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Financial Distress in U.S. Oilfield Services: A Multi-Model Analysis with Oil Price Dynamics

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Abstract

Background: The oilfield services sector operates in a cyclical environment characterized by volatile oil prices, capital-intensive operations, and fluctuating upstream investment. These conditions increase firms' exposure to financial distress and emphasize the importance of reliable prediction models.
Objective: This study compares the classification performance of four financial distress prediction models and examines the determinants of financial distress among publicly listed U.S. oilfield services firms.
Methods: Panel data from ten publicly listed U.S. oilfield services firms during 2010–2023, consisting of 140 firm-year observations, were analyzed using the Altman Z″, Zmijewski, Grover, and Springate models. Model classification differences were examined using nonparametric tests, while binary logistic regression was applied to evaluate the effects of leverage, profitability, firm size, oil price, oil price volatility, and the moderating effect of oil price volatility.
Results: The results reveal significant differences among the four models, demonstrating that financial distress classification varies depending on the model applied. The Springate model identified the highest number of distressed observations. Profitability was found to have a significant negative effect on financial distress, while leverage, firm size, oil price, and oil price volatility had no significant direct effects. However, oil price volatility significantly moderated the relationship between leverage and financial distress.
Conclusion: Financial distress in the oilfield services industry is primarily associated with internal financial performance, particularly profitability, while external market uncertainty affects financial vulnerability indirectly through leverage conditions. This study contributes to financial distress research by integrating model comparisons and industry-specific determinants, providing practical insights for managers, investors, and creditors.

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INTRODUCTION

Oilfield services (OFS) firms operate in a highly cyclical and capital-intensive industry that is closely tied to upstream oil and gas investment and fluctuations in global crude oil markets (International Energy Agency, 2023; American Petroleum Institute, 2025). Unlike exploration and production (E&P) companies, OFS firms primarily provide drilling, completion, and production support services in response to upstream demand. Thus, a decline in upstream investment may reduce equipment utilization, revenue, and profitability, thereby weakening the financial position of OFS firms, particularly during energy market downturns (Kilian & Zhou, 2022).

The industry's vulnerability became particularly evident during the 2014–2016 oil price collapse and the COVID-19 pandemic in 2020. During these periods, the sharp decline in crude oil prices led many energy firms to postpone or cancel exploration and production projects, substantially reducing demand for oilfield services while firms continued to bear high fixed operating and financing costs (Cathcart et al., 2020; Mousavi et al., 2024; Isynuwardhana & Putri, 2021). According to the International Energy Agency (2023), global upstream investment contracted significantly during the pandemic before gradually recovering, reflecting the industry's strong dependence on market conditions. Similarly, industry reports documented a wave of restructurings and bankruptcies among OFS firms, including BJ Services and Pioneer Energy, highlighting the financial vulnerability of firms operating in this sector (Reuters, 2020; The Wall Street Journal, 2020; Haynes Boone, 2022).

These developments underscore the importance of early financial distress detection, particularly in cyclical sectors exposed to persistent energy market volatility. Financial distress refers to a period of financial deterioration in which a firm experiences increasing difficulty in meeting its financial obligations before reaching formal bankruptcy or insolvency (Altman et al., 2019; Kristanti, 2019). Financial distress is widely regarded as an early indicator of potential business failure; therefore, its timely identification and assessment are essential for managers, investors, creditors, and regulators in making informed strategic and financial decisions.

Among the most widely used approaches to assessing financial distress across developed and emerging markets are accounting-based prediction models, including the Altman Z″, Zmijewski, Grover, and Springate models (Aliyu, 2022; Ibrahim et al., 2024; Klištincová, 2023; Mavengere & Gumede, 2024; Michalkova & Ponisciakova, 2025).

Although accounting-based models remain widely used because of their simplicity and interpretability, the broader bankruptcy prediction literature has evolved considerably over time (Bellovary et al., 2023; Insani et al., 2024; Zhao et al., 2024). More recent studies have increasingly incorporated machine learning and explainable artificial intelligence (XAI) to capture complex and nonlinear relationships in financial distress prediction (Barboza et al., 2017; Kristanti et al., 2025; Nguyen et al., 2025; Lin et al., 2025; Vukčević et al., 2024). Nevertheless, conventional models remain relevant for financial distress assessment, particularly when interpretability and comparability across firms are important.

From a theoretical perspective, financial distress arises from the interaction between firm-specific financial conditions and external economic pressures. Trade-off Theory suggests that excessive leverage increases financial vulnerability because higher debt obligations reduce financial flexibility during economic downturns. Signaling Theory proposes that profitability conveys important information regarding a firm's financial health and future sustainability. Meanwhile, the External Shock Transmission framework argues that macroeconomic shocks, including oil price fluctuations, influence firms indirectly through their effects on profitability, cash flow generation, operational efficiency, and financing capacity rather than through direct mechanisms alone (Kilian & Zhou, 2022; Chen et al., 2024). These complementary perspectives suggest that financial distress is shaped not only by internal financial characteristics but also by the interaction between firm-level conditions and external industry uncertainty.

