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Unique and Common Effects of Financial Ratios on Financial Risk Estimation

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Abstract

This study examines the determinants of financial risk using both a binary bankruptcy indicator and an ordinal credit rating measure. The empirical analysis is based on a large sample of Finnish firms and employs linear regression combined with commonality analysis to decompose the coefficient of determination (R^2) into unique and shared contributions of key financial ratios, including solvency (Equity ratio), profitability (Return on assets), liquidity (Quick ratio), and cash flow measures (Traditional and Operating cash flows). The regression results indicate that solvency is the most important individual predictor of financial risk, followed by profitability, while liquidity exhibits weaker and partly counterintuitive effects. Traditional (accrual-based) cash flow consistently outperforms operating (cash-based) cash flow in explaining both bankruptcy risk and credit ratings. The explanatory power is substantially higher for the credit rating model than for the binary bankruptcy model. Commonality analysis reveals that the majority of explained variance arises from shared effects among the financial ratios rather than from their unique contributions. Negative lower-order communalities indicate substantial overlap and redundancy among predictors, while large higher-order shared components suggest that financial risk is best understood as a multidimensional construct captured by the joint interaction of financial indicators. Overall, the findings highlight the importance of considering both individual and joint effects of financial ratios and suggest that accrual-based measures provide more comprehensive information about financial risk. The results contribute to the literature by integrating regression analysis with variance decomposition techniques to provide a more nuanced understanding of financial risk prediction.

Keywords

Financial Risk, Financial Ratios, Communality Analysis, Unique Effects, Common Effects, Regression Analysis, Finnish Firms

1. Introduction

The prediction of corporate bankruptcy and financial distress has been a central topic in accounting and finance research for more than half a century. The central area of this topic deals with assessing the contribution of financial ratios on prediction. The history of research on importance of financial ratios in failure prediction includes several contributive milestones starting from Beaver (1966), who applied a univariate framework to assess the predictive ability of individual ratios. Altman (1968) demonstrated that predictive accuracy improves when ratios are used jointly despite potential redundancy. Pinches et al. (1973) showed that ratios can be classified into a limited number of underlying dimensions (e.g., profitability, liquidity, leverage), implying that many ratios share common variance. This provided early empirical evidence of multicollinearity and overlapping information.

The development of probabilistic models further clarified the relative importance of financial ratios. Ohlson (1980) and Zmijewski (1984) introduced logit and probit models, respectively. These studies consistently found that profitability and leverage retain strong statistical significance in multivariate settings, indicating substantial unique contribution. In contrast, liquidity ratios often became insignificant when included alongside other variables, suggesting that their explanatory power is largely overlapping with profitability and leverage.

Laitinen (1980) introduced a theoretical model to explain interdependencies between financial ratios. He argues that there are basic economic factors which affect financial ratios making them depend on each other. For example, profitability ratios are strongly affected by the internal rate of return whereas cash flow ratios are sensitive to the differences between internal rate of return and growth rate. Gentry et al. (1987) demonstrated that cash flow–based measures provide additional predictive power but are also correlated with earnings-based ratios. Shumway (2001) introduced a hazard model framework. Shumway (2001) demonstrated that some traditional ratios lose significance when more informative variables (including market-based measures) are added.

In the 2010s, literature expanded with comprehensive reviews and new modeling approaches. Sun et al. (2014) and Alaka et al. (2018) confirmed that financial ratios remain the core predictors in most models. However, these studies also highlighted the widespread use of highly correlated variables, suggesting persistent issues of multicollinearity and redundancy (Pereira et al., 2016). Recent research using machine learning and regularization techniques has provided more explicit evidence on these issues. Studies employing methods such as Lasso and feature importance analysis show that many financial ratios contribute little additional information once key variables are included. For example, recent work demonstrates that a relatively small subset of ratios can achieve comparable predictive performance to larger models, implying that a substantial proportion of explanatory power is due to shared variance (overlap) rather than unique effects (e.g., Magrini, 2025).

Despite the extensive body of research on financial distress prediction, several important gaps remain. First, most studies evaluate financial ratios based on statistical significance or overall model accuracy (e.g., classification accuracy, AUC), rather than explicitly decomposing their contribution into unique and overlapping components. As a result, it remains unclear how much each ratio contributes independently to model performance and how much of its explanatory power is shared with other ratios.

Second, although the literature recognizes the existence of redundancy among financial ratios, there is limited empirical research that systematically quantifies this redundancy in terms of explained variance. In particular, few studies attempt to decompose the explanatory power of regression models into components attributable to individual ratios and their combinations.

Third, while prior research has compared accrual-based and cash flow–based measures, the relative performance of traditional accrual-based ratios versus cash flow–based indicators in explaining financial distress remains insufficiently understood. Existing studies typically examine these measures separately or include them jointly without explicitly evaluating their incremental contributions.

The purpose of this study is to address these gaps by providing a comprehensive analysis of the unique and overlapping contributions of key financial ratios in explaining corporate bankruptcy and financial distress. Specifically, the study focuses on four widely used financial ratios representing core dimensions of financial analysis: Equity ratio (solvency), Return on assets (profitability), Quick ratio (liquidity), and Cash flow to sales ratio (cash flow adequacy), including both accrual-based (traditional) and cash-based (operating) formulations. Laitinen (1994) demonstrated that traditional cash flow is generally a more stable and reliable predictor of bankruptcy than operating cash flow. However, other studies suggest that combining both measures may improve predictive performance.

