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Comparative Analysis of Financial Distress Prediction Models in U.S. Oilfield Services Firms: Evidence from 2010-2023

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ABSTRACT

Purpose: This study examines financial distress in U.S. oilfield services firms by comparing classification outcomes across four prediction models and investigating how industry characteristics influence financial distress detection within a cyclical and capital-intensive environment.
Method: Using panel data from ten publicly listed firms over the period 2010–2023 (140 firm-year observations), this study applies the Altman Z″, Zmijewski, Grover, and Springate models. Differences among models are evaluated using non-parametric tests, including the Friedman test, Kendall's W, Cochran's Q, and McNemar test. Binary logistic regression is subsequently employed to examine the effects of oil price, leverage, profitability (ROA), firm size, and oil price volatility on financial distress.
Findings: The results reveal significant differences in financial distress classifications across models, indicating strong model dependency. The Springate model appears more responsive to early-stage financial deterioration than the Altman Z″, Zmijewski, and Grover models. Profitability (ROA) is the only variable that significantly affects financial distress, while oil price, leverage, firm size, and oil price volatility do not exhibit significant direct effects. The findings further suggest that external shocks influence financial distress indirectly through firm-level financial performance.
Implications: The findings highlight the importance of profitability and operational performance in maintaining financial resilience within cyclical industries. Managers, investors, and creditors should therefore place greater emphasis on profitability as an indicator of financial vulnerability than on external market conditions alone.
Novelty/Value: This study contributes by explaining how the structural characteristics of a cyclical and capital-intensive industry shape the sensitivity of financial distress prediction models. The findings suggest that profitability-oriented models identify financial deterioration earlier than leverage-oriented models because industry downturns initially affect asset utilization, revenue generation, and profitability before materially affecting leverage and solvency indicators.

Keywords: financial distress prediction, oilfield services industry, profitability, model sensitivity, oil price volatility, panel data analysis.

INTRODUCTION

The oil and gas industry plays a major role in economic growth and energy security. The industry is highly dependent on energy prices, decisions related to upstream investments, and technological advancements in exploration and production (E&P) (International Energy Agency, 2023; American Petroleum Institute, 2025). Thus, these factors directly determine the activities of the industry. As a result, they create a direct influence on the demand for oilfield services (OFS), making OFS firms heavily dependent on the levels of upstream activities as well as industry cycles (Mousavi et al., 2024).

The United States provides an appropriate setting for examining these dynamics because it is one of the world's largest oil-producing countries and a key contributor to global oil market developments (Kilian & Zhou, 2022; U.S. Energy Information Administration, 2026). The OFS industry possesses three characteristics that make it particularly vulnerable to financial distress: capital intensity, operational rigidity, and strong cyclical dependence on upstream investment activity (Cathcart et al., 2020; Mousavi et al., 2024). During industry downturns, declining investment reduces service demand, asset utilization, and revenues, while substantial fixed costs and financial obligations remain. Consequently, firms face increasing pressure on profitability and financial stability.

These trends were noted over the period. The industry expanded from 2010 to 2014. This was followed by a major downturn after the collapse of oil prices from 2014 to 2016, and then a recovery from 2017 to 2019. The COVID-19 pandemic led to a sharp contraction in 2020, after which the industry slowly began to recover (U.S. Energy Information Administration, 2026). Several major firms, including Weatherford International, Noble Corporation, and Diamond Offshore Drilling, subsequently entered Chapter 11 restructuring proceedings, illustrating how cyclical shocks can translate into severe financial distress within capital-intensive industries (Haynes and Boone, 2021).

Financial distress is commonly assessed using accounting-based prediction models such as Altman Z″, Zmijewski, Grover, and Springate (Altman et al., 2019; Kristanti, 2019; Zhao et al., 2024). Most of these models have been used extensively in literature but rarely produced similar classification outcomes for the same firm-year observations. Hence, a realistic view of financial distress is that it evolves gradually as a process that occurs prior to formal bankruptcy, signaled by changes in profitability, liquidity, leverage, and operational performance (Kristanti, 2019; Maria et al., 2021, Farida & Sugesti, 2023). Industry characteristics have been largely unexplored in previous research as a factor that might influence model sensitivity, with most of the discrepancies attributed to methodological differences (Insani et al., 2024; Vukčević et al., 2024).

This limitation is particularly important in the OFS industry. Financial deterioration typically emerges through declining asset utilization, revenues, and profitability before significantly affecting leverage and solvency. Thus, a model oriented toward profitability may detect financial distress earlier than a model based on leverage and balance-sheet indicators. The importance of these distinctions is that financial distress should be considered a process and not an event that happens suddenly.

In addition, previous research primarily examines the determinants of financial distress either by firm-level characteristics such as leverage, profitability, and size of the firm or external industry factors like oil prices and volatility in oil prices (Fan et al., 2021; Hasan et al., 2022; Maghyereh & Al-Zoubi, 2025). Thus, there is no clear evidence on how external shocks and firm-level financial conditions interact to determine the financial distress within the OFS industry.

To address these gaps, this study applies four classical financial distress prediction models—Altman Z″, Zmijewski, Grover, and Springate—to the same set of firm-year observations from ten publicly listed U.S. oilfield services firms during 2010–2023. The study first evaluates differences in classification outcomes across models and then examines the effects of leverage, profitability, firm size, oil prices, and oil price volatility on financial distress.

The study has three major contributions to literature. First, it extends the research on financial distress to the oilfield services industry. This is a capital-intensive and cyclical exposure sector. Second, it clears how industry characteristics influence model sensitivity. It shows that profitability-oriented models are better at detecting the early stages of financial deterioration than those focused on leverage. Third, it integrates firm-level and macroeconomic factors within a single analytical framework. It shows that external shocks mainly influence financial distress by their effects on internal financial performance.

LITERATURE REVIEW

Grand Theory

This study is based on the framework of external shocks, which suggests that financial distress results from the interaction between firm-level financial situations and external economic pressures (Kilian & Zhou, 2022; Chen et al., 2024). In cyclical industries, external shocks such as commodity price fluctuations and investment contractions do not immediately create financial distress. Instead, they affect firms through internal transmission mechanisms, particularly profitability, cash flow generation, asset utilization, and financing capacity (Mousavi et al., 2024; Maghyereh & Al-Zoubi, 2025).

Empirical evidence indicates that external shocks can cause major economic disruptions and, therefore, greatly affect both corporate and market conditions. For instance, it has been documented that the COVID-19 pandemic altered market responses, reflecting increased sensitivity of firms to outside economic uncertainties (Isynuwardhana and Putri, 2021). This, therefore, supports the idea that external shocks help to create a situation of financial vulnerability through their interaction with firm-level financial conditions.

Such a view is especially applicable to the oilfield services sector, which is characterized by capital intensity, operational rigidity, and strong dependence on upstream exploration and production activity. When the industry experiences a downturn, reduced investments upstream generally lead to decreased service demand and asset utilization, which in turn reduces profitability and can eventually lead to more serious impacts on leverage and long-term solvency. Hence, different types of financial deterioration could be experienced at various stages of the industry cycle.