Although financial distress has been extensively investigated, three important gaps remain. First, previous studies commonly examine either the performance of financial distress prediction models or the determinants of financial distress, leaving limited evidence that integrates both perspectives within a single analytical framework. Second, empirical studies on financial distress have been conducted across various institutional and industry settings, including banking and insurance, while evidence from highly cyclical industries such as oilfield services remains comparatively limited (Kristanti, Isynuwardhana, & Rahayu, 2019; Kebede et al., 2024; Toudas et al., 2024; Sharma & Kumar, 2024). Third, although oil price uncertainty has been associated with financing decisions, investment behavior, organizational capital, and firm performance (Hasan et al., 2022; Ilyas et al., 2021; Kamal et al., 2022; Huang et al., 2025), its role in shaping the relationship between firm-level financial characteristics and financial distress remains insufficiently examined. These gaps indicate the need for an integrated analysis that combines financial distress model comparison with firm-level determinants and industry-specific market uncertainty.

The novelty of this study lies in integrating comparative financial distress classifications with firm-level financial determinants and oil price dynamics within a single analytical framework specifically tailored to the oilfield services industry. Rather than examining prediction models and financial distress determinants separately, this study links differences in model classifications to internal financial characteristics and external market conditions associated with financial vulnerability in a highly cyclical industry.

Therefore, this study compares financial distress classifications generated by the Altman Z″, Zmijewski, Grover, and Springate models and examines the effects of leverage, profitability, firm size, oil price, and oil price volatility on financial distress among publicly listed U.S. oilfield services firms. In addition, the study evaluates whether oil price volatility moderates the relationship between leverage and financial distress.

Hypothesis Development

Differences between Financial Distress Prediction Models

Different financial distress prediction models employ different combinations of financial ratios, weighting structures, and classification thresholds. Consequently, the same firm-year observation may receive different financial distress classifications depending on the model applied. Previous comparative studies have consistently reported discrepancies among accounting-based prediction models because each model emphasizes different aspects of corporate financial performance, including profitability, liquidity, solvency, and operating efficiency (Altman et al., 2019; Zhao et al., 2024). These differences are expected to be more pronounced in highly cyclical and capital-intensive industries, where financial conditions can change rapidly following fluctuations in commodity prices and investment activities. Therefore, the first hypothesis is formulated as follows:

H1: Financial distress classifications differ significantly across the Altman Z″, Zmijewski, Grover, and Springate models.

The Influence of Leverage on Financial Distress

Trade-off Theory suggests that firms with higher leverage face greater fixed financial obligations, reducing financial flexibility during periods of declining cash flow and operating performance. In highly cyclical industries such as oilfield services, where revenues fluctuate with upstream investment activity, excessive debt may increase the likelihood of financial distress because firms remain obligated to meet debt repayments despite declining operating income. Accordingly, leverage is expected to increase financial distress risk.

H2: Leverage positively affects the probability of financial distress.

The Influence of Profitability on Financial Distress

Signaling Theory argues that profitability conveys important information regarding a firm's financial health and prospects. Firms with stronger profitability generally possess greater internal resources, stronger cash flow generation, and higher operational efficiency, enabling them to absorb adverse market shocks more effectively than less profitable firms. Consequently, profitability is expected to reduce the likelihood of financial distress.

H3: Profitability negatively affects the probability of financial distress.

The Influence of Firm Size on Financial Distress

Firm size is generally associated with greater access to external financing, diversified operations, and stronger resource availability. Larger firms may also benefit from economies of scale and greater operational flexibility, enabling them to respond more effectively to adverse economic conditions. These advantages are expected to reduce their exposure to financial distress.

H4: Firm size negatively affects the probability of financial distress.

The Influence of Oil Price on Financial Distress

Within the External Shock Transmission framework, oil price represents an important macroeconomic factor influencing investment decisions throughout the upstream oil and gas industry. Declining oil prices typically reduce exploration and production expenditures, resulting in lower demand for drilling, completion, and production support services. Consequently, lower oil prices are expected to be associated with a higher probability of financial distress among oilfield services firms.

H5: Oil price negatively affects the probability of financial distress.

The Moderating Role of Oil Price Volatility

Previous studies indicate that oil price uncertainty influences corporate financing decisions, debt exposure, and default risk, particularly among firms operating in energy-related industries (Fan et al., 2021; Amin et al., 2025; Maghyereh & Al-Zoubi, 2025). During periods of elevated oil price volatility, the financial consequences of leverage may change because firms must manage fixed debt obligations under greater uncertainty in revenues and operating conditions. Accordingly, the effect of leverage on financial distress may depend on the level of oil price volatility rather than remaining constant across market conditions.

H6: Oil price volatility moderates the relationship between leverage and financial distress.

METHOD

This study develops an integrated analytical framework to examine financial distress in U.S. oilfield services firms by combining a comparative assessment of financial distress prediction models with an analysis of firm-level and industry-specific determinants. Financial distress is evaluated using four established accounting-based prediction models—Altman Z″, Zmijewski, Grover, and Springate—to determine whether different models produce consistent classifications within a highly cyclical and capital-intensive industry.

The framework is grounded in Trade-off Theory, Signaling Theory, and the External Shock Transmission framework. Trade-off Theory provides the basis for examining leverage as a source of financial vulnerability, while Signaling Theory supports the role of profitability as an indicator of financial health. The External Shock Transmission framework explains how changes in external market conditions may influence firms through financial and operational channels. Accordingly, oil price and oil price volatility represent external industry conditions, whereas leverage, profitability, and firm size represent firm-specific financial characteristics. Oil price volatility is further incorporated as a moderating variable to examine whether market uncertainty alters the relationship between leverage and financial distress.