The empirical part of the study is based on financial statement data from a sample of Finnish firms from a period before the COVID-19 pandemic. In the empirical analysis, two kinds of dependent variables are used. First, the traditional binary measure (0 = non-bankrupt firm and 1 = bankrupt firm) is used to approximate financial risk. Second, the dependent variables are specified as the ten-class credit rating score of the firms ranging from C (= 1) to AAA (= 10). Using these independent variables a regression model is estimated for both types of independent variable. The models are estimated using regression analysis, allowing for the evaluation of both statistical significance and explanatory power. The coefficients of determination for both models are then decomposed to show the unique and shared effects of the financial ratios. Based on previous studies, it is expected that the unique contributions are strongest for solvency and profitability, whereas liquidity and cash flow play a minor role.

By addressing these objectives, the study contributes to the literature by providing a more nuanced understanding of how financial ratios function as predictors of financial distress—not only individually, but also in combination. This study is organized in the following way. In this introductory section, a short discussion of previous studies was presented and gaps in this research discussed. Based on these gaps, a set of objectives for the study was presented. In the second section, relevant prior studies are discussed more precisely to form a background for the study in the historical context. No hypotheses are presented in addition to the expected ranking of financial ratios according to their contributions. The third section presents the empirical results separately for both dependent variables. Finally, the last section summarizes the study, discusses the results, and gives outlines for future research.

2. Review of Prior Studies

Since the pioneering work of Beaver (1966), financial statement-based ratios have been widely used to assess firms' financial condition and to predict failure. Beaver (1966) demonstrated that individual accounting ratios—particularly traditional cash flow to total debt and net income to total assets—contain significant predictive information several years prior to bankruptcy. One year before failure the total error rate in classification of failed and non-failed firms was only 13% for both financial ratios. Beaver also analyzed debt ratio and current ratio which were not as efficient in classification. Thus, Beaver showed that especially (traditional) cash flow and profitability are best univariate predictors, whereas solvency (leverage) and liquidity do not perform as efficiently. His findings established the empirical relevance of financial ratios and laid the foundation for subsequent multivariate modeling approaches.

Building on this work, Altman (1968) introduced the Z-score model, which combined multiple financial ratios into a single discriminant function. Altman's model incorporated profitability, liquidity, solvency, and activity measures, and showed that combining ratios significantly improves predictive accuracy relative to univariate approaches. In his model, especially profitability dimension played an important role. The total error rate in his model on a prospect of one year was only 5% but the rate increased rapidly when the time horizon grew. This model marked a transition toward viewing financial distress as a multidimensional phenomenon, where different aspects of financial performance jointly determine failure risk.

Subsequent research refined these approaches using probabilistic models. Ohlson (1980) developed a logit-based bankruptcy prediction model, while Zmijewski (1984) employed a probit framework. These models consistently identified profitability and leverage as the most important predictors of financial distress, while liquidity measures often played a secondary role. At the same time, studies such as those by Gentry et al. (1987) emphasized the importance of cash flow–based measures, suggesting that operating cash flows provide incremental information beyond accrual-based ratios. They showed that operating cash flow components provide additional predictive power, particularly for short-term distress. However, these measures were often correlated with profitability, suggesting partial redundancy.

Despite these advances, early research largely focused on identifying statistically significant predictors rather than understanding the structure of relationships among financial ratios. However, already in the early 1970s, Pinches et al. (1973) used factor analysis to demonstrate that financial ratios exhibit strong intercorrelations (multicollinearity) and cluster into underlying (factor) dimensions or groups. The composition of these ratio groups is reasonably stable over time. This empirical finding implies that many ratios may contain overlapping information, raising concerns about redundancy and multicollinearity in empirical models. Later, Gombola and Ketz (1983) also reported considerable time series stability of the financial ratio factors. They also showed that cash position ratios have different correlation structures than do the ratios traditionally grouped under the liquidity category.

Laitinen (1980) published a comprehensive theoretical and empirical study aimed at explaining the empirical interdependencies among financial ratios. According to his findings, these interdependencies arise because financial ratios are influenced by a common set of underlying economic determinants, referred to as basic economic factors. These factors include the internal rate of return on expenditures, the growth rate of expenditures, and the time lag between expenditures and the revenues they generate. The empirical relationships among financial ratios are not perfect, however, because the sensitivity of individual ratios to these underlying factors differs. For instance, the return on assets is highly sensitive to the internal rate of return, whereas cash flow is influenced by the difference between the internal rate of return and the growth rate. Consequently, the strength of the relationship between these ratios depends on the variation of the underlying economic factors across firms.

If cross-sectional differences in growth rates are relatively small, both return on assets and cash flow become primarily driven by the internal rate of return. In such a case, the correlation between these ratios is strong, as both effectively measure the same underlying dimension—profitability. This leads to redundancy: the unique contribution of each ratio decreases, while their shared variance increases. In contrast, when there is substantial variation in growth rates across firms, the correlation between these ratios weakens. This is because cash flow is sensitive to differences in growth rates, whereas return on assets is not. As a result, the two ratios capture more distinct aspects of financial performance, reducing overlap and increasing their respective unique contributions.