To explain firm-level financial vulnerability, this study also draws on Trade-Off Theory and Signaling Theory. Trade-Off Theory suggests that debt increases financing capacity but simultaneously raises financial risk through fixed obligations, particularly when operating performance deteriorates (Altman et al., 2019; Zhao et al., 2024). On the other hand, Signaling Theory sees profitability as an important sign of financial well-being. High profitability shows that a company is strong while low profitability means that the company might have problems (Kristanti, 2019; Song et al., 2024; Arifin & Koerniawan, 2025). Financial distress is generally preceded by weakening profitability and operating performance before progressing to more severe stages of financial deterioration (Kristanti, 2019).

Recent studies further emphasize the role of information, literacy, and behavioral responses in shaping financial decision-making under uncertainty (Fitriani & Soma, 2026; Ramadhani et al., 2026). While these studies primarily deal with individual financial behavior and not corporate financial distress, they help support the general argument that economic outcomes depend on how economic agents respond to available information and perceived risks. Together, these perspectives suggest that profitability works as an important channel external shocks use to affect firm-level financial vulnerability.

Financial Distress Prediction Models

Financial distress refers to a condition in which a firm experiences deterioration in its financial capacity before reaching formal bankruptcy (Altman et al., 2019; Kristanti, 2019; Michalkova & Ponisciakova, 2025). Typically, this weakening is evidenced by falling profits, falling liquidity, rising leverage, and an inability to meet financial obligations. Comparable results have been found in emerging markets, where financial distress is also found to be significantly predicted by profitability and financial structure (Kristanti et al., 2019; Kristanti et al., 2025). Because financial distress is a condition that builds up over time, it is very important that managers, investors, and creditors can identify the signs of it early.

Financial distress prediction models have evolved from traditional accounting-based approaches to more sophisticated statistical and machine-learning methods. Nevertheless, classical ratio-based models remain widely used because they provide transparent, theoretically interpretable, and economically meaningful assessments of financial condition (Altman et al., 2019; Zhao et al., 2024). Although machine learning approaches may offer higher predictive accuracy, classical models remain valuable when the objective is to understand the financial mechanisms underlying distress rather than solely maximizing predictive performance (Kristanti et al., 2025). Recent evidence from emerging markets also shows that machine learning techniques can improve prediction accuracy; however, model interpretability remains important when the objective is to understand the economic mechanisms underlying financial distress (Kristanti et al., 2025).

Recent studies continue to highlight the rapid development of bankruptcy and financial distress prediction research. Advances in machine learning, textual analysis, and artificial intelligence have also added to better predictions by accounting for more complex and non-linear relationships outside the scope of traditional accounting ratios. For example, recent evidence has it that narrative disclosures in annual reports provide more bankruptcy information than the traditional financial indicators; AI-based methods might strengthen early warning systems to identify firms that could run into financial trouble (Zhang et al., 2026; Rech et al., 2025). However, this paper also points out that the most recent prediction techniques do not always outperform interpretable models in all scenarios particularly where transparency and theoretical motivation are important (Kostrzewa et al., 2025). Therefore, ratio-based classical models are still relevant to studying the economic foundations of financial distress, especially in industry-specific contexts where interpretability matters.

Previous studies consistently report that financial distress classifications differ across prediction models because each model emphasizes different financial dimensions, including profitability, liquidity, leverage, solvency, and operational efficiency (Insani et al., 2024; Ibrahim et al., 2024; Vukčević et al., 2024). In cyclical and capital-intensive industry distinction is particularly relevant because in most cases when financial health is deteriorating, it first shows through declining profitability and operational performance before the leverage and solvency indicators are affected.

The four models used in this study represent different methodological approaches and financial viewpoints. The Altman Z″ model concentrates on liquidity, accumulated profitability, and solvency; the Zmijewski model focuses on profitability, leverage, and liquidity; the Grover model focuses on operating performance and profitability, while the Springate model emphasizes profitability and asset efficiency. As a result, each model may detect financial deterioration at different stages of the distress process. Table 1 summarizes the main characteristics of the four prediction models used in this study.

Table 1. Summary of Financial Distress Prediction Models

Model	Method	Variables (Ratios)	Focus	Classification Approach
Altman Z″	Multiple Discriminant Analysis	WC/TA, RE/TA, EBIT/TA, BVE/TL	Liquidity, profitability, solvency	Safe Zone Grey Area Distress Zone
Zmijewski	Probit Regression	NI/TA (ROA), TL/TA, CA/CL	Profitability, leverage, liquidity	Distress Non-Distress
Grover	Discriminant Analysis	WC/TA, EBIT/TA, NI/TA	Operating performance, profitability	Safe Zone Grey Area Distress Zone
Springate	Discriminant Analysis	WC/TA, EBIT/TA, EBT/CL, Sales/TA	Profitability, efficiency	Distress Non-Distress

Source: Adapted from model formulations (Altman et al., 2019; Zmijewski, 1984; Grover, 2001; Springate, 1978)

Despite growing interest in financial distress prediction, three gaps remain. First, most studies focus on manufacturing firms, banking institutions, or cross-industry samples, while evidence from oilfield services firms remains limited. Second, previous studies generally compare prediction models descriptively without explaining why model sensitivity differs across industry conditions. Third, firm-level determinants and macroeconomic factors are often examined separately, limiting understanding of how external shocks and internal financial conditions jointly influence financial distress. To address these gaps, this study applies four classical prediction models to identical firm-year observations from U.S. oilfield services firms during 2010–2023 and combines model comparison with an analysis of firm-level and macroeconomic determinants.

Research Framework

The oilfield services industry operates within a highly cyclical environment in which firm performance is strongly influenced by fluctuations in upstream exploration and production activity. Changes in oil prices affect upstream investment decisions, which subsequently influence demand for oilfield services. When oil prices decline, reductions in exploration and production spending decrease service demand, asset utilization, revenues, and operating profitability. Because oilfield services firms operate with substantial fixed assets and relatively inflexible cost structures, prolonged downturns can place considerable pressure on financial performance (International Energy Agency, 2023; Mousavi et al., 2024).

