW test	(2.72)***	(3.04)***	(2.54)**	(2.67)***
Panel B: S&P24: Pre VS Post-Corporate Events				
	Mean	Median	Mean	Median
Pre-Events	18.17	18.00	17.32	17.00
Post-Events	17.13	17.00	19.10	19.00
Diff - Pre VS Post	1.62	1.00	−1.78	−2.00
T-test / MW test	(2.34)**	(3.64)***	(2.43)**	(4.12)***
Panel C: S&P22: Pre VS Post-Corporate Events				
Pre-Events	12.27	12.00	11.39	11.00
Post-Events	11.43	11.00	12.47	12.00
Diff - Pre VS Post	0.84	1.00	−1.08	−1.00
T-test / MW test	(2.09)**	(2.74)***	(2.40)**	(2.87)***
Panel D: S&P17: Pre VS Post-Corporate Events				
Pre-Events	8.84	8.00	7.56	7.00
Post-Events	8.11	8.00	8.45	8.00
Diff - Pre VS Post	0.73	0.00	−0.89	−1.00
T-test / MW test	(1.98)**	(1.87)*	(2.18)**	(2.12)**

(*continued on next page*)

Table A2 (*continued*)

	M&As		Divestures	
	Mean	Median	Mean	Median
Panel E: Effect of Firm Complexity on M&As & Divestures				
			M&As	*Divestures*
COMPLEX			−0.0287	0.0754
			(−2.98)***	(3.87)***
Constant			1.3498	−1.1432
			(10.76)***	(−8.67)***
Control variables			Yes	Yes
Pseudo R^2			0.2643	0.2095
Nobs			3921	1214

This table reports the mean and median values of firm complexity (Panel A) and debt ratings (Panels B—D) for the two years before and after an M&A or a divestiture. We select firms that engage in cross-industry acquisitions, including those that complete more than two cross-industry acquisitions per year. Cross-industry classification is measured at the 2-digit SIC code level. It also presents the results of a *t*-test (Mann-Whitney test) comparing the mean (median) differences for each variable between the pre- and post-event periods. In Panel E, we examine the impact of complexity on M&As and divestitures using Probit. In the first model, the dependent variable is a dummy that takes the value of 1 if a firm engages in an M&A, and 0 otherwise. In the second model, the dependent variable is a dummy that takes the value of 1 if a firm engages in divestitures, and 0 otherwise. Detailed definitions of the variables are provided in Appendix A. The *t*-statistics shown in parentheses are based on standard errors that are adjusted for heteroscedasticity and are clustered at the firm level. We winsorize continuous variables at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

Table A3
Dynamic relation between changes in complexity and credit ratings

	Δ S&P24	Δ S&P22	Δ S&P17
Panel A: Mergers and Acquisitions			
Δ COMPLEX	−0.5043	−0.4547	−0.5283
	(−7.31)***	(−6.65)***	(−5.45)***
Constant	16.8498	14.4362	4.7634
	(36.48)***	(32.17)***	(19.76)***
Δ Control variables	Yes	Yes	Yes
Fixed effects	YI	YI	YI
Adj R2	0.6458	0.6370	0.5945
Nobs	3876	3876	3876
Panel B: Divestures			
Δ COMPLEX	−0.1327	−0.1152	−0.2433
	(−3.31)***	(−2.87)***	(2.43)***
Constant	11.7643	10.5432	1.9863
	(23.76)***	(20.32)***	(6.43)***
Δ Control variables	Yes	Yes	Yes
Fixed effects	YI	YI	YI
Adj R^2	0.5637	0.5436	0.4865
Nobs	1031	1031	1031

This table presents the regression analysis of changes (first differences) in firm debt ratings in relation to changes in complexity over time following M&A (Panel A) and divestitures (Panel B). We select firms that engage in cross-industry M&A, including those completing more than two cross-industry acquisitions per year. Cross-industry classification is measured at the 2-digit SIC code level. The changes in complexity are computed as the difference between the complexity measures in the two-year pre-event and two-year post-event windows. Similarly, the changes in debt ratings are calculated by subtracting the debt rating at the beginning of the event window (two years prior) from the debt rating at the end of the event window (two years after). Detailed definitions of the variables are provided in Appendix A. The t-statistics, shown in parentheses, are calculated using standard errors adjusted for heteroscedasticity and clustered at the firm level. Continuous variables are winsorized at the 1 % and 99 % levels. Superscripts *, **, and *** indicate significance levels of 10 %, 5 %, and 1 %, respectively.