Similarly, Dechow (1994) and Sloan (1996) demonstrated that accrual-based earnings and cash flow measures capture different aspects of firm performance. Dechow showed that under certain circumstances cash flows are predicted to suffer severely from timing and matching problems that reduce their ability to reflect firm performance. While accrual measures better reflect economic performance due to matching principles, cash flow measures provide more direct information about liquidity and financial flexibility. Sloan investigated whether stock prices reflect information about future earnings contained in the accrual and cash flow components of current earnings. These studies highlight that financial ratios may exhibit both complementarity and redundancy, depending on their underlying measurement properties.

Shumway (2001) proposed a hazard model that integrates accounting and market-based variables. Shumway showed that some traditional financial ratios lose significance when more informative variables are included. This reinforces the importance of evaluating incremental explanatory power rather than relying solely on univariate or standalone measures. Shumway used the independent variables separately taken from Altman (1968) and Zmijewski (1984) as well as some new market-driven independent variables. When using the traditional methodology, all the financial ratios were statistically significant. However, when using the hazard model with market-driven variables, only EBIT/Total assets (profitability) of the traditional financial ratios in Altman (1968), was significant. For the variables from Zmijewski (1984) the results were similar, since in the hazard model only Net income/Total assets (profitability) and Total liabilities/Total assets (leverage or solvency) were significant. However, these ratios were strongly correlated, suggesting that Zmijewski's model is essentially a one-variable model.

In the 2010s and 2020s, empirical research expanded rapidly with the adoption of machine learning techniques. Comprehensive reviews, such as Sun et al. (2014) confirm that financial ratios remain the core inputs in most prediction models, despite methodological innovations. The authors demonstrated that combining financial ratios with text-based variables improves prediction. However, financial ratios remain the most important explanatory variables. Similarly, Alaka et al. (2018) regarded qualitative variables important but showed that the core financial ratios consistently appear across models, indicating their robustness. They also said that results produced by different models are not easily interpretable, since the coefficients of the ratios do not represent their importance, making results hard to interpret. Further, sometimes models yield counter intuitive signs to variables due to multicollinearity.

More recent research has increasingly focused on variable importance and redundancy. For example, studies using regularization techniques (e.g., Lasso) and variable importance metrics demonstrate that many financial ratios are highly correlated and that a smaller subset of variables can achieve similar predictive performance (Pereira et al., 2016). Thus, the authors undertook the Lasso and Ridge approaches, since these methods deal well with multicollinearity. This kind of multicollinearity suggests that a substantial portion of explanatory power in bankruptcy models arises from shared variance among ratios, rather than purely unique contributions. However, a major development in recent literature is the recognition that financial ratios exhibit substantial overlapping in explanatory power. For example, studies such as those by Magrini (2025) found using Lasso that from 12.5% up to 46.9% of financial ratio information may be redundant, reflecting substantial overlap.

In summary, empirical evidence confirms that financial ratio–based models remain central to bankruptcy and credit risk prediction (Zhao et al., 2024). Across both empirical studies and systematic reviews, four key dimensions—profitability, solvency, liquidity, and cash flow adequacy—continue to form the foundation of predictive models. The results of empirical studies on the importance of independent variables using different estimation methods (for example, probabilistic and linear regression, regularization, and machine learning) can be summarized as the following findings: solvency (leverage) is the strongest and most consistent predictor of failure, profitability is strong in univariate models, weaker in multivariate settings, cash flow adequacy provides important incremental (unique) information, and liquidity shows lower importance, often overlapping with other variables.

3. Empirical Data and Methods

3.1. Empirical Data

The empirical data for this study were extracted from the Bureau van Dijk (BvD) Orbis database under the restriction that each selected firm must be a Finnish industrial company with at least ten consecutive years of available financial statements. A longer time series was required because the credit rating system adopted in this study is based on long-term past financial performance. To avoid potential bias arising from abnormal behavior in financial ratios, the sample was restricted to years preceding the COVID-19 pandemic. For 75.2% of the firms, the final accounting year in the time series was 2015, and for an additional 20.0%, it was 2016. In total, 13,494 firms were initially extracted from the database. According to the Orbis classification, the sample consisted of 18.1% small, 64.9% medium-sized, 15.9% large, and 1.1% very large firms. Because of the requirement of long time-series data, small firms are underrepresented relative to the overall population of Finnish firms, where the majority employ fewer than ten individuals. Longer time-series are rarely published by very small (micro) firms. The average age of firms is 25 years.

Firms with missing values in any of the independent variables were excluded, resulting in a final sample of 11,903 firms. For these firms, credit ratings were computed using time-series data. The credit rating assessment developed by a Finnish financial company is based on seven key financial ratios and 22 risk factors, some of which are derived from time-series characteristics. The data source used in the study is proprietary and cannot be here named. The rating scale comprises ten categories, ranging from AAA (lowest risk) to C (highest risk). The average number of employees in the final sample was 19.8, corresponding approximately to the mean size of medium-sized firms in the Orbis classification. The average net sales amounted to EUR 6,995 thousand, while the average net profit was EUR 236 thousand. The sample firms primarily operated in wholesale or retail trade (25.4%), manufacturing (19.5%), or construction (14.8%). The final sample included 501 bankrupt firms and 11,402 non-bankrupt firms, yielding a bankruptcy rate of 4.2%. Among the bankrupt firms, 80.2% were classified into the lowest rating category (C), and 10.8% in the second lowest category (B).