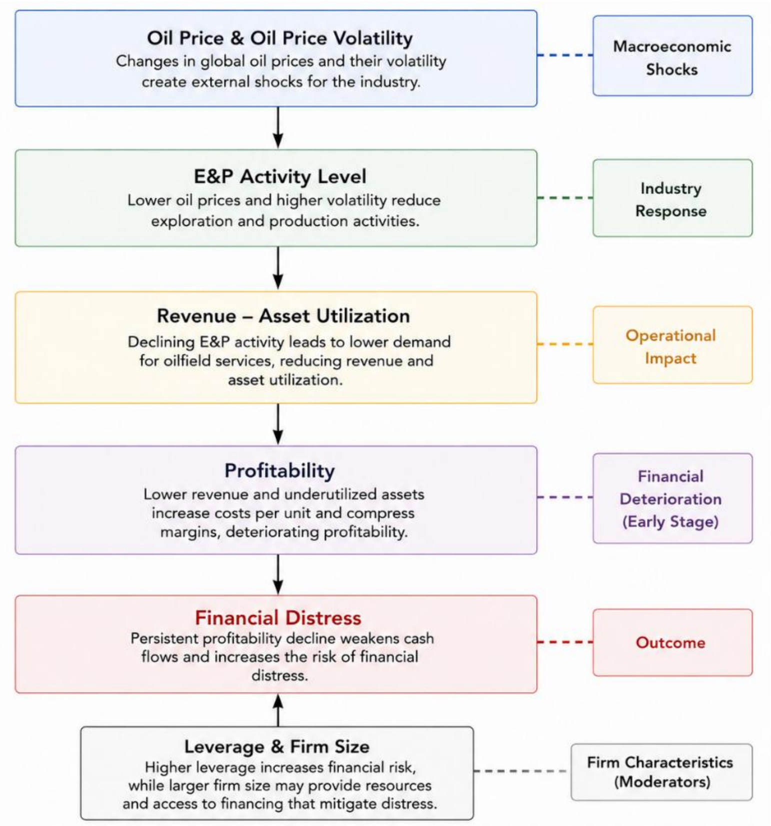

Figure 1. Research Framework
Source: Author's Design (2026)

The external shock framework argues that external economic disturbances do not directly trigger financial distress. Rather, their effects are transmitted through firm-level financial mechanisms, particularly profitability, cash flow generation, asset utilization, and financing capacity (Kilian & Zhou, 2022; Chen et al., 2024). In this perspective, financial distress emerges when external pressures weaken a firm's financial performance and resilience, making it more appropriate to view distress as the result of the interaction between external shocks and internal financial conditions rather than either factor alone.

This study includes firm-level and macroeconomic variables. Leverage, profitability, and firm size are internal financial characteristics that contribute to financial resilience, while oil prices reflect external economic conditions that influence industry activity. The study also posits oil price volatility as a moderating variable, as uncertainty within the energy market may change the relationship between leverage and financial distress.

Based on Figure 1, financial distress in oilfield services firms is conceptualized as a dynamic process resulting from the interaction between industry-level shocks and firm-level financial characteristics. External shocks first affect operating performance and profitability, which subsequently influence financial vulnerability and are captured by different prediction models according to their respective structures and sensitivities. Figure 1 presents the conceptual framework of the study.

Hypothesis Development

Financial distress prediction models employ different combinations of financial ratios, weighting structures, and classification thresholds. Consequently, identical firm-year observations may produce different classification outcomes depending on the model applied. Prior studies consistently report that financial distress identification is inherently model-dependent because each model emphasizes different dimensions of financial performance, including profitability, liquidity, leverage, solvency, and operational efficiency (Altman et al., 2019; Zhao et al., 2024; Ibrahim et al., 2024). In cyclical and capital-intensive industries such as oilfield services, where profitability tends to deteriorate before leverage and solvency indicators, differences in model classifications are expected.

H_1: There is a significant difference among the financial distress classifications of the Altman Z″, Zmijewski, Grover, and Springate models.

At the firm level, financial characteristics are important determinants of financial distress. According to Trade-Off Theory, leverage increases financing capacity but simultaneously raises fixed financial obligations and financial risk. In capital-intensive industries such as oilfield services, firms often rely on debt financing to support substantial investments in operational assets. Consequently, higher leverage may increase vulnerability to financial distress, particularly during periods of industry contraction.

H_2: Leverage has a positive effect on the probability of financial distress

Consistent with Signaling Theory, profitability reflects a firm's financial strength and ability to generate internal resources. Firms with stronger profitability are generally better positioned to absorb external shocks, maintain operations, and meet financial obligations. Therefore, profitability is expected to reduce the likelihood of financial distress.

H_3: Profitability has a negative effect on the probability of financial distress.

Firm size may also influence financial resilience. Larger firms generally possess greater access to financing, broader operational diversification, and stronger resource availability, which may reduce exposure to financial distress during adverse economic conditions.

H_4: Firm size has a negative effect on the probability of financial distress.

Beyond model differences, financial distress is influenced by both external and internal factors. Oil prices play an important role in shaping exploration and production activity, which subsequently influences demand for oilfield services, revenues, and operating performance. Therefore, oil price movements are expected to affect the probability of financial distress.

H_5: Oil prices have a significant effect on the probability of financial distress.

The relationship between leverage and financial distress may depend on external market conditions. Oil price volatility represents uncertainty in the energy market and may alter the extent to which leverage affects financial vulnerability. During periods of high oil price volatility, firms face greater uncertainty regarding future revenues and cash flows, while debt obligations remain relatively fixed. Consequently, highly leveraged firms may experience greater financial pressure under conditions of elevated oil price uncertainty.

H_6: Oil price volatility moderates the relationship between leverage and financial distress.

RESEARCH METHOD

Research Design

This study uses a quantitative research design to examine financial distress in U.S. oilfield services firms through both descriptive and explanatory analyses. The descriptive phase assesses financial distress classifications created by the Altman Z", Zmijewski, Grover, and Springate models, while the explanatory phase looks at the determinants of financial distress using firm-level and macroeconomic variables. A deductive approach is used to test the panel data empirically, where hypotheses based on the external shock framework, Trade-Off Theory, and Signaling Theory are derived and tested.

This study covers publicly listed U.S. oilfield services companies from 2010 to 2023, a period marked by various phases of expansion, downturn, contraction, and recovery in the industry cycle. The measurement of financial distress is carried out in two steps. First, the four prediction models are used on the same firm-year observations to check for differences in classification outcomes. Then, financial distress is turned into a binary variable for regression analysis.

The Springate model is used as the benchmark classification because it emphasizes profitability and operational efficiency, dimensions expected to deteriorate earlier than leverage and solvency indicators in cyclical and capital-intensive industries. Consequently, the model is considered more appropriate for capturing early-stage financial deterioration in oilfield services firms.

The Springate model was not selected because it generated the highest proportion of distress classifications. Rather, it was selected because its profitability-oriented structure is theoretically consistent with the external shock transmission mechanism proposed in this study, where financial deterioration is expected to emerge first through profitability and operational efficiency before affecting leverage and solvency indicators.

To study the determinants of financial distress, binary logistic regression is used with leverage, profitability (measured by ROA), firm size, oil price, and oil price volatility as explanatory variables. An interaction term between leverage and oil price volatility is included to test the moderating effect of market uncertainty.

Although machine learning approaches have demonstrated higher predictive accuracy in some settings, classical ratio-based models are adopted because they provide greater transparency and theoretical interpretability. Furthermore, the objective of this study is not to develop a predictive accuracy benchmark but to examine differences in model sensitivity and financial distress detection mechanisms within a cyclical and capital-intensive industry. Therefore, limited validation against selected Chapter 11 restructuring events is provided only as supporting evidence rather than as a formal accuracy assessment.