The framework integrates these determinants with the comparative assessment of the four financial distress prediction models. Following the model comparison, the Springate classification is used as the dependent variable in the binary logistic regression analysis. The Springate model is selected because its emphasis on profitability and asset utilization is theoretically consistent with the operational characteristics of the oilfield services industry, where financial deterioration may initially be reflected in weakening operating performance.

By integrating model comparison with firm-level financial characteristics and external industry conditions, the framework enables financial distress to be examined from both classification and explanatory perspectives across different phases of the oil industry cycle from 2010 to 2023. This approach also addresses the study's objective of assessing financial vulnerability within an industry whose operating and financial performance is strongly exposed to changes in energy market conditions. The resulting relationships among the external conditions, firm-level characteristics, financial distress prediction models, and regression analysis are summarized in Figure 1.

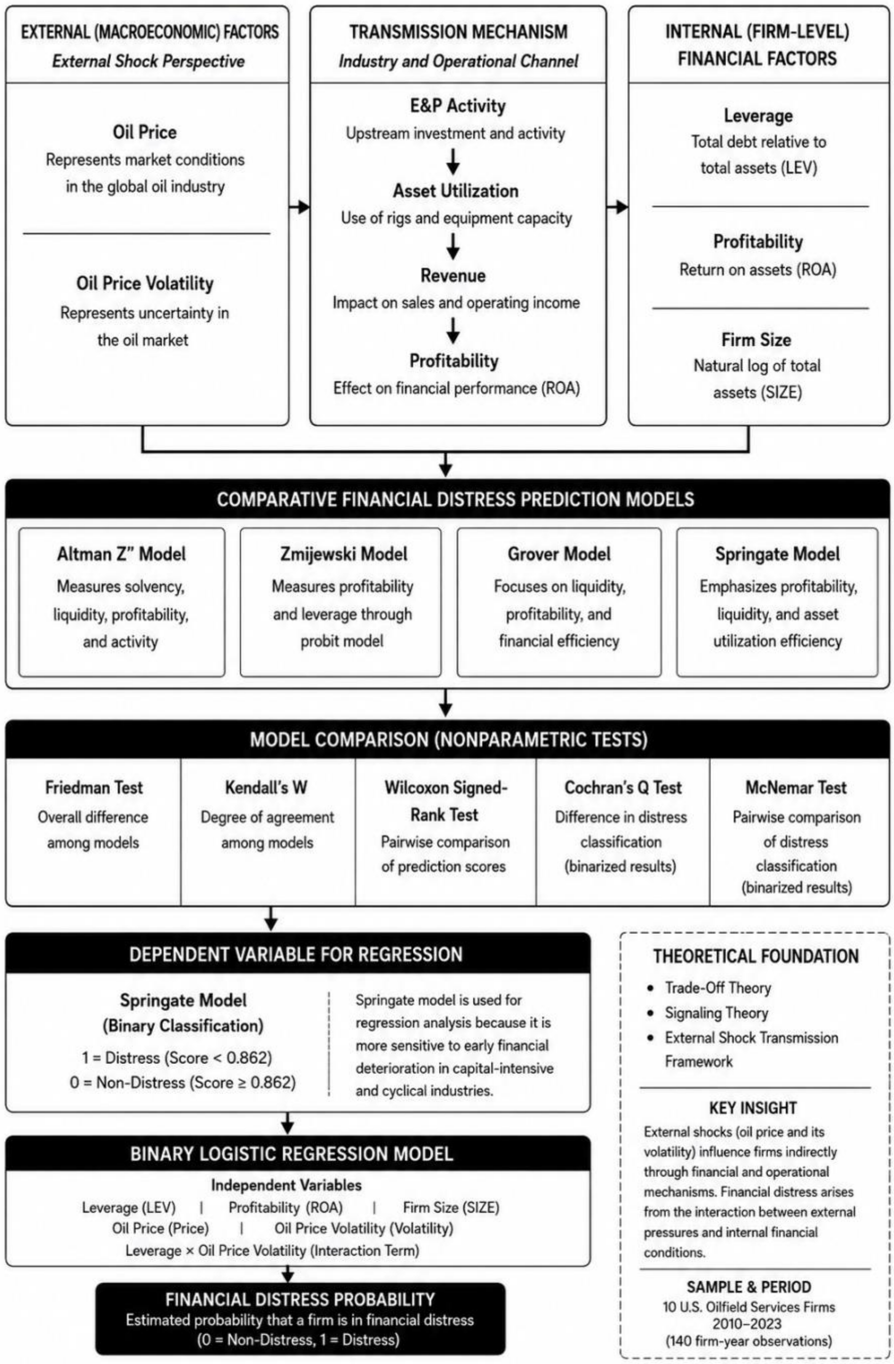

Figure 1. Research Framework
Source: Author's Design (2026)

This study employed a quantitative research design with descriptive and explanatory components to examine financial distress among publicly listed oilfield services firms in the United States (Saunders et al., 2023; Field, 2024; Hair et al., 2019). A deductive approach was adopted to test hypotheses derived from Trade-off Theory, Signaling Theory, and the External Shock Transmission framework. Panel data covering the period from 2010 to 2023 were used to capture firm-level financial conditions across different phases of the oil industry cycle.

The empirical analysis incorporated leverage, profitability, and firm size as firm-level financial characteristics, together with oil price and oil price volatility as external industry conditions. Oil price volatility was additionally specified as a moderating variable to examine whether market uncertainty influences the relationship between leverage and financial distress. The analysis combined descriptive assessment, comparison of financial distress classifications across the four prediction models, and binary logistic regression to examine the determinants of financial distress.