3.2. Empirical Variables and Methods

This study employs two types of dependent variables. First, financial risk is measured using a binary indicator, where 0 denotes a non-bankrupt firm and 1 denotes a bankrupt firm ($Y_1 \in \{0,1\}$). Second, financial risk is measured using a ten-category ordinal credit rating ($Y_2 \in \{1, \ldots ,10\}$). These dependent variables are modeled using ordinary least squares regression with four financial ratios as independent variables. The estimated regression equation is:

$$Y_1 \text{ or } Y_2 = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + \varepsilon \tag{1}$$

where a_0 is the intercept, $a_1 - a_4$ are regression coefficients, ε is the error term, and $X_1 - X_4$ denote the explanatory variables.

Linear regression analysis relies on several standard assumptions: (i) a linear relationship between dependent and independent variables, (ii) independence of error terms, (iii) homoscedasticity (constant variance of errors), and (iv) approximate normality of residuals. In addition, the model assumes the absence of perfect or severe multicollinearity among independent variables and correct model specification. Violations of these assumptions may compromise the unbiasedness and consistency of coefficient estimates and render statistical inference (e.g., t-tests and p-values) unreliable. However, such violations are not central to the present study, as the primary focus is not on individual coefficients but on the coefficient of determination (R^2), which measures the proportion of variation in financial risk explained by the model. The analysis further emphasizes the redundancy (relevance) and unique contributions of individual financial ratios.

When linear regression is applied to a binary dependent variable (Y_1), the resulting model corresponds to a Linear Probability Model (LPM), in which the predicted values can be interpreted as estimates of the probability of an event occurring (e.g., bankruptcy). In this framework, the regression coefficients have a straightforward interpretation as marginal effects: they indicate the change in the predicted probability associated with a one-unit change in an explanatory variable. The situation differs in the case of credit rating data. Unlike bankruptcy, which represents a realized binary outcome, credit ratings reflect an assessed level of risk expressed on an ordinal scale (e.g., 1 to 10). Consequently, the dependent variable does not measure an observed event but rather an ordered categorization of risk levels. From a strict methodological perspective, the use of ordinary least squares (OLS) regression in this context is not fully appropriate, as OLS assumes that the dependent variable is measured on at least an interval scale, with meaningful and equal distances between values.

Nevertheless, in this study, linear regression is applied to the ordinal credit rating variable as an approximation. This approach can be understood as a pragmatic simplification, whereby a complex ordinal outcome is modeled using a continuous framework. While this entails a violation of the interval-scale assumption, the method remains informative for capturing general patterns of association between financial ratios and creditworthiness. Importantly, the use of OLS in both the binary (LPM) and ordinal settings ensures methodological consistency, allowing for a comparable decomposition of explained variance (R^2) across models. This comparability is central to the analysis, particularly in the application of commonality analysis, where the relative contributions of explanatory variables to the overall explanatory power are of primary interest.

The LPM has, however, well-known limitations in addition to the interval scale. Predicted probabilities may fall outside the [0, 1] interval, and the error variance is inherently heteroskedastic, as it depends on the values of the independent variables. Moreover, the error terms are not normally distributed, which affects statistical inference. While these limitations are acknowledged, they are not critical in this study due to the focus on R^2. An alternative approach would be logistic regression, which ensures that predicted probabilities lie within the unit interval and better reflects the nonlinear nature of binary outcomes. However, in logistic regression, the coefficient of determination is more complex and not easily decomposed into additive components. For this reason, linear regression is preferred in the present analysis.

The independent variables in the regression model consist of key financial ratios that represent the core dimensions of financial ratio analysis identified in prior research. These ratios are presented below in the order of their hypothesized importance in explaining financial risk:

Solvency:

1. Solvency ratio (%) = (Shareholders' Equity/Total Assets) · 100

Profitability:

2. Return on total assets (%) = (Profit/Loss Before Tax/Total Assets) · 100

Liquidity:

3. Liquidity ratio = (Current Assets − Stocks)/Current Liabilities

Cash flow adequacy:

4.a. Traditional cash flow to sales ratio (%) = (Net Income + Depreciation & Amortization + Other Non-Cash Charges)/Net sales) · 100

4.b. Operating cash flow to sales ratio (%) = (Net Income + Non-cash Items + Changes in Working Capital) /Net sales) · 100

In this context, the solvency ratio is traditionally referred to as the equity ratio, while the liquidity ratio is commonly termed the quick ratio. Cash flow is represented by two alternative measures—traditional cash flow and operating cash flow—to assess the relative importance of different cash flow dimensions. Traditional cash flow, defined as an accrual-based measure, is closely associated with profitability, whereas operating cash flow, as a cash-based measure, closely reflects liquidity.

These cash flow-based ratios were selected for this study because they are central financial indicators and have also served as key benchmarks in prior failure research (Laitinen, 1994). In the selection process, these measures were preferred over the widely used free cash flow metric, typically defined as operating cash flow minus capital expenditures. The rationale for this choice lies in the structural differences between distressed and successful firms. Companies experiencing financial difficulties tend to have very low levels of capital expenditures, whereas successful firms typically exhibit substantial investment activity. As a result, the differences in free cash flow between distressed and non-distressed firms are smaller than those observed in operating cash flow. Consequently, operating cash flow provides a more discriminating measure for distinguishing between failing and successful firms.