Data and Sample

This study uses secondary data obtained from audited annual reports and Form 10-K filings of oilfield services firms listed on the New York Stock Exchange (NYSE) and NASDAQ during 2010–2023. Data were collected from publicly available filings submitted to the U.S. Securities and Exchange Commission (SEC), ensuring consistency and comparability across firms and years.

A purposive sampling approach was employed. Firms were included if they (1) operated primarily in the oilfield services industry, (2) were listed on the NYSE or NASDAQ, (3) maintained complete financial reporting throughout 2010–2023, and (4) were not permanently delisted during the observation period. Applying these criteria resulted in a final sample of ten firms and 140 firm-year observations in a balanced panel dataset.

The sample represents the major segments of the U.S. oilfield services industry, including integrated oilfield services, offshore drilling, land drilling, oilfield equipment, pressure pumping, and subsea services. The sample composition is presented in Table 2.

Financial statement variables include total assets, total liabilities, working capital, retained earnings, net income, EBIT, EBT, current assets, current liabilities, book value of equity, and sales. These variables are used to construct the financial ratios required by the Altman Z″, Zmijewski, Grover, and Springate models.

Table 2. Research 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 (IMR), offshore support

Source: Author's Data Processed (2026)

For regression purposes, financial distress is transformed into a binary variable based on the Springate classification. Oil price is measured using the annual average Brent crude oil price, leverage is measured as total liabilities divided by total assets, profitability is measured using ROA, and firm size is proxied by the natural logarithm of total assets. Oil price volatility is measured as the annual standard deviation of monthly Brent crude oil prices. An interaction term between leverage and oil price volatility is constructed to evaluate the moderate effect.

Analytical Method

The analysis consists of three stages: model comparison, classification analysis, and regression analysis. First, financial distress scores generated by the four prediction models are compared using descriptive statistics. The Shapiro–Wilk test is used to assess normality. Because the score distributions are non-normal, differences among model scores are evaluated using the Friedman test and Kendall's W, followed by pairwise Wilcoxon Signed-Rank tests with Bonferroni adjustment.

Second, model scores are converted into binary classifications according to each model's cut-off criteria. For Altman Z″ and Grover, observations within the grey area are conservatively classified as distressed. Differences in classification proportions are evaluated using Cochran's Q test and pairwise McNemar tests.

Third, the determinants of financial distress are examined using binary logistic regression applied to panel data. The baseline model evaluates the effects of oil price, leverage, profitability, and firm size, while the extended model incorporates oil price volatility and the interaction between leverage and oil price volatility.

The baseline model evaluates the direct effects of leverage (LEV), profitability (ROA), firm size (SIZE), oil price (OILPRICE), oil price volatility (OILVOL) and the probability of financial distress:

$$\text{Logit}(\text{Distress}_{\{i,t\}}) = \beta_0+\beta_1 LEV_{\{i,t\}}+\beta_2 ROA_{\{i,t\}}+\beta_3 SIZE_{\{i,t\}}+\beta_4 OILPRICE_{\{t\}}+\beta_5 OILVOL+\varepsilon_{\{t\}} \text{ ……... (1)}$$

To examine the moderating role of oil price volatility, the model is extended by incorporating oil price volatility and an interaction term between leverage and oil price volatility:

$$\text{Logit}(\text{Distress}_{\{i,t\}}) = \beta_0+\beta_1\text{LEV}_{\{i,t\}}+\beta_2\text{ROA}_{\{i,t\}}+\beta_3\text{SIZE}_{\{i,t\}}+\beta_4\text{OILPRICE}_{\{t\}}+\beta_5\text{OILVOL}+\beta_6(\text{LEV}_{i,t}\times\text{OILVOL}_t)+\varepsilon_{\{i,t\}} \ldots\ldots (2)$$

All analyses are conducted using Microsoft Excel and IBM SPSS Statistics 26 at a 5 percent significance level.

RESULTS AND DISCUSSION

Results

Descriptive Statistic

Table 3 presents the descriptive statistics of financial distress scores generated by the Altman Z″, Zmijewski, Grover, and Springate models. The results indicate considerable variation across models, suggesting that each model captures different dimensions of firms' financial conditions. Altman Z″ exhibits the highest mean score (3.571) and the largest dispersion (SD = 2.982), reflecting substantial heterogeneity in financial conditions across the sample firms. Meanwhile, the Springate model records the lowest minimum score (−3.404), indicating greater responsiveness to financial deterioration. In contrast, the Zmijewski and Grover models produce narrower score distributions and lower variability, suggesting more stable classification patterns. Overall, these findings provide preliminary evidence that financial distress measurement varies across prediction models, supporting the need for further statistical testing to evaluate whether the observed differences are statistically significant.

Table 3. 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: Author's Data Processed (2026)

Model Financial Distress Classification

The classification results reveal substantial variation across the four financial distress prediction models, indicating that identical firm-year observations may be interpreted differently depending on the model employed. As shown in Table 4, the Altman Z″, Zmijewski, and Grover models classify most observations as non-distressed, whereas the Springate model identifies a substantially larger proportion of distressed observations. Specifically, the proportion of distress classifications reaches 79.3 percent under the Springate model, compared with 15.0 percent, 12.1 percent, and 10.7 percent under the Altman Z″, Zmijewski, and Grover models, respectively.

Table 4. Financial Distress Classification Results

Model	Observation	Non-Distress		Grey Area		Distress	
		Count	Percentage	Count	Percentage	Count	Percentage
Altman Z″	140	97	69.3%	22	15.7%	21	15%
Zmijewski	140	123	87.9%	0	0.0%	17	12.1%
Grover	140	122	87.1%	3	2.1%	15	10.7%
Springate	140	29	20.7%	0	0.0%	111	79.3%

Source: Author's Data Processed (2026)

These differences suggest that financial distress identification is strongly influenced by model structure and classification criteria. The Altman Z″ model occupies an intermediate position because it includes a grey-area category that captures firms experiencing early signs of financial deterioration without being clearly distressed. In contrast, the Springate model consistently generates a larger number of distress classifications, indicating greater responsiveness to changes in financial performance.

The temporal pattern of financial distress further reflects the cyclical nature of the oilfield services industry. As presented in Table 5 and Figure 2, distress classifications increased during the 2015–2016 oil price downturn and the COVID-19 disruption in 2020, periods characterized by substantial reductions in upstream investment and drilling activity. The pattern suggests that financial conditions in the industry are closely linked to external economic and industry shocks.