The data were obtained from audited annual reports and publicly available Form 10-K filings of oilfield services firms listed on the New York Stock Exchange (NYSE) and NASDAQ. Because audited financial statements are subject to regulatory reporting standards, they provide reliable and consistent financial information suitable for empirical analysis. Data consistency was verified by cross-checking financial statement figures across annual reports, while observations with incomplete financial information required for calculating the financial distress models or regression variables were excluded from the sample. Purposive sampling was applied using the following criteria: (1) firms operating in the upstream oilfield services sector; (2) continuously listed on the NYSE or NASDAQ throughout the observation period; (3) no permanent delisting during 2010–2023; and (4) complete financial information necessary to calculate the Altman Z″, Zmijewski, Grover, and Springate models as well as all regression variables. The final sample consisted of ten firms, yielding 140 firm-year observations, as presented in Table 1.

Table 1.
U.S. Oilfield Services Firms Sample

No	Company	Code	Exchange	Main Services
1	Schlumberger Ltd	SLB	NYSE	Reservoir characterization, drilling services, well construction, production systems, digital solutions
2	Halliburton Company	HAL	NYSE	Drilling services, well completion, hydraulic fracturing, cementing, production optimization
3	Baker Hughes Company	BKR	NASDAQ	Energy technology, drilling services, turbomachinery, LNG solutions, digital and industrial services
4	Weatherford International Plc	WFRD	NASDAQ	Well construction, drilling tools, completions, production optimization, artificial lift
5	NOV Inc.	NOV	NYSE	Oilfield equipment, drilling rigs, wellbore technologies, automation systems
6	Transocean Ltd	RIG	NYSE	Offshore drilling services, ultra-deepwater and harsh environment rig operations
7	Nabors Industries Ltd	NBR	NYSE	Land drilling services, rig automation, directional drilling, drilling software solutions
8	Noble Corporation Plc	NE	NYSE	Offshore contract drilling, deepwater and high-spec jack-up rig operations
9	RPC Inc.	RES	NYSE	Pressure pumping, hydraulic fracturing, coiled tubing, cementing services
10	Oceaneering International, Inc.	OII	NYSE	Subsea engineering, ROV services, inspection, maintenance & repair, offshore support

Source: Data Processed (2026)

Four accounting-based prediction models, including Altman Z″, Zmijewski, Grover, and Springate, were used to measure financial distress. These models are among the most widely used approaches to financial distress assessment because they rely on objective accounting data and have been extensively applied across industries and countries (Fridson & Alvarez, 2022). For binary classification purposes, observations falling within the grey zone of the Altman Z″ model were grouped into the financially distressed category to maintain a consistent binary classification across the four models.

Financial variables used were total assets, total liabilities, working capital, retained earnings, net income, earnings before interest and tax (EBIT), earnings before taxes (EBT), current assets, current liabilities, sales and book value of equity. The annual average price of Brent crude oil published by the U.S. Energy Information Administration (2026) was used as a measure of oil price, and the annual standard deviation of monthly Brent crude oil returns was used as a measure of oil price volatility. Leverage was calculated as total liabilities divided by total assets; profitability was calculated as return on assets (ROA); and firm size was measured by the natural log of total assets.

The empirical analysis was conducted in two stages. First, the four financial distress prediction models were compared to evaluate differences in their score distributions and classification outcomes. The comparison included both continuous distress scores and binary distress classifications. Following this comparison, the Springate classification was used as the dependent variable for the subsequent regression analysis because the model emphasizes profitability and asset utilization, two dimensions that are particularly relevant to the operational characteristics of the oilfield services industry. The comparative results regarding differences in distress classification across the four models are subsequently presented in the Results section.

For binary classification purposes, firm-year observations with Springate scores below 0.862 were classified as financially distressed (1), whereas observations with scores equal to or greater than 0.862 were classified as non-distressed (0).

Descriptive statistics were initially performed to summarize the distribution of financial distress scores. The Shapiro–Wilk test indicated that the score distributions deviated significantly from normality; therefore, nonparametric statistical procedures were adopted. Differences among the four prediction models were evaluated using the Friedman test, while Kendall's W was used to assess the level of agreement among the models. Pairwise comparisons were subsequently conducted using the Wilcoxon Signed-Rank Test with Bonferroni-adjusted significance levels. Differences in binary classification outcomes were further examined using Cochran's Q test and the McNemar test.

The second stage employed binary logistic regression to identify the determinants of financial distress. Logistic regression was selected because the dependent variable consisted of a binary classification (distressed versus non-distressed), making this approach appropriate for estimating the probability of financial distress while accommodating both continuous explanatory variables and interaction effects (Wooldridge, 2023). Regression coefficients (β) and odds ratios [Exp(β)] were reported to indicate the direction and relative magnitude of the estimated relationships. Model adequacy was evaluated using the Omnibus Test of Model Coefficients, Nagelkerke R^2, the Hosmer–Lemeshow goodness-of-fit test, and overall classification accuracy. Prior to constructing the interaction term, leverage and oil price volatility were standardized using Z-scoring, which transformed the variables to a mean of zero and a standard deviation of one, thereby reducing potential multicollinearity associated with the interaction term. Multicollinearity among the explanatory variables was subsequently assessed using Variance Inflation Factor (VIF) and tolerance values.

$$\text{Logit}(\text{Distress}\{i,t\}) = \beta_0 + \beta_1\text{Leverage}\{i,t\} + \beta_2\text{ROA}\{i,t\} + \beta_3\text{Size}\{i,t\} + \beta_4\text{OilPrice}\{t\} + \beta_5\text{OilVolatility}\{t\} + \beta_6(\text{Leverage}\{i,t\} \times \text{OilVolatility}\{t\}) + \varepsilon\{i,t\} \quad (1)$$

where *Distress* denotes the binary financial distress classification based on the Springate model. *Leverage* is measured as total liabilities divided by total assets, *ROA* represents profitability, *Size* is measured as the natural logarithm of total assets, *OilPrice* refers to the annual average Brent crude oil price, and *OilVolatility* represents the annual standard deviation of monthly Brent crude oil returns. The interaction term captures the moderating effect of oil price volatility on the relationship between leverage and financial distress.