Table 1 reports the descriptive statistics of the dependent and independent research variables. The mean solvency ratio (44.9%) indicates a generally strong level of solvency among the sample firms. The average return on assets (13.5%) suggests that overall profitability is moderate rather than high. This interpretation is reinforced by the median value of 10.0%, which, together with the mean, points to an average level of profitability. The mean liquidity ratio (quick ratio) of 3.08 indicates an excellent level of liquidity, whereas the median value of 1.21 reflects a more moderate, yet still sound, position. The substantial difference between the mean and the median values is explained by the highly positively skewed distribution of the liquidity ratio. The average values of the cash flow ratios are relatively similar (approximately 10%), as are the median values (approximately 7%). These figures suggest a generally adequate level of cash flow. However, it should be noted that cash flow ratios are strongly influenced by industry-specific characteristics.

Table 1. Descriptive statistics on the dependent and independent variables of the study (N = 11,903).

Variable	Minimum	Maximum	Mean	St. Dev.	Skewness	Kurtosis	Median
Y_1 (binary measure of risk)	0	1	0.042	0.201	4.562	18.811	0
Y_2 (credit ratíng 1 - 10)	1	10	6.122	2.710	−0.125	−1.046	6
Solvency ratio	−74.740	99.520	44.931	37.086	−0.857	0.937	47.650
Return on assets ratio	−57.210	109.840	13.483	27.910	0.803	2.829	10.002
Liquidity ratio	0.090	35.650	3.075	6.073	4.098	17.582	1.206
Traditional cash flow	−42.240	73.770	10.106	19.609	0.755	3.094	7.178
Operating cash flow	−63.430	107.420	10.662	27.698	0.989	4.176	6.891

In this study, the focus is to analyze how strongly financial ratios affect the coefficient of determination estimated for the risk models where the dependent variable Y is explained by the four predictors (X_1 – X_4). In this analysis an all-subsets regression framework will be adopted. In this framework, the decomposition of the coefficient of determination (R^2) is analyzed in a systematic way to assess both the unique contributions of individual variables and their shared (overlapping) explanatory power. The total explained variance can be partitioned into components attributable uniquely to each predictor and components jointly explained by different combinations of predictors. The unique contribution of a variable (e.g., X_1) is defined as the incremental increase in R^2 when that variable is added to a model already containing all other predictors. In contrast, shared variance (or communality) reflects the portion of explained variance that cannot be uniquely attributed to any single predictor but instead arises from their joint explanatory power. These shared components can be further decomposed into pairwise, third-order, and higher-order communalities using inclusion-exclusion principles based on R^2 values from all possible subset models (Seibold et al., 1979; McPhee et al., 1979).

4. Empirical Findings

4.1. Correlation and Regression Analysis Results

Table 2 reports the Pearson correlation coefficients for the study variables. The correlation between the two risk measures, Y_1 and Y_2, is relatively low (0.271), which can be attributed to the binary nature of Y_1. Among the explanatory variables, the strongest correlation with Y_1 is observed for the solvency ratio X_1 (−0.317), whereas the weakest correlations are found for the operating cash flow ratio X_{4b} (−0.071) and the quick ratio X_3 (−0.082). These relatively low correlations suggest a limited linear association between these ratios and the binary measure of financial risk. In contrast, the financial ratios exhibit stronger correlations with the credit rating variable Y_2 than with Y_1. The strongest associations with Y_2 are observed for the solvency ratio X_1 (−0.747) and traditional cash flow X_{4a} (−0.513), indicating a substantial relationship between credit ratings and these financial indicators. The two cash flow measures, X_{4a} and X_{4b}, are moderately correlated (0.497). Notably, traditional cash flow X_{4a} shows a stronger association with the return on assets ratio X_2 (0.394) and the solvency ratio X_1 than does operating cash flow X_{4b}. This finding suggests that traditional cash flow is more closely aligned with profitability-related measures, as expected. Furthermore, the correlations of traditional cash flow X_{4a} with both risk measures (Y_1 and Y_2) are stronger than those of operating cash flow X_{4b}, implying a greater contribution to the explained variance in financial risk.

Panels A and B of **Table 3** present linear regression results for the binary bankruptcy indicator. The explanatory power of the models is modest, with R^2 values of 0.120 (Panel A) and 0.118 (Panel B), which is typical for linear probability models. Across both specifications, solvency ratio (X_1) is the most influential predictor of bankruptcy risk. The standardized coefficients (Beta = −0.309 and −0.321) indicate a strong negative relationship, implying that higher solvency significantly reduces the likelihood of bankruptcy. This result is highly statistically significant ($p < 0.001$) and consistent across both models. Return on assets (X_2) also exhibits a statistically significant negative effect (Beta = −0.096 and −0.116), suggesting

Table 2. Pearson correlations between the research variables (p-values below) (N = 11,903).

Variables	Y_1	Y_2	X_1	X_2	X_3	X_{4a}	X_{4b}
Y_1 (binary measure of risk)	1.000	0.271	−0.317	−0.176	−0.082	−0.185	−0.071
		<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Y_2 (credit rating 1 - 10)	0.271	1.000	−0.747	−0.350	−0.463	−0.513	−0.262
	<0.001		<0.001	<0.001	<0.001	<0.001	<0.001
Solvency ratio (X_1)	−0.317	−0.747	1.000	0.189	0.436	0.345	0.179
	<0.001	<0.001		<0.001	<0.001	<0.001	<0.001
Return on assets ratio (X_2)	−0.176	−0.350	0.189	1.000	0.018	0.394	0.176
	<0.001	<0.001	<0.001		0.048	<0.001	<0.001
Liquidity ratio (X_3)	−0.082	−0.463	0.436	0.018	1.000	0.260	0.125
	<0.001	<0.001	<0.001	0.048		<0.001	<0.001
Traditional cash flow (X_{4a})	−0.185	−0.513	0.345	0.394	0.260	1.000	0.497
	<0.001	<0.001	<0.001	<0.001	<0.001		<0.001
Operating cash flow (X_{4b})	−0.071	−0.262	0.179	0.176	0.125	0.497	1.000
	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	