Table 5. Yearly Financial Distress Classification Pattern (%)

Year	Altman Z″ Distress (%)	Zmijewski Distress (%)	Grover Distress (%)	Springate Distress (%)
2010	10	0	0	60
2011	10	0	0	50
2012	10	0	0	50
2013	0	0	0	60
2014	20	0	0	60
2015	20	10	10	100
2016	20	20	30	100
2017	30	10	20	100
2018	40	10	20	90
2019	60	10	30	100
2020	60	60	60	100
2021	60	30	10	100
2022	50	20	0	80
2023	40	0	0	60

Source: Author's Data Processed (2026)

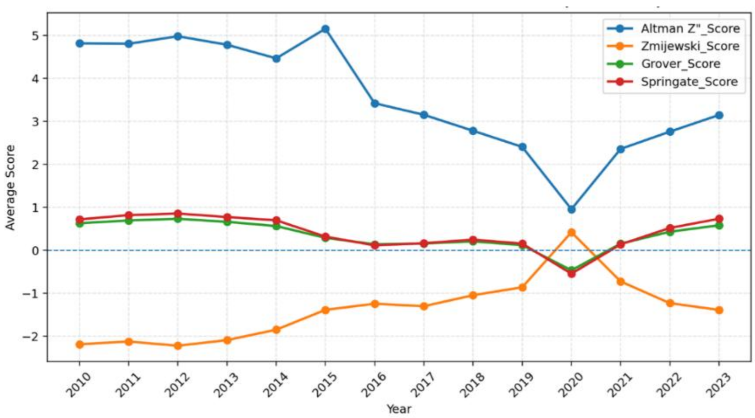

Figure 2. Trend of Financial Distress Score
Source: Author’s Design (2026)

Among the four models, the Springate model consistently identifies elevated levels of distress throughout the downturn and recovery periods. This is in line with the model's focus on indicators of profitability and operational efficiency, which usually deteriorate before the decline of leverage and solvency measures during contractions in the industry. On the other hand, the Zmijewski and Grover models place a relatively small number of firms in the distressed category until their financial health worsens and that weakness is sustained over time.

The classification patterns also broadly match some of the major distress events observed during the sample period. Weatherford International went into Chapter 11 restructuring in 2019, Noble Corporation filed for Chapter 11 protection in 2020. The elevated distress classifications identified before these events suggest that the financial deterioration unfolded gradually and was evident in accounting-based indicators before formal restructuring commenced.

To provide additional context regarding the practical relevance of the classification results, Table 6 compares selected model classifications with actual distress events observed during the sample period. Although the objective of this study is not to evaluate predictive accuracy formally, the comparison offers illustrative evidence regarding the ability of the models to identify financial deterioration before restructuring occurs.

Table 6. Illustrative Validation Against Actual Distress Events

Company	Actual Distress Event	Altman Z″	Zmijewski	Grover	Springate
Weatherford International Plc	Chapter 11 Restructuring	Distress	Non-Distress	Non-Distress	Distress
Noble Corporation Plc	Chapter 11 Restructuring	Distress	Distress	Distress	Distress
Diamond Offshore Drilling, Inc.	Chapter 11 Restructuring	Distress	Distress	Distress	Distress

Source: Author's Data Processed (2026)

The evidence indicates that the Springate model consistently classified Weatherford International, Noble Corporation, and Diamond Offshore Drilling as distressed prior to their Chapter 11 restructuring events. Although this comparison is not intended as a formal predictive accuracy assessment, it provides preliminary evidence of the practical validity of profitability-oriented models in identifying early-stage financial deterioration within cyclical industries. These findings support the argument that indicators related to profitability and operational efficiency tend to deteriorate before leverage and solvency measures become critically impaired. Future research may extend this analysis by conducting formal predictive validation using a broader set of bankruptcy, restructuring, and default events.

Overall, the results indicate that differences among prediction models are systematic rather than random. The findings suggest that the models capture different dimensions and potentially different stages of financial deterioration, providing an important basis for the subsequent statistical comparison and hypothesis testing.

Figure 3 further illustrates the distribution of scores generated by each model. While all models capture variation in firm financial conditions, the distributions differ substantially in shape and spread. These differences provide preliminary evidence that the models may not evaluate financial deterioration in the same manner, thereby motivating the comparative statistical analysis presented in the subsequent sections.

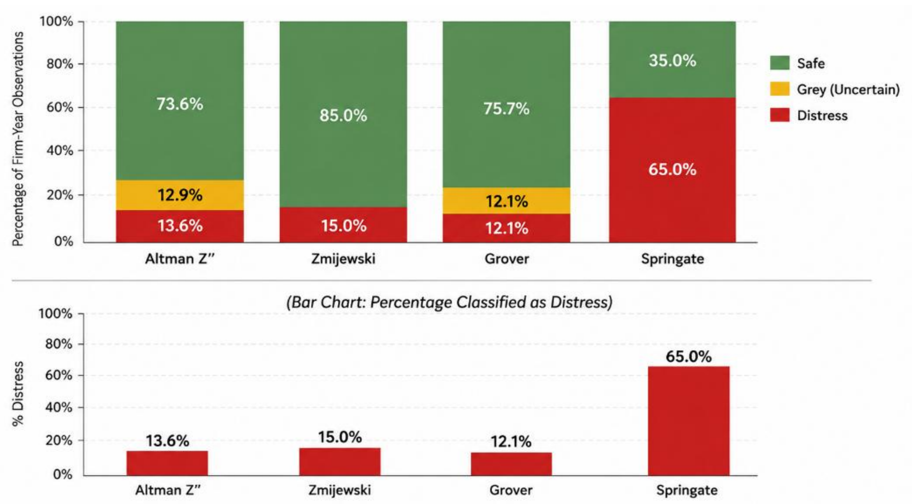

Figure 3. Comparison of Financial Distress Classification Results
Source: Author's Design (2026)

Statistical Test Results

To determine whether the observed differences among financial distress prediction models are statistically significant, a series of non-parametric tests were conducted. The Shapiro–Wilk test indicated that all score distributions were non-normal ($p < 0.001$), supporting the use of non-parametric procedures.

As shown in Table 7, the Friedman test reveals significant differences in financial distress scores across the Altman Z″, Zmijewski, Grover, and Springate models ($\chi^2(3) = 244.740$, $p < 0.001$). This finding indicates that the four models do not produce equivalent assessments of firm financial condition. In addition, Kendall's W value of 0.583 suggests a moderate level of agreement, implying that although the models generally rank firms in a similar order of financial strength and weakness, they differ in their classification outcomes.

At the classification level, Cochran's Q test confirms significant differences in the proportions of distress classifications across models (Q = 213.474, $p < 0.001$). Pairwise McNemar tests further indicate that the Zmijewski and Grover models do not differ significantly in their classifications (Exact p = 1.000), whereas all comparisons involving the Springate model are statistically significant ($p < 0.001$). These results suggest that the Springate model generates classification outcomes that differ substantially from those produced by the other models.

Overall, the statistical evidence demonstrates that financial distress identification is model-dependent. The significant differences observed across models indicate that each model captures different dimensions of financial deterioration, supporting the need for a multi-model approach when assessing financial vulnerability in cyclical industries such as oilfield services.

The results of the non-parametric tests used to evaluate differences and agreement among the four financial distress prediction models are summarized in Table 7.