All statistical analyses were conducted at a 5% significance level ($\alpha = 0.05$). Financial distress scores were calculated using Microsoft Excel, while all statistical analyses were performed using IBM SPSS Statistics version 26.

Because this study relied exclusively on publicly available secondary data and did not involve human or animal participants, ethical approval was not required. Nevertheless, all data were collected and analyzed in accordance with accepted academic research standards.

RESULTS AND DISCUSSION

Results

The empirical analysis is based on 140 firm-year observations from ten publicly listed U.S. oilfield services firms during the 2010–2023 period. The findings are presented in four stages. First, descriptive statistics summarize the distribution of financial distress scores across the four prediction models. Second, financial distress classification results are reported. Third, nonparametric statistical tests evaluate differences among the prediction models. Finally, binary logistic regression is employed to identify the determinants of financial distress.

Descriptive Statistics

Table 2 presents the descriptive statistics of the four financial distress prediction models. Among the evaluated models, the Altman Z″ score recorded the highest mean (3.571) and the largest standard deviation (2.982), indicating the greatest variability of scores across the sample. Its value ranged from −6.588 to 21.610. The Zmijewski model reported a mean score of −1.373 with a standard deviation of 1.306. Meanwhile, the Grover and Springate models produced mean scores of 0.351 and 0.409 with standard deviations of 0.509 and 0.590, respectively. Overall, the descriptive statistics indicate substantial variation in the distributions of financial distress scores across the four prediction models.

Table 2.
Descriptive Statistics

Model	N	Mean	Std. Deviation	Minimum	Maximum
Altman Z″	140	3.571	2.982	-6.588	21.610
Zmijewski	140	-1.373	1.306	-3.559	5.872
Grover	140	0.351	0.509	-3.028	1.456
Springate	140	0.409	0.590	-3.404	1.638

Source: Data Processed (2026)

Following the descriptive analysis, the normality of the financial distress scores was examined using the Shapiro–Wilk test. The results indicate that all four prediction scores significantly deviated from normality ($p < 0.001$), indicating that the assumption of normality was not satisfied. Consequently, subsequent analyses employed nonparametric statistical procedures.

Figure 2 illustrates the annual trend of average financial distress scores during the observation period. Financial conditions deteriorated during the 2014–2016 oil price downturn and again during the COVID-19 contraction in 2020 before gradually improving during the subsequent recovery period.

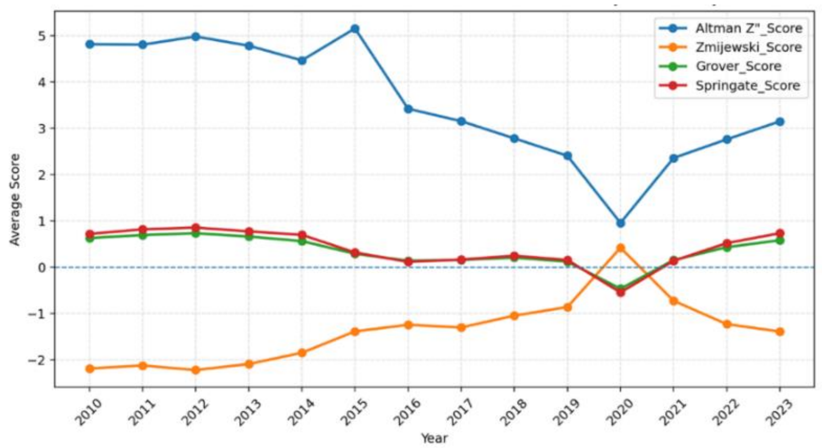

Figure 2. Trend of Financial Distress Score
Source: Data Processed (2026)

Financial Distress Classification

To facilitate comparison across prediction models, observations classified within the grey zone of the Altman Z″ model were grouped into the financially distressed category, consistent with the binary classification adopted throughout the statistical analyses. The resulting proportions of distressed and non-distressed observations generated by each model are presented in Table 3.

Table 3.
Financial Distress Classification Results

Model	Distress	Non-Distress
Altman Z″	30.7%	69.3%
Zmijewski	12.1%	87.9%
Grover	12.9%	87.1%
Springate	79.3%	20.7%

Source: Data Processed (2026)

The Springate model classified the largest proportion of firm-year observations as financially distressed (79.3%), followed by the Altman Z″ model (30.7%). In contrast, the Zmijewski and Grover models identified substantially lower distress proportions of 12.1% and 12.9%, respectively. These findings demonstrate noticeable differences in financial distress classifications across the prediction models evaluated.

Statistical Test Results

The differences among financial distress prediction models were evaluated using nonparametric statistical procedures because the Shapiro–Wilk test indicated that all score distributions significantly deviated from normality ($p < 0.001$).