Table A4
The effect of changes in corporate governance (*CG*), shareholder voting on M&A and divestitures.

Panel A: Changes in corporate governance (CG) score	
	COMPLEX
Δ CG	−0.1987
	(−6.54)***
Constant	6.5487
	(23.87)***

(*continued on next page*)

Table A4 (*continued*)

Panel A: Changes in corporate governance (CG) score	
	COMPLEX
Control variables	Yes
Fixed effects	YI
Adj R^2	0.4378
Nobs	2984

Panel B: Voting on M&As	
	COMPLEX
VOTE_M&A	0.0988
	(1.97)**
Constant	2.6548
	(8.87)***
Control variables	Yes
Fixed effects	YI
Adj R^2	0.2876
Nobs	768

Panel C: Voting on divestitures	
VOTE_Divestitures	−0.0476
	(−1.33)
Constant	1.7532
	(7.59)***
Control variables	Yes
Fixed effects	YI
Adj R^2	0.1984
Nobs	544

This table presents the regression analysis of changes in the corporate governance (CG) index (Panel A) and shareholder voting on mergers (Panel B) and divestitures (Panel C) in relation to firm complexity. We use the inverse anti-takeover G-index (Gompers et al., 2003) as a proxy for governance quality. Detailed variable definitions are provided in Appendix A. The t-statistics (in parentheses) are calculated using standard errors adjusted for heteroscedasticity and clustered at the firm level. Continuous variables are winsorized at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

Table A5
The results of Hadri unit root test.

Variable	*p*-levels
COMPLEX	0.1138
LNFILE	0.0874
SIZE	0.0938
LEV	0.0891
NI/TA	0.0948
MB	0.0786
TANG	0.0838
INTCOV	0.0661
SDRET	0.0800
IO	0.0699

This table we report the results when estimating Hadri unit root test.

Table A6
Economy-wide explanatory variables

Variables	S&P24	S&P22	S&P17
	(1)	(2)	(3)
COMPLEX	−0.6969	−0.6991	−0.2167
	(−16.24)***	(−16.36)***	(−14.40)***
LNFILE	0.0165	0.0149	0.0105
	(3.48)***	(2.72)***	(2.32)**
STATE_EDU	0.6693	0.6725	0.4241
	(1.57)	(1.59)	(1.08)

(*continued on next page*)

Table A6 (*continued*)

Variables	S&P24	S&P22	S&P17
	(1)	(2)	(3)
STATE_INCOME	0.9957	0.9916	0.8848
	(2.31)**	(2.28)**	(2.19)**
COUNTY_EDU	0.4982	0.4975	0.3553
	(1.24)	(1.17)	(0.96)
COUNTY_INCOME	1.3439	1.3473	1.1802
	(3.08)***	(3.13)***	(2.93)***
Constant	13.1275	11.6177	7.2783
	(24.20)***	(22.45)***	(15.62)***
Control variables	Yes	Yes	Yes
Industry and Year effects	Yes	Yes	Yes
Adj R^2	0.6825	0.6797	0.6758
Nobs	9276	9276	9276

This table reports results when estimating our baseline regression as in Table 2 with additional macro-economic controls. Detailed definitions of the variables are provided in Appendix A. The *t*-statistics shown in parentheses are based on standard errors that are adjusted for heteroscedasticity and are clustered at the firm level. We winsorize continuous variables at the 1 % and 99 % levels. Superscripts *, **, and *** denote significance levels of 10 %, 5 %, and 1 %, respectively.

Data availability

Data will be made available on request.

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