Table 7. Statistical Test Results

Test	Statistic	p-value	Interpretation
Friedman test	$\chi^2(3) = 244.740$	< 0.001	Significant differences in model scores
Kendall's W	W = 0.583	–	Moderate agreement among models
Cochran's Q	Q = 213.474	< 0.001	Significant differences in classification outcomes
McNemar (Zmijewski vs Grover)	Exact p = 1.000	1.000	No significant classification difference
McNemar (pairs involving Springate)	p < 0.001	< 0.001	Significant classification differences

Source: Author's Data Processed (2026)

Regression Results

Prior to interpreting the regression coefficients, the overall adequacy of the logistic regression model was evaluated. As presented in Table 8, the omnibus test of model coefficients is statistically significant ($\chi^2 = 88.866$, $p < 0.001$), indicating that the explanatory variables collectively improve the prediction of financial distress relative to the intercept-only model. In addition, the Hosmer–Lemeshow goodness-of-fit test is not significant ($p = 0.574$), suggesting that the model adequately fits the observed data. The model also achieves an overall classification accuracy of 88.6 percent, while the Nagelkerke R^2 value of 0.735 indicates substantial explanatory power.

Overall, the regression results suggest that the selected firm-level and macroeconomic variables provide a meaningful explanation of financial distress among U.S. oilfield services firms. Among the explanatory variables, profitability emerges as the most influential factor, while leverage, firm size, oil price, and oil price volatility do not exhibit significant direct effects. These findings indicate that financial distress within the oilfield services industry is more closely associated with internal operating performance than with external market conditions.

The results further suggest that external shocks do not directly generate financial distress once firm-level financial performance is considered. Instead, their effects appear to operate indirectly through internal financial mechanisms, particularly profitability. Consequently, profitability serves not only as a key explanatory variable but also as an important channel through which external industry conditions are translated into firm-level financial vulnerability.

Hypothesis Testing

This section evaluates the proposed hypotheses using the results of the non-parametric model comparison tests and binary logistic regression analysis. The summary of hypothesis testing results is presented in Table 8.

The results indicate that H1 is supported. The Friedman test ($\chi^2(3) = 244.740$, $p < 0.001$) and Cochran's Q test ($Q = 213.474$, $p < 0.001$) confirm significant differences among the Altman Z″, Zmijewski, Grover, and Springate models, indicating that financial distress classification is model-dependent.

With respect to the determinants of financial distress, profitability is the only variable that exhibits a significant effect. Profitability (ROA) has a negative and statistically significant relationship with financial distress ($\beta = -106.737$, $p < 0.001$), supporting H3. This finding indicates that firms with stronger profitability are less likely to experience financial distress.

By contrast, leverage ($\beta = 5.416$, $p = 0.134$), firm size ($\beta = 0.328$, $p = 0.315$), and oil price ($\beta = -0.030$, $p = 0.210$) do not have significant effects on financial distress. Therefore, H2, H4, and H5 are not supported.

The moderating effect of oil price volatility is also not significant ($\beta = -0.674$, $p = 0.188$), indicating that oil price volatility does not significantly alter the relationship between leverage and financial distress. Accordingly, H6 is not supported.

Overall, the results suggest that financial distress in the oilfield services industry is primarily associated with firm-level profitability, while leverage, firm size, oil price, and oil price volatility do not exhibit significant direct effects within the regression framework. The complete summary of hypothesis testing results is presented in Table 8.

Table 8. Panel Logistic Regression Results

Hypothesis	Statement	Result	Key Statistics
H1	There is a significant difference among the financial distress classifications of the Altman Z″, Zmijewski, Grover, and Springate models	Supported	Friedman $\chi^2(3) = 244.740$; $p < 0.001$
H2	Leverage has a positive effect on the probability of financial distress.	Not supported	$\beta = 5.416$; $p = 0.134$
H3	Profitability has a negative effect on the probability of financial distress	Supported	$\beta = -106.737$; $p < 0.001$
H4	Firm size has a negative effect on the probability of financial distress	Not supported	$\beta = 0.328$; $p = 0.315$
H5	Oil prices have a significant effect on the probability of financial distress	Not supported	$\beta = -0.030$; $p = 0.210$
H6	Oil price volatility moderates the relationship between leverage and financial distress	Not supported	$\beta = -0.674$; $p = 0.188$

Source: Author's Data Processed (2026)

Discussion

Model Financial Distress Classification

The results indicate significant differences in financial distress classifications among the Altman Z″, Zmijewski, Grover, and Springate models. This finding supports H1 and confirms that financial distress identification is inherently model-dependent. Consistent with previous studies (Altman et al., 2019; Insani et al., 2024; Vukčević et al., 2024; Zhao et al., 2024), the results demonstrate that different prediction models may generate different classifications for the same firm-year observations because each model emphasizes different financial dimensions and applies different classification thresholds.

Also, the findings imply that the observed differences are not only due to how the studies were conducted. In the context of the external shock model, financial distress comes as a slow process through which external shocks at the industry level first start affecting the performance of a firm and then later spread to damage broad aspects of financial health (Chen et al., 2024; Mousavi et al., 2024). For instance, in the oilfield services sector, a decrease in upstream investment activities translates into decreased demand for services, asset utilization, and revenues — all of which will subsequently reduce operating profitability before such reduction impacts leverage, liquidity, and solvency measures. Therefore, different financial ratios will respond to deterioration at different phases of the industry cycle.

This mechanism helps explain why the Springate model generated substantially higher distress classifications than the Altman Z″, Zmijewski, and Grover models. Unlike Altman Z″ and Zmijewski, which place greater emphasis on leverage and solvency measures, the Springate model incorporates profitability and operational efficiency indicators through EBIT/TA, EBT/CL, and Sales/TA ratios. These indicators are closely linked to revenue generation and asset utilization, both of which are typically affected during the early stages of industry downturns. Consequently, the Springate model appears more responsive to early financial deterioration within cyclical and capital-intensive industries.

The findings are also consistent with the temporal classification pattern observed during the 2015–2016 oil price downturn and the COVID-19 contraction in 2020. During these periods, Springate consistently identified higher levels of financial distress than the other models. Similar patterns were observed prior to the Chapter 11 restructurings of Weatherford International (2019), Noble Corporation (2020), and Diamond Offshore Drilling (2020), suggesting that profitability and operational efficiency indicators may provide warning signals earlier than leverage and solvency measures.

These results support the argument that financial distress should be viewed as a dynamic process rather than a single event. Consistent with the financial distress framework proposed by Altman et al. (2019), Kristanti (2019), and Michalkova and Ponisciakova (2025), deterioration generally begins with declining operating performance before progressing to liquidity, solvency, and default problems. Therefore, prediction models emphasizing profitability and efficiency may identify financial vulnerability earlier, whereas models emphasizing leverage and solvency may detect distress only after financial weakness becomes more persistent and structurally embedded.