The Friedman test identified statistically significant differences among the four prediction models ($\chi^2(3) = 244.740$, $p < 0.001$), while Kendall's W indicated a moderate level of agreement among the models ($W = 0.583$, $p < 0.001$).

Similarly, Cochran's Q test confirmed significant differences in the binary classification outcomes across the four prediction models ($Q = 213.474$, $p < 0.001$). Pairwise McNemar tests showed significant differences for all model pairs except the comparison between the Zmijewski and Grover models (Exact $p = 1.000$).

The Wilcoxon Signed-Rank tests further demonstrated statistically significant differences in financial distress scores across all model pairs, including the comparison between the Zmijewski and Grover models (all $p < 0.001$).

The results of the nonparametric analyses are summarized in Table 4.

Table 4.
Statistical Test Results

Test	Statistic	p-value	Interpretation
Friedman test	$\chi^2(3) = 244.740$	< 0.001	Significant differences across model scores
Kendall’s W	W = 0.583	< 0.001	Moderate agreement across models
Cochran’s Q	Q = 213.474	< 0.001	Classification outcomes differ significantly
Wilcoxon Signed Rank Test	All model pairs significant	< 0.001	Significant score differences across models
McNemar Test (Zmijewski vs Grover)	Exact Sig. = 1.000	1.000	Not significantly different
McNemar Test (pairs involving Springate)	χ^2 varies	< 0.001	Significantly different

Source: Data Processed (2026)

Pairwise comparisons based on the McNemar test are presented in Table 5. Significant differences were observed for all model pairs involving the Springate model as well as the comparisons between Altman Z″ and the Zmijewski and Grover models. The only non-significant comparison was between the Zmijewski and Grover models (Exact p = 1.000).

Table 5.
Pairwise Binary Classification Comparison

Model Pair	McNemar χ^2	p-value	Interpretation
Altman Z″ vs Zmijewski	20.833	< 0.001	Significantly different
Altman Z″ vs Grover	19.862	< 0.001	Significantly different
Altman Z″ vs Springate	64.129	< 0.001	Significantly different
Zmijewski vs Grover	-	1.000	Not significantly different
Zmijewski vs Springate	92.011	< 0.001	Significantly different
Grover vs Springate	91.011	< 0.001	Significantly different

Source: Data Processed (2026)

Binary Logistic Regression Results

The binary logistic regression model was estimated to identify the determinants of financial distress among U.S. oilfield services firms. Prior to interpreting the regression coefficients, several goodness-of-fit statistics were evaluated.

The Omnibus Test of Model Coefficients was statistically significant ($\chi^2 = 88.866$, $p < 0.001$), indicating that the set of explanatory variables significantly improved the prediction of financial distress compared with the intercept-only model. The model achieved a Nagelkerke R^2 value of 0.735, suggesting substantial explanatory power. Furthermore, the Hosmer–Lemeshow goodness-of-fit test was not statistically significant ($\chi^2 = 6.657$, $p = 0.574$), indicating that the model adequately fitted the observed data. The overall classification accuracy of the model was 88.6%.

The regression results indicate that profitability (ROA) and the interaction between leverage and oil price volatility significantly affect the probability of financial distress, whereas leverage, firm size, oil price, and oil price volatility do not exhibit statistically significant direct effects.

Leverage was positively associated with financial distress ($\beta = 0.380$, $Exp(\beta) = 1.463$), although the relationship was not statistically significant ($p = 0.436$). Profitability (ROA) had a significant negative effect on financial distress ($\beta = -65.694$, $p < 0.001$). Firm size also showed no statistically significant effect ($\beta = 0.454$, $p = 0.198$), while oil price ($\beta = -0.026$, $p = 0.244$) and oil price volatility ($\beta = -12.700$, $p = 0.467$) were not statistically significant. The interaction term between leverage and oil price volatility was statistically significant ($\beta = -1.957$, $Exp(B) = 0.141$, $p = 0.040$), indicating the presence of a moderating effect.

Multicollinearity diagnostics indicated no evidence of problematic multicollinearity among the explanatory variables, with all Variance Inflation Factor (VIF) values below 2.0 and tolerance values above 0.50. The results of binary logistic regression and hypothesis testing are summarized in Table 6.

Table 6.
Binary Logistic Regression Results and Hypothesis Testing

Variable	Coefficient (β)	S.E.	Wald	*p*-value	Odds Ratio (Exp(β))	Hypothesis
Leverage	0.380	0.488	0.606	0.436	1.463	H2 Not Supported
ROA	-65.694	15.490	17.987	<0.001	0.000	H3 Supported
Firm Size	0.454	0.352	1.657	0.198	1.574	H4 Not Supported
Oil Price	-0.026	0.023	1.359	0.244	0.974	H5 Not Supported
Oil Price Volatility	-12.700	17.456	0.529	0.467	0.000	Not Significant
Leverage × Oil Price Volatility	-1.957	0.955	4.201	0.040	0.141	H6 Supported

Source: Data Processed (2026)

Discussion

Model Sensitivity and Financial Distress Classification

The comparative analysis demonstrates that financial distress classification is highly sensitive to the prediction model employed. Both the Friedman and Cochran's Q tests showed the four models were significantly different, but Kendall's W showed only moderate agreement. These findings indicate that, although the models exhibit a moderate degree of agreement in ranking firms according to financial condition, they differ substantially in their sensitivity to financial deterioration and in the stage at which such deterioration is identified.