that more profitable firms are less likely to fail. Interestingly, the liquidity ratio (X_3) shows a small but statistically significant positive coefficient (Beta = 0.070 and 0.060). This counterintuitive result may reflect redundancy or multicollinearity in the ratio. However, variance inflation factor (VIF) does not reveal any multicollinearity. The role of cash flow differs markedly between the two specifications. In Panel A, traditional cash flow (X_{4a}) has a small but significant negative effect (Beta = −0.059), indicating that stronger accrual-based cash flow reduces bankruptcy risk. In Panel B, operating cash flow (X_{4b}) is statistically insignificant (p = 0.958), which suggests negligible explanatory power for bankruptcy risk in this specification. Generally, VIFs are low, indicating that multicollinearity is not a concern.

Panels C and D of Table 3 report results for the ordinal credit rating variable. The explanatory power is substantially higher than for the binary measure, with R^2 = 0.665 (Panel C) and R^2 = 0.640 (Panel D). Again, solvency ratio (X_1) is the dominant predictor, with very large standardized coefficients (Beta = −0.577 and −0.611). This indicates that firms with stronger capital structures receive significantly better credit ratings. Both profitability (X_2) and liquidity (X_3) have statistically significant negative effects, suggesting that higher profitability and stronger liquidity are associated with lower (better) risk ratings. Cash flow variables are also important. Traditional cash flow (X_{4a}) has a substantial negative effect (Beta = −0.213), making it one of the most important predictors in Panel C. Operating cash flow (X_{4b}) is also significant in Panel D (Beta = −0.092), but its effect is clearly weaker. Overall, the results indicate that credit ratings capture a broader and more systematic relationship with financial ratios than the binary bankruptcy measure.

In addition, accrual-based cash flow measures capture more comprehensive information about firm performance and risk, than cash-based cash-flow measures.

Table 3. Regression analysis models for the risk measures Y_1 and Y_2.

Panel A. Regression model of Y_1 (binary measure) with traditional cash flow ratio X_{4a}.						
Independent variable	B	Std. Error	Beta	t-test	*p*-value	VIF
Constant	0.126	0.003		45.690	<0.001	
Solvency ratio (X_1)	−0.002	0.000	−0.309	−31.024	<0.001	1.344
Return on assets ratio (X_2)	−0.001	0.000	−0.096	−10.119	<0.001	1.208
Liquidity ratio (X_3)	0.002	0.000	0.070	7.196	<0.001	1.277
Traditional cash flow (X_{4a})	−0.001	0.000	−0.059	−5.929	<0.001	1.338
$R^2 = 0.12016$						
Panel B. Regression model of Y_1 (binary measure) with operating cash flow ratio X_{4b}.						
Independent variable	B	Std. Error	Beta	t-test	*p*-value	VIF
Constant	0.125	0.003		45.415	<0.001	
Solvency ratio (X_1)	−0.002	0.000	−0.321	−32.715	<0.001	1.302
Return on assets ratio (X_2)	−0.001	0.000	−0.116	−13.070	<0.001	1.067
Liquidity ratio (X_3)	0.002	0.000	0.060	6.272	<0.001	1.247
Operating cash flow (X_{4b})	0.000	0.000	0.000	−0.052	0.958	1.060
$R^2 = 0.11758$						
Panel C. Regression model of Y_2 (credit rating) with traditional cash flow ratio X_{4a}.						
Independent variable	B	Std. Error	Beta	t-test	*p*-value	VIF
Constant	8.728	0.023		381.487	<0.001	
Solvency ratio (X_1)	−0.042	0.000	−0.577	−93.912	<0.001	1.344
Return on assets ratio (X_2)	−0.015	0.001	−0.155	−26.523	<0.001	1.208
Liquidity ratio (X_3)	−0.068	0.003	−0.153	−25.539	<0.001	1.277
Traditional cash flow (X_{4a})	−0.029	0.001	−0.213	−34.731	<0.001	1.338
$R^2 = 0.66547$						
Panel D. Regression model of Y_2 (credit rating) with operating cash flow ratio X_{4b}.						
Independent variable	B	Std. Error	Beta	t-test	*p*-value	VIF
Constant	8.754	0.024		367.298	<0.001	
Solvency ratio (X_1)	−0.045	0.000	−0.611	−97.211	<0.001	1.302
Return on assets ratio (X_2)	−0.021	0.001	−0.215	−37.880	<0.001	1.067
Liquidity ratio (X_3)	−0.081	0.003	−0.181	−29.525	<0.001	1.247
Operating cash flow (X_{4b})	−0.009	0.001	−0.092	−16.239	<0.001	1.060
$R^2 = 0.63954$						

4.2. Unique and Common Effects

The results reported in Panels A-D of Table 4 provide an all-subsets decomposition of the coefficient of determination (R^2) into unique effects (U) and common (shared) effects (C) for four financial ratios explaining financial risk measured either as bankruptcy (Y_1) or credit rating (Y_2). In panel A and B, the overall explanatory power is modest, with total R^2 ranging from approximately 0.117 to 0.120, which is typical for linear (binary) probability models of bankruptcy. The findings indicate that for Y_1 solvency ratio (X_1) clearly dominates, accounting for the largest share of unique explanatory power with U1 = 0.0712 (Panel A) and 0.0794 (Panel B). In addition, profitability (X_2) has a modest but meaningful role. Its unique contribution increases when using operating cash flow (0.0127 vs. 0.0076). This indicates that the role of return on investment ratio becomes more important as a measure of profitability, when the model does not include the accrual cash flow ratio. In this model, liquidity (X_3) and cash flow (X_4) have very limited unique contributions. Especially operating cash flow (X_{4b}) does not show virtually unique effect at all ($U_4 = 0$).