It can be concluded that the existing literature on financial distress is extended by the findings, as model sensitivity is influenced not only by the statistical methodology but also by the economic characteristics of the industry under consideration. In the oilfield services sector, indicators of financial decline typically involve decreasing levels of asset utilization and revenue generation along with operating profitability; solvency and leverage indicators are affected later. This provides a theoretical basis for the observed differences in classification outcomes and, therefore, a more context-sensitive understanding of financial distress prediction. Hence, the above findings provide evidence that model sensitivity differs in economic features besides the statistical methodology used in developing the model.

Effects of Leverage on Financial Distress

The results indicate that leverage has a positive but statistically insignificant effect on financial distress. This finding suggests that higher debt levels do not necessarily increase the probability of financial distress among the sampled oilfield services firms. Therefore, H2 is not supported.

Trade-Off Theory would argue that leverage provides the benefits of financing at the same time increasing the risk of a firm through fixed debt obligations (Altman et al., 2019; Zhao et al., 2024). Higher leveraged firms are generally expected to have higher financial distress, especially when their business is not doing well since they have fixed charges to meet. However, the results show that leverage by itself is not enough to explain financial distress in the oilfield services industry.

This phenomenon could be explained by the nature of the industry, which is capital intensive. Oilfield services companies require heavy investments in drilling rigs, equipment, subsea infrastructure, and assets for specialized operations. Thus, the use of debt financing is more a feature that is built into the structure of the industry rather than an indirect measure of financial weakness (Cathcart et al., 2020; Mousavi et al., 2024). In such a scenario, if firms continue to earn enough income and cash flows to meet their financial obligations, they can maintain relatively high leverage while being considered financially healthy.

This finding is consistent with the literature that argues leverage does not always exert a direct effect on financial distress when firms have good operational performance and financial flexibility (Fan et al., 2021; Mousavi et al., 2024). Therefore, the results also provide evidence for the claim that financial vulnerability is not created by the mere existence of debt but by the inability of a firm to create enough profit to service its debt. In other words, leverage becomes a problem only with accompanying deteriorating operational performance and decreasing profitability.

Therefore, the insignificant effect of leverage reinforces the view that financial distress in the oilfield services industry is driven more by operating performance than by capital structure alone. This finding helps explain why profitability, rather than leverage, emerges as the dominant determinant of financial distress within the regression model.

Effects of Profitability on Financial Distress

The results indicate that profitability has a negative and statistically significant effect on financial distress, supporting H3 and identifying profitability as the most influential determinant in the model. This finding suggests that firms with stronger profitability are less likely to experience financial distress, whereas firms with declining profitability face a greater risk of financial deterioration.

This result is consistent with Signaling Theory, which views profitability as an important signal of a firm's financial strength and operational effectiveness (Zhao et al., 2024; Arifin & Koerniawan, 2025). Higher profitability reflects a firm's ability to generate earnings, maintain liquidity, and fulfill its financial obligations. Consequently, profitable firms are generally better positioned to withstand adverse economic conditions and industry downturns.

The finding is also consistent with previous studies that identify profitability as one of the most important predictors of financial distress (Kristanti et al., 2019; Kristanti et al., 2025; Song et al., 2024; Zhao et al., 2024; Maghyereh & Al-Zoubi, 2025). In cyclical industries such as oilfield services, profitability often deteriorates before leverage, liquidity, and solvency indicators show substantial weakness. Reductions in upstream investment activity typically lower service demand, asset utilization, and revenues, which subsequently weaken operating profitability. As a result, profitability serves as an early indicator of financial deterioration.

From the perspective of the external shock framework, profitability appears to function as a key transmission channel linking external industry conditions to firm-level financial vulnerability. While oil prices and other external shocks do not directly affect financial distress in the regression model, their effects are reflected through changes in operating performance and earnings. This finding suggests that external shocks become financially relevant when they impair a firm's ability to generate profits and sustain operations.

The significance of profitability also helps explain why the Springate model produced substantially higher distress classifications than the other prediction models. Because the Springate model places greater emphasis on profitability and operational efficiency indicators, it is more responsive to the early stages of financial deterioration that emerge during industry downturns. Therefore, the results reinforce the argument that profitability is not only the strongest determinant of financial distress but also one of the earliest indicators of financial vulnerability in cyclical and capital-intensive industries.

Effects of Firm Size on Financial Distress

The results indicate that firm size does not have a statistically significant effect on financial distress, indicating that larger firms are not necessarily less vulnerable to financial distress than smaller firms within the oilfield services industry. Therefore, H4 is not supported.

In general, larger firms are expected to possess greater access to external financing, broader resource availability, and stronger operational flexibility, which may enhance their ability to withstand adverse economic conditions. Previous studies have often associated larger firm size with lower financial distress risk because larger firms tend to benefit from economies of scale, diversified operations, and stronger market positions (Altman et al., 2019; Zhao et al., 2024).

However, the findings suggest that these advantages may not be sufficient to offset the effects of severe industry downturns in the oilfield services sector. Unlike many industries, oilfield services firms are highly dependent on upstream exploration and production activity. During periods of declining oil prices and reduced investment, both large and small firms face similar pressures in the form of lower service demand, reduced asset utilization, and weaker operating performance. Consequently, firm size alone does not guarantee financial resilience.

This finding is consistent with studies suggesting that industry-specific conditions may weaken the protective effect of firm size, particularly in cyclical and capital-intensive sectors (Kebede et al., 2024; Georgievski et al., 2024). In such industries, financial stability depends more on a firm's ability to maintain profitability and operational efficiency than on its scale of operations. As a result, larger firms remain vulnerable to financial distress when prolonged downturns significantly reduce revenues and earnings.

The insignificant effect of firm size further reinforces the central finding of this study that profitability is a more important determinant of financial distress than structural characteristics such as firm size. This suggests that financial resilience in the oilfield services industry is driven primarily by operating performance rather than by the scale of the firm itself.

Effects of Oil Price on Financial Distress

The results indicate that oil prices do not have a statistically significant direct effect on financial distress, indicating that fluctuations in oil prices alone are insufficient to explain the probability of financial distress among oilfield services firms. Therefore, H5 is not supported.

At first glance, this finding may appear inconsistent with the characteristics of the oilfield services industry, which is highly dependent on upstream exploration and production activity. Changes in oil prices are generally expected to influence drilling activity, capital expenditure, and demand for oilfield services. However, the results suggest that the relationship between oil prices and financial distress is more complex than a direct cause-and-effect relationship.

This finding is consistent with the external shock framework, which argues that macroeconomic shocks affect firms through internal transmission mechanisms rather than through direct effects alone (Chen et al., 2024; Mousavi et al., 2024). In the oilfield services industry, changes in oil prices first influence upstream investment decisions, service demand, asset utilization, revenues, and operating profitability before affecting financial stability. Consequently, the effect of oil prices may already be reflected in firm-level financial variables included in the regression model, particularly profitability.

The result is also consistent with studies suggesting that oil price shocks influence corporate financial risk indirectly through earnings, investment activity, and financial structure rather than through a direct impact on financial distress (Fan et al., 2021; Maghyereh & Al-Zoubi, 2025). This explanation is particularly relevant for oilfield services firms because the effect of oil price changes is often transmitted through reductions in exploration and production spending, which subsequently affect revenues and operating performance.