The Springate model classified the largest proportion of observations as financially distressed and differed significantly from the Altman Z″, Zmijewski, and Grover models. By contrast, the Zmijewski and Grover models produced statistically equivalent binary classifications. These results suggest that accounting-based financial distress models should not be regarded as substitutes since each model emphasizes different dimensions of financial performance and may therefore capture different stages of financial deterioration.

The higher proportion of financially distressed observations identified by the Springate model may be attributable to its emphasis on profitability, working capital efficiency, and asset utilization. In the oilfield services sector, operational deterioration may initially manifest through declining profitability and equipment utilization, eventually leading to more severe liquidity or solvency problems. Accordingly, prediction models that place greater emphasis on operational performance than on leverage or solvency measures may be more responsive to early signs of financial deterioration in the oilfield services industry. This interpretation is consistent with the External Shock Transmission framework, whereby external market shocks may initially affect operating performance, profitability, and asset utilization before contributing to more severe liquidity and solvency pressures.

The results also show that the four prediction models have different classification patterns. Models that classify a larger proportion of observations as financially distressed may be more sensitive to potential signs of financial deterioration. Alternatively, models that classify fewer observations as distressed may reflect a more conservative approach to identifying financial distress. The Zmijewski and Grover models exhibited more conservative classification patterns than the Springate model in this study. For this reason, the selection of the prediction model should be guided by the research goal, depending on whether the objective is to identify potential financial deterioration earlier or to adopt a more conservative definition of financial distress.

The findings of this study have broader implications for research on financial distress in cyclical industries. Recent evidence further indicates that energy commodity shocks can affect financial stability because their effects on energy markets may propagate to corporate financing conditions and broader macro-financial vulnerability (Sánchez-García et al., 2024). This study does not identify a single universally superior prediction model; rather, it demonstrates that model performance may vary according to industry characteristics and the stage of financial deterioration being assessed. In the oilfield services industry, financial deterioration may initially manifest through declining profitability and operational efficiency before developing into more severe solvency problems. Prediction models that place greater emphasis on these operational dimensions may therefore exhibit greater sensitivity to financial vulnerability. This study contributes to the financial distress literature by demonstrating that industry characteristics are important considerations in the selection of prediction models, rather than assuming that a particular accounting-based model performs consistently across industries.

The findings also have broader international relevance for other commodity-dependent and highly cyclical industries, including mining, offshore drilling, shipping, and energy services, which are similarly exposed to commodity price fluctuations and investment cycles. These findings suggest that model selection should be tailored to industry-specific financial dynamics, particularly in sectors where operational performance is highly sensitive to external market shocks.

Financial Distress Determinants and Practical Implications

The regression results are consistent with the External Shock Transmission framework, which suggests that macroeconomic shocks may influence financial distress through firm-level financial and operational mechanisms rather than solely through direct effects. In the oilfield services industry, fluctuations in oil prices can affect upstream investment activity, equipment utilization, and operating revenues, which may subsequently influence firms' financial conditions. The absence of significant direct effects of oil price and oil price volatility, together with the significant role of profitability, suggests that operational and financial performance may represent an important channel through which external market conditions are associated with financial vulnerability.

Among the explanatory variables, profitability emerged as the strongest determinant of financial distress. The significant negative relationship between return on assets and financial distress supports Signaling Theory, which argues that profitability conveys credible information regarding a firm's financial health and future sustainability. Firms with stronger profitability possess greater internal financial resources and operational resilience, enabling them to absorb adverse market conditions more effectively than less profitable firms. More broadly, previous studies indicate that internal financial characteristics, including profitability and liquidity, are important in explaining firms' exposure to financial distress (Arifin & Koerniawan, 2025; Mousavi et al., 2024).

By contrast, leverage did not exhibit a statistically significant direct effect on financial distress. This result provides only limited support for the expected relationship derived from Trade-off Theory. In the context of this study, leverage alone appears insufficient to explain variation in financial distress, suggesting that the financial consequences of debt may depend on other firm-specific or market conditions. This interpretation is further supported by the significant interaction between leverage and oil price volatility. At the same time, the significant effect of profitability suggests that the ability to sustain earnings and operational performance may be more important than capital structure alone in determining financial resilience.

Similarly, firm size did not significantly influence the probability of financial distress. This finding suggests that large firms are not automatically protected from financial distress in industries characterized by strong cyclical fluctuations. Previous evidence also indicates that financial distress may vary according to firm- and industry-specific characteristics, including market structure and diversification (Kristanti, Isynuwardhana, & Rahayu, 2019). During periods of declining oil prices, both large and small firms experience reductions in equipment utilization, drilling activity, and service demand. Consequently, industry-wide shocks may reduce the traditional advantages associated with firm size, including economies of scale and easier access to external financing.

Oil price and oil price volatility also did not exhibit statistically significant direct effects. Nevertheless, this result should not be interpreted as evidence that external market conditions are unimportant. Instead, it indicates that oil prices affect financial distress indirectly through their influence on upstream investment decisions, operational demand, profitability, and cash flow generation. The absence of a direct statistical relationship therefore supports the view that macroeconomic shocks operate through intermediate financial and operational mechanisms rather than acting independently.

An important contribution of this study lies in the moderating effect of oil price volatility.