Table 4. Unique effects (Ui) and common effects (Cij) of the independent variables.

Panel A. Effects on R^2 of Y_1 (binary measure) with traditional cash flow ratio X_{4a}.				
	Independent variables:			
Communalities	X_1	X_2	X_3	X_{4a}
U1	0.0712			
U2		0.0076		
U3			0.0038	
U4				0.0026
C12	−0.0170	−0.0170		
C13	−0.0028		−0.0028	
C14	−0.0278			−0.0278
C23		−0.0005	−0.0005	
C24		−0.0184		−0.0184
C34			−0.0055	−0.0055
C123	−0.0005	−0.0005	−0.0005	
C124	0.0136	0.0136		0.0136
C134	0.0070		0.0070	0.0070
C234		0.0014	0.0014	0.0014
C1234	0.0855	0.0855	0.0855	0.0855
Sum	0.1292	0.0716	0.0884	0.0584

Continued

Panel B. Effects on R^2 of Y_1 (binary measure) with operating cash flow ratio X_{4b}.				
	Independent variables:			
Communalities	X_1	X_2	X_3	X_{4b}
U1	0.0794			
U2		0.0127		
U3			0.0029	
U4				0.0000
C12	−0.0170	−0.0170		
C13	−0.0028		−0.0028	
C14	−0.0048			−0.0048
C23		−0.0005	−0.0005	
C24		−0.0034		−0.0034
C34			−0.0013	−0.0013
C123	−0.0005	−0.0005	−0.0005	
C124	0.0032	0.0032		0.0032
C134	0.0014		0.0014	0.0014
C234		0.0006	0.0006	0.0006
C1234	0.0477	0.0477	0.0477	0.0477
Sum	0.1065	0.0428	0.0476	0.0434

Panel C. Effects on R^2 of Y_2 (credit rating) with traditional cash flow ratio X_{4a}.				
	Independent variables:			
Communalities	X_1	X_2	X_3	X_{4a}
U1	0.2480			
U2		0.0198		
U3			0.0183	
U4				0.0339
C12	−0.0774	−0.0774		
C13	−0.1911		−0.1911	
C14	−0.1891			−0.1891
C23		−0.0058	−0.0058	
C24		−0.0967		−0.0967
C34			−0.0980	−0.0980
C123	0.0109	0.0109	0.0109	
C124	0.0668	0.0668		0.0668
C134	0.0887		0.0887	0.0887
C234		0.0177	0.0177	0.0177
C1234	0.8196	0.8196	0.8196	0.8196
Sum	0.7762	0.7548	0.6603	0.6428

Continued

Panel D. Effects on R^2 of Y_2 (credit rating) with operating cash flow ratio X_{4b}.				
	Independent variables:			
Communalities	X_1	X_2	X_3	X_{4b}
U1	0.2863			
U2		0.0435		
U3			0.0264	
U4				0.0080
C12	−0.0774	−0.0774		
C13	−0.1911		−0.1911	
C14	−0.0515			−0.0515
C23		−0.0058	−0.0058	
C24		−0.0272		−0.0272
C34			−0.0263	−0.0263
C123	0.0109	0.0109	0.0109	
C124	0.0202	0.0202		0.0202
C134	0.0243		0.0243	0.0243
C234		0.0069	0.0069	0.0069
C1234	0.5924	0.5924	0.5924	0.5924
SUM	0.6141	0.5635	0.4377	0.5468

Generally, in Panel A and B pairwise common (shared) effects (e.g., C_{12}, C_{14}) are predominantly negative, indicating redundancy and multicollinearity among financial ratios. However, higher-order effects are positive, particularly c_{1234} (0.0855 in Panel A and 0.0477 in Panel B). This finding implies that most explanatory power arises from the joint interaction of all variables, rather than isolated effects. Traditional cash flow X_{4a} (Panel A) yields higher total R^2 and larger shared effects (especially c_{1234}), than operating cash flow X_{4b}. This suggests that accrual-based cash flow contains more predictive information for bankruptcy.

Credit rating Y_2 results in Panels C and D show a substantially higher explanatory power than for Y_1. Total R^2 is remarkably higher up to 0.78 (Panel C) and 0.61 (Panel D), which reflects the use of an ordinal scale in credit rating instead of a binary measure. In unique effects, solvency ratio X_1 remains dominant with U_1 = 0.2480 (Panel A) and 0.2863 (Panel D). Moreover, traditional cash flow X_{4a} shows a meaningful unique contribution, being particularly strong in Panel C (0.0339). The contribution of operating cash flow X_{4b} is clearly weaker (0.0080). The shared effects show strongly negative pairwise effects, especially C_{13} and C_{14}. In addition, the results indicate extremely large higher-order effect C_{1234} (0.8196 in Panel C and 0.5924 in Panel D). These findings imply that the vast majority of explained variance is jointly shared by all variables and that financial ratios form a highly interdependent system: financial ratios are strongly intercorrelated, and their explanatory power is largely non-additive so that most of the predictive content arises from combined effects rather than individual ratios.