Therefore, the insignificant effect of oil price does not imply that oil prices are unimportant. Rather, it suggests that external industry conditions become financially relevant only when they affect a firm's ability to generate earnings and sustain operations. This finding reinforces the central argument of this study that profitability functions as the primary channel through which external shocks are translated into firm-level financial vulnerability.

Moderating Effect of Oil Price Volatility

The results indicate that oil price volatility does not significantly moderate the relationship between leverage and financial distress. The interaction term between leverage and oil price volatility is statistically insignificant, indicating that the effect of leverage on financial distress does not become stronger under conditions of higher oil price uncertainty. Therefore, H6 is not supported.

From a theoretical perspective, oil price volatility is expected to increase financial risk because uncertainty in commodity markets may reduce the predictability of future revenues and cash flows. Under such conditions, highly leveraged firms are generally expected to face greater financial pressure because debt obligations remain relatively fixed while business conditions become more uncertain (Fan et al., 2021; Amin et al., 2025). However, the findings suggest that this mechanism does not operate directly within the sampled oilfield services firms.

One possible explanation relates to the cyclical nature of the industry. Oilfield services firms have historically operated in an environment characterized by recurring commodity-price fluctuations and investment cycles. As a result, firms may have adapted their financing, operational, and risk-management strategies to accommodate periods of elevated oil price volatility. Consequently, additional uncertainty in oil prices may not materially intensify leverage-related financial risk.

The finding is also consistent with the broader results of this study, which show that external factors do not directly explain financial distress once firm-level financial performance is considered. Like oil prices, the effects of oil price volatility appear to be transmitted indirectly through profitability, revenue generation, and operating performance rather than through direct interaction with leverage. This interpretation is consistent with the external shock framework, which argues that external disturbances affect financial vulnerability primarily through internal financial mechanisms (Chen et al., 2024; Mousavi et al., 2024).

Therefore, the insignificant moderating effect suggests that oil price volatility does not materially strengthen or weaken the relationship between leverage and financial distress in the oilfield services industry. Instead, financial vulnerability appears to depend more on a firm's ability to maintain profitability and operational performance under changing market conditions than on the interaction between leverage and commodity-price uncertainty.

Research Implications

This study contributes to the financial distress literature by demonstrating that financial distress identification is both model-dependent and context-sensitive. The findings indicate that differences among prediction models are influenced not only by methodological characteristics, but also by the way financial deterioration develops within cyclical and capital-intensive industries. In particular, the results highlight profitability as an important transmission channel through which external industry shocks are translated into firm-level financial vulnerability.

The findings also support previous evidence from emerging markets indicating that profitability remains a fundamental determinant of financial distress regardless of prediction methodology. While recent machine-learning approaches may improve predictive accuracy, the present study demonstrates that classical accounting-based models continue to provide valuable insights into the economic mechanisms underlying financial deterioration (Kristanti et al., 2025).

From a methodological perspective, the significant differences observed among the Altman Z″, Zmijewski, Grover, and Springate models underscore the importance of adopting a multi-model approach in financial distress research. The findings suggest that different models capture different dimensions and stages of financial deterioration, implying that reliance on a single prediction model may provide an incomplete assessment of financial risk.

From a practical perspective, the findings emphasize the importance of profitability and operational performance in maintaining financial resilience. For managers, investors, and creditors, profitability should be treated as a key indicator of financial vulnerability and an early warning signal of financial deterioration. In cyclical industries such as oilfield services, the ability to sustain profitability appears to be more important for financial stability than leverage, firm size, or external market conditions alone.

CONCLUSION

This study examines financial distress in U.S. oilfield services firms during 2010–2023 using the Altman Z″, Zmijewski, Grover, and Springate models. The findings lead to several conclusions.

First, significant differences exist among the four financial distress prediction models, indicating that financial distress classification is model-dependent. Among the models examined, the Springate model produces the highest proportion of distress classifications and appears more responsive to early-stage financial deterioration.

Second, leverage does not have a significant effect on the probability of financial distress. This finding suggests that higher debt levels do not necessarily increase financial vulnerability within the sampled firms.

Third, profitability has a significant negative effect on the probability of financial distress. Firms with stronger profitability are less likely to experience financial distress, indicating that profitability is the most important determinant of financial resilience in the oilfield services industry.

Fourth, firm size does not significantly affect the probability of financial distress. Larger firms are not necessarily more resilient to financial distress than smaller firms within this industry context.

Fifth, oil prices do not have a significant direct effect on the probability of financial distress. This finding suggests that external industry conditions influence financial distress indirectly through firm-level financial performance rather than through direct transmission.

Sixth, oil price volatility does not significantly moderate the relationship between leverage and financial distress. The results indicate that oil price uncertainty does not materially strengthen the effect of leverage on financial vulnerability.

Overall, the findings suggest that financial distress in the oilfield services industry is primarily associated with internal financial performance, particularly profitability, while external factors influence financial vulnerability indirectly through their impact on firm operations and earnings.

This study has several limitations. First, the sample is limited to publicly listed U.S. oilfield services firms, which may restrict the generalizability of the findings. Second, the analysis relies primarily on accounting-based indicators and does not incorporate market-based measures of financial distress. Third, although profitability is theoretically identified as a transmission channel linking external shocks to financial distress, this mechanism was not formally tested using mediation analysis. Future research may address these limitations by expanding sample coverage, incorporating market-based indicators, and applying mediation or structural equation approaches to examine the transmission process more explicitly.

List of Abbreviations

API – American Petroleum Institute
CR – Current Ratio
EBIT – Earnings Before Interest and Taxes
EBT – Earnings Before Taxes
EIA – U. S. Energy Information Administration
E&P – Exploration and Production
GAAP – Generally Accepted Accounting Principles
LEV – Leverage
MDA – Multiple Discriminant Analysis
NASDAQ – National Association of Securities Dealers Automated Quotations
NI – Net Income
NYSE – New York Stock Exchange
OP – Oil Price
ROA – Return on Assets
SEC – U.S. Securities and Exchange Commission
TA – Total Assets
TL – Total Liabilities
U.S. GAAP – United States Generally Accepted Accounting Principles
WC – Working Capital

Declaration of Generative AI And AI-Assisted Technologies in the Manuscript Preparation Process

During the preparation of this work the author(s) used OpenAI to improve the readability and language quality of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and took(s) full responsibility for the content of the published article.

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Authors' Contribution

RB was responsible for developing the research concept, collecting the data, conducting the formal analysis, and preparing the initial draft of the manuscript. AMS provided supervision on the research methodology, validated the analytical approach, and contributed to the review and improvement of the manuscript. All authors have reviewed and approved the final version of the manuscript.

Conflict of Interest

The authors declare no competing interests.

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Availability of Data and Materials

The financial data used in this study were obtained from publicly available annual reports and 10-K filings. The processed dataset is available from the corresponding author upon reasonable request.

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