Corporate Governance and Risk Management: Cash Flow Indicators in Credit Risk Prediction

Suzi Mikulić[1] and Nikola Škobić[2]
[1]Profin Consulting Ltd, Široki Brijeg, Bosnia and Herzegovina
[2]Faculty of Economics, University of Mostar, Bosnia and Herzegovina

suzi.mikulic@gmail.com
nikola.skobic@ef.sum.ba

Abstract: Credit risk management and its prediction are critical to the success of any organisation, as bad debts-a major source of credit risk-can lead to significant financial difficulties. While the issue of credit risk is prevalent in banks and the financial sector, it is also relevant for companies in non-financial sectors. Nevertheless, the prediction of credit risk in non-financial companies remains an under-researched area in the literature. The mandatory application of the international accounting standard IFRS 9 in 2018, which requires the estimation of expected credit losses in non-financial companies as well, highlights the need for reliable predictive indicators for both financial reporting and internal risk management, which is a key principle of effective corporate governance. This study examines the role of cash flow-based indicators in complementing traditional accrual-based measures in assessing and predicting credit risk from the perspective of companies managing their receivables. Using a sample of large non-financial companies over a five-year period, statistical analysis was performed with logistic regression in SAS Enterprise Miner. The results indicate that several cash flow indicators have explanatory value for fluctuations in credit risk, but are insufficient on their own for predictive modelling. The findings suggest that cash flow indicators should be integrated with other financial and non-financial measures to enhance credit risk assessment models, supporting better decision-making and overall corporate governance practices.

Keywords: Corporate governance, Credit risk management, Cash flow indicators, Credit risk prediction, Non-Financial companies

1. Introduction

Analysing corporate performance using financial indicators is an integral part of decision-making and risk management in companies (Iswahyudi et al, 2023). According to the OECD Guidelines on Corporate Governance (2023), timely and accurate financial information is necessary not only for transparency and accountability to stakeholders, but also for effective risk management, which protects a company's long-term stability. Among these risks, credit risk-defined as the probability that a company will not collect its receivables within the agreed terms, potentially leading to financial losses (Wojcicka-Wojtowicz, 2018; Oyetola et al, 2023) plays a particularly important role in non-financial companies, where sales on deferred payment terms are common. In practice, a common measure used by non-financial companies to monitor trade receivables is days sales outstanding (DSO), which reflects the average time taken to collect receivables. As a static, backward-looking indicator, DSO alone cannot capture the full spectrum of credit risk exposure and is most effective when complemented by additional financial indicators (Siekelova et al, 2017).

Most previous research on credit risk determinants has focused on banks, due to their long-standing development and use of credit risk models under Basel regulations. In recent years, reporting requirements for non-financial companies have also evolved. With the mandatory application of IFRS 9 in 2018, the accounting treatment of receivables in non-financial companies adopted a forward-looking approach, recognising expected credit losses (ECL) that may arise from credit risk or the non-collection of receivables. This treatment has become more closely aligned with Basel banking risk practices. Baesens and Smedts (2025) highlight that lessons from bank risk management provide a valuable basis for informative and proactive reporting, bridging risk management and financial management functions.

A review of the existing literature reveals a significant gap regarding the determinants of credit risk in business-to-business transactions among non-financial companies. Interest in this area has increased following IFRS 9, which defines two approaches for estimating ECL: the simplified approach, based on historical loss rates and does not take changes in credit risk into account, and the general approach, based on the probability of default (PD). In this study the general approach (PD approach) is particularly relevant, as it assesses the level of credit risk. According to Hladika et al (2017) PD measures a customer's risk exposure and estimates potential losses over a year in case of default.

Following the above and taking into account the limited availability of studies on cash flow indicators in non-financial companies, which are less frequently analysed than accrual-based measures (Bhandari, 2019; Litvinenko & Alver, 2023; Alvi et al, 2024; Litvinenko, 2024), the purpose of this study is to investigate whether, and to what extent, cash flow-based indicators influence credit risk assessment in non-financial companies. While accrual-based measures dominate credit risk research in banks, recent studies highlight the potential complementary role of cash flow indicators. Findings are mixed: some show that cash flow measures better capture companies' ability to meet obligations (Zeller & Stanko, 1994; Litvinenko & Alver, 2023; Seretidou et al, 2025), while others report limited predictive power unless combined with accrual ratios (Gupta et al, 2013; Piatti, 2014). Despite these insights, there is still certain gap in research. Therefore, the study is guided by the following research questions:

RQ1: Do cash flow indicators have informational value in explaining credit risk in non-financial companies?

RQ2: Do cash flow indicators have predictive power in the evaluation of credit risk models in non-financial companies?

By addressing these questions, the study clarifies the role of cash flow indicators in both explaining and predicting credit risk in non-financial companies, contributing to the limited literature in this area. Although the primary purpose of this study is to analyse credit risk from the perspective of companies managing their receivables in business to business transactions, the findings are also relevant for financial reporting, as IFRS 9 explicitly links accounting standards to proactive risk management.

2. Literature Review

Traditionally, credit risk research has focused on banks, where standard credit risk models have been developed based on accrual accounting indicators derived from financial statement analysis (Benos & Papanastasopoulos, 2007; Nehrebecka, 2015; Wali, 2018). In recent years, these models have been extended to incorporate qualitative information about debtors, alongside traditional financial ratios (Grebenar 2018; Ganbat et al, 2021; Cetin et al, 2023; Nayak 2024). Cash flow indicators, although they are direct monetary financial measures, have been incorporated less frequently in such models compared to accrual-based measures (Karas & Reznakova, 2020; Litvinenko 2023; Litvinenko & Alver, 2023). One of the reasons why cash flow-based indicators are less represented in analyses, models, and academic research compared to accrual-based indicators is that the requirement to prepare cash flow statements was introduced by the Financial Accounting Standards Board (FASB) only in 1987. In contrast the development of accrual-based indicators dates back to the late nineteenth century, when banks began to require financial statements for lending purposes. Even today, many companies, such as micro and small enterprises, are not required to prepare cash flow statements.

The literature offers divergent findings on the role of cash flow indicators in credit risk modelling. Zeller and Stanko (1994), in their study of U.S. non-financial retail companies, conclude that cash flow-based indicators provide a more accurate measure of a firm's capacity to meet obligations than accrual-based ratios. Karas and Reznakova (2020) argue that accrual-based measures are susceptible to manipulation, potentially distorting a company's true performance, whereas insolvency and financial distress more directly arise from insufficient cash flow. They therefore emphasise the predictive reliability of cash-based indicators, particularly operating cash flow. In contrast, Gupta et al (2013), using a UK based non-financial SME sample, find that although operating cash flow indicators have discriminatory power, they do not improve the predictive accuracy of default models beyond accrual-based ratios. Kamal and Quader (2010; 2011) also caution against positioning cash flow ratios as superior to accrual-based indicators, instead suggesting a complementary approach in which both sets of measures provide distinct but valuable information.

Several studies highlight the benefits of integrated approaches. Piatti (2014), in a study of Italian non-financial SMEs, shows that cash flow ratios alone lack predictive strength in assessing creditworthiness but become more important when used in combination with other financial ratios. Bhandari et al (2019), testing financial failure models based on accrual and cash-based indicators, find that the strongest predictive power comes from a combined model using both accrual-based (current ratio, net return on assets) and cash-based ratios (cash coverage of current and total liabilities).

More recent contributions seek to address this imbalance. Litvinenko (2023) compares accrual-based and cash-based models, noting that the former dominate the literature while the latter remain less common, despite their potential. Building on this, Litvinenko and Alver (2023) develop a modified cash flow-based credit risk model to better assess credit risk, default probability, and pre-insolvency status. Their findings show that the cash-based credit risk model provides sufficient visibility of a company's likelihood of default. Seretidou et al (2025), in a systematic analysis of 21 studies across various industries and regions, found that cash flow ratios generally outperform traditional financial ratios in predicting financial distress and highlight their potential to enhance credit risk assessment, as distressed firms are more likely to default.

3. Research Methodology

The aim of this study is to determine whether cash-based indicators have explanatory and predictive power in assessing the credit risk of non-financial companies, expressed by the probability of default (PD). By performing regression analyses, it is possible to describe and understand the relationships between observed phenomena, but also to predict the value of the dependent variable based on the known values of one or more independent variables (Ault et al, 2025). In this particular case, the influence of several independent variables, cash-based indicators, on the dependent variable, i.e. the probability of default (credit risk), is observed. Accordingly, the analytical model of the study can be represented as follows:

PD = ƒ CFI (CCLib, CCTLib, CCInt, QPro, CInv, CFin, CRoa, CRoce, CRoe, FCF I, FCF II)

Where: PD-Probability of default; CFI-Cash flow indicators (CCLib, CCTLib, CCInt, QPro, CInv, CFin, CRoa, CRoce, CRoe, FCF I, FCF II).

For the empirical data analysis, logistic regression was used, which has been applied in numerous previous studies related to the banking sector (Streitenberger & Miloš Sprčić 2011; Grebenar 2018; Nehrabecka 2019). Data processing was carried out in SAS Enterprise Miner.

3.1 Data Collection and Sample

The study was conducted on a sample of large companies from three main non-financial sectors in Bosnia and Herzegovina (B&H): manufacturing, trade (wholesale and retail), and construction, covering the period from 2015 to 2019, that is, prior to the emergence of macroeconomic imbalances in 2020, which continue to this day. This period provides a good basis for the type of research to be conducted in this paper because: (1) studies on factors influencing credit risk in non-financial companies are underrepresented and (2) the research was conducted in a stable period that was not affected by macroeconomic fluctuations that could bias the interpretation of the results. The sample includes large companies from the entire territory of B&H and covers all administrative units. The classification of companies by size was based on the criteria prescribed in the applicable accounting laws in B&H during the study period. A company was categorised as large if it met at least two of the following criteria: more than 250 employees, a balance sheet total of more than EUR 2 million and an annual turnover of more than EUR 4 million. The number of large companies included in the sample per year was as follows: 2015 = 939; 2016 = 955; 2017 = 966; 2018 = 979; 2019 = 1,017. The total number of large companies in the entire non-financial sector at B&H level was between 1,198 and 1,294: 2015 = 1,198; 2016 = 1,221; 2017 = 1,234; 2018 = 1,251; 2019 = 1,294. These figures show that the companies included in the sample represent almost 80 % (78.35 %) of all large companies in the non-financial sector, which confirms the representativeness of the sample. The total number of observation units during the study period was 4,828. The financial indicators required for the research, are taken from the L.R.C. Ltd. Sarajevo database.

3.2 Dependent Variable

The probability of default (PD) is the dependent variable in this study. It is a key component in credit risk modelling that is essential for determining the amount of expected credit losses under the general approach of IFRS 9, which is based on risk categories. PD is defined as the estimated probability that a default will occur within a certain period of time. It is expressed as a probability, where 0 means no default risk and 1 means a default (Nordgren & Göransson, 2018).

According to the rules for credit (banking) institutions (Regulation (EU) No 575/2013), a debtor is considered to be in default if they are more than 90 days overdue on a credit obligation. Several previous studies on the determinants of credit risk at banks have categorised debtors based on this criterion (Jović, 2017; Grebenar, 2018; Nordgren & Göransson, 2018; Nehrebecka, 2019). In the non-financial sector in B&H, the statutory payment period for obligations between companies is up to 60 days (Law in the Federation of B&H, 2016; Law in the Republic of Srpska, 2018). The timely settlement of obligations is a key criterion for categorising exposures into risk categories (Streitenberger & Miloš Sprčić, 2011). Accordingly, the companies in the sample are categorised as follows: 0-companies that settle their liabilities within 60 days and 1–companies that settle their liabilities after 60 days. This binary categorisation meets the requirements of logistic regression, in which the dependent variable must be strictly dichotomous, i.e. it can only assume binary values of 0 or 1 (Anderson et al, 2011).

3.3 Independent Variables

This study uses the cash flow indicators systematised and presented by Carslaw & Mills in 1991. They laid the foundation for the wider use of these indicators in academic research and for their application in business analysis in practice. In addition, two free cash flow indicators, as presented in the study by Gulin & Hladika (2018), are analysed. The indicators and their calculation methods are listed in the table below.

Table 1*:* Overview of cash flow indicators included in the research

Symbol	Indicator Name	Formula
CFI_CCInt	Interest coverage ratio[1]	CFO/Interest
CFI_CCLib	Cash coverage of current liabilities[1]	CFO/Current liabilities
CFI_CCTLib	Cash coverage of total liabilities[1]	CFO/Total liabilities
CFI_QPro	Earnings quality[1]	CFO/Operating profit
CFI_CInv	Investment indicator[1]	CFI/CFF
CFI_CFin	Financing indicator[1]	CFI/CFO+CFF
CFI_CRoa	Cash return on total assets[1]	(CFO + interest + tax) /Total assets
CFI_CRoce	Cash return on capital and liabilities[1]	CFO/(Equity + Liabilities)
CFI_CRoe	Cash return on equity[1]	CFO/Equity
CFI_FCF I	Free cash flow I[2]	CFO - CE
CFI_FCF II	Free cash flow II[2]	CFO + CFI

Note. Abbreviations used in the table are as follows: CFO-cash flow from operations; CFI-cash flow from investing activities; CFF-cash flow from financing activities; CE-capital expenditures. Source: [1]Žager et al (2017, p. 304-310); [2]Gulin & Hladika (2018, p. 110).

4. Research Results and Discussion

4