5. Concluding Remarks

This study analyzes the determinants of financial risk using both a binary bankruptcy indicator and an ordinal credit rating measure. The study employs a linear regression based on four financial ratios: solvency, profitability, liquidity, and cash flow (either traditional or operating cash flow ratio). For the binary measure, the models exhibit modest explanatory power, which is typical for linear probability models based on a binary dependent variable. Across both specifications, solvency is the dominant predictor, with a strong and statistically significant negative effect. Profitability also shows a significant negative relationship with bankruptcy risk, although its effect is notably smaller.

The liquidity ratio has a weak but statistically significant positive coefficient. While counterintuitive, this may reflect potential redundancy of the ratio information. However, a positive regression coefficient for the quick ratio may also have an economic explanation. Firms experiencing financial distress often have customers who are themselves in financial difficulty. As a result, receivables from such customers may lose their economic value, yet they are still recorded on the balance sheet at their nominal value. Consequently, financially distressed firms may carry a substantial amount of uncollectible receivables that have not been written off. This can lead to an unusually high quick ratio, despite the firm's underlying weak liquidity position.

The role of cash flow depends on the specification: traditional cash flow is statistically significant and negatively related to bankruptcy risk, whereas operating cash flow is insignificant. Generally, variance inflation factors remain low across all models, indicating no serious multicollinearity concerns. For the credit rating measure, the explanatory power is substantially higher. Solvency again emerges as the most influential variable, with large standardized coefficients. Profitability and liquidity are also significant predictors, both negatively associated with risk. Unlike the bankruptcy models, both cash flow measures are significant. However, traditional cash flow exhibits a stronger effect than operating cash flow.

To complement the regression results, commonality analysis decomposes R^2 into unique and shared contributions. This provides insight into the extent to which explanatory power arises from individual variables versus their joint effects. For the bankruptcy models, solvency has the largest unique contribution, while the unique effects of the other variables are small. A substantial portion of R^2 is explained by the four-variable shared component, indicating that explanatory power is primarily generated by the joint interaction of financial ratios. At the same time, many pairwise components are negative, suggesting redundancy and suppression effects among predictors. For the credit rating models, shared effects dominate even more strongly. Although solvency retains the largest unique contribution, the majority of explained variance is attributable to the combined effect of all variables. The large higher-order commonality component indicates that credit ratings reflect a multidimensional assessment of financial condition rather than isolated indicators. Across both dependent variables, traditional cash flow contributes more to both unique and shared variance than operating cash flow, reinforcing its stronger explanatory role.

The combined evidence from regression and commonality analysis highlights several key findings. First, solvency is consistently the most important individual determinant of financial risk. Second, the majority of explanatory power arises from shared variance, indicating that financial ratios operate as an interdependent system rather than as independent predictors. Third, negative lower-order commonalities suggest substantial overlap in the information captured by the ratios, which complicates the interpretation of regression coefficients in isolation. Fourth, traditional (accrual-based) cash flow outperforms operating cash flow across both model types, suggesting that it captures broader aspects of financial performance. Finally, the results differ markedly between the two dependent variables: credit ratings exhibit a stronger and more systematic relationship with financial ratios than the binary bankruptcy indicator. The findings are consistent with prior research on financial distress prediction. Solvency plays the dominant role in financial risk estimation followed by profitability, whereas liquidity and cash flows play a minor role.

The findings of this study have important implications for stakeholders such as credit analysts and corporate managers. Overall, the results suggest that greater emphasis should be placed on the holistic evaluation of financial ratios, given the dominance of shared (common) effects in explaining risk. Accordingly, systematic risk assessment should be based on a set of interrelated financial indicators and their joint dynamics, rather than relying on individual ratios in isolation. The unique effects of individual financial ratios are generally modest. However, solvency — measured by the equity ratio — exhibits a clearly strong and statistically significant unique contribution to risk indicators. This underscores its central role as a core metric in risk assessment frameworks. In contrast, profitability, as measured by the return on assets ratio, shows only a limited unique effect in cross-sectional analysis. However, despite its relatively small contemporaneous contribution, profitability plays a critical role in the longer term. Sustained weak profitability gradually erodes solvency, thereby increasing the likelihood of financial distress, including bankruptcy or liquidity crises. In this dynamic perspective, declining profitability typically serves as an early warning signal of rising risk, which is subsequently reflected in a deterioration of solvency.

Several avenues for future research emerge from the present findings. First, future studies could apply nonlinear models, such as logistic regression or machine learning techniques, to examine whether the strong shared effects observed here persist under alternative specifications. Second, future research could explore whether the structure of shared and unique contributions differs across industries. Third, extending the analysis to firms in different countries would allow assessment of whether the observed dominance of shared variance and the superiority of accrual-based cash flow are context-specific or generalizable. Fourth, future models could incorporate market-based indicators (e.g., stock returns or volatility) to evaluate how accounting-based and market-based measures jointly explain financial risk. Finally, methods such as dominance analysis or Shapley value decomposition could be applied to validate and extend the findings on the relative importance of predictors.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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