Although oil price volatility did not exhibit a significant direct effect, its interaction with leverage was statistically significant ($\beta = -1.957$, $p = 0.040$), confirming that the relationship between leverage and financial distress varies with oil price volatility. The negative interaction coefficient indicates that the effect of leverage on the probability of financial distress changes as oil price volatility increases. Therefore, leverage should not be interpreted independently of market uncertainty. However, because the direction and magnitude of an interaction in a logistic regression depend on the combined values of the interacting variables, the moderating effect should be interpreted cautiously rather than simply as a strengthening effect. This finding is consistent with recent evidence showing that oil market shocks propagate through financial systems by increasing systemic financial risk, particularly during periods of heightened market uncertainty (Wang et al., 2024). This result expands the External Shock Transmission framework by demonstrating that financial vulnerability emerges from the interaction between firm-level financial characteristics and external market uncertainty rather than from either factor in isolation.

From a practical perspective, these findings provide several implications for stakeholders operating in highly cyclical industries. Managers should prioritize maintaining profitability through operational efficiency, asset utilization, cost discipline, and cash flow management rather than focusing exclusively on capital structure adjustments. Investors should place greater emphasis on profitability indicators and operational performance when assessing long-term financial resilience, particularly during periods of commodity price volatility. Likewise, creditors should complement leverage-based assessments with measures of earnings quality, profitability, and operating efficiency when evaluating credit risk. More broadly, organizations should strengthen strategic flexibility, technology adoption, and managerial decision-making capabilities to improve their capacity to respond to changing business conditions. The importance of organizational readiness and technology-related decision-making has also been highlighted in studies examining technology adoption in different business contexts (Edo et al., 2024).

The findings also contribute to the financial distress literature by integrating comparative prediction models with firm-level financial characteristics and industry-specific external conditions within a single analytical framework. Previous corporate finance research further indicates that firm-level outcomes are associated with broader organizational and financial practices, including tax-related decisions, earnings management, and governance mechanisms (Pratomo et al., 2021; Pratomo & Sudibyo, 2023). Unlike previous studies that generally focus either on prediction model performance or on financial distress determinants, this study demonstrates that financial vulnerability in cyclical industries cannot be explained adequately by either accounting indicators or macroeconomic variables alone. Instead, financial distress results from the interaction between internal financial performance and external market conditions. This integrated perspective provides a more comprehensive explanation of financial distress in commodity-dependent industries and may serve as a useful framework for future studies examining other cyclical sectors.

The implications may also extend to other commodity-dependent industries, such as mining, offshore drilling, shipping, and energy services, where financial performance is similarly exposed to commodity price and investment cycles. Future comparative research across these industries could determine whether the model sensitivity observed in the U.S. oilfield services sector is also present in other cyclical settings.

Several limitations should be acknowledged. First, the study is limited to ten publicly listed U.S. oilfield services firms, which may restrict the generalizability of the findings to privately held firms or firms operating in different institutional environments. Second, the analysis relies primarily on accounting-based financial indicators, which may not fully capture market expectations, investor sentiment, or behavioral dimensions of financial decision-making. Studies in other financial contexts indicate that financial literacy, perceived risk, digital literacy, and behavioral factors can influence financial decisions (Fitriani & Soma, 2026; Ramadhani et al., 2026). Although these factors are outside the scope of the present study, future research may examine whether behavioral and decision-making dimensions provide additional information for understanding financial vulnerability. Third, the regression model does not explicitly address potential endogeneity between financial performance and financial distress, nor does it incorporate industry-specific variables such as drilling activity, rig utilization, or capital expenditure that may influence financial vulnerability. Finally, although binary logistic regression provides an interpretable analytical framework, it may not fully capture complex non-linear relationships among financial variables. Future research could therefore incorporate market-based indicators, industry activity measures, dynamic panel techniques, and machine-learning approaches to improve predictive accuracy and provide a more comprehensive understanding of financial distress in highly cyclical industries (Kristanti et al., 2025).

CONCLUSION

This study demonstrates that financial distress assessment in the U.S. oilfield services industry depends substantially on the prediction model employed. Significant differences were identified among the Altman Z″, Zmijewski, Grover, and Springate models, with the Springate model exhibiting the highest sensitivity in identifying financially distressed firms. The regression analysis further indicates that profitability is the primary determinant of financial distress, whereas leverage, firm size, oil price, and oil price volatility do not exert significant direct effects. However, the significant interaction between leverage and oil price volatility indicates that the relationship between leverage and financial distress varies with the level of uncertainty in the energy market. These findings demonstrate that financial distress in highly cyclical industries is shaped primarily by firm-level financial performance while external market conditions influence vulnerability indirectly through their interaction with internal financial characteristics.

The study contributes to the financial distress literature by integrating comparative evaluation of multiple prediction models with firm-level financial characteristics and industry-specific external conditions within a single analytical framework. The findings suggest that selecting an appropriate financial distress prediction model should account for industry-specific characteristics rather than assume that a single model performs equally well across sectors. From a practical perspective, managers should prioritize profitability, operational efficiency, and cash flow management to strengthen financial resilience, while investors and creditors should complement leverage-based assessments with indicators of profitability and operational performance. Future research may extend this framework by incorporating market-based variables, energy-market transmission indicators, and machine-learning approaches to better capture how commodity shocks propagate into firm-level financial vulnerability under different market conditions.

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AUTHOR CONTRIBUTION STATEMENT

The first author, Rio Budiman, contributed to the conceptualization of the study, data curation, formal analysis, and preparation of the original draft. The second author, Abdul Mukti Soma, provided methodological supervision, validated the analytical approach, and contributed to the review and improvement of the manuscript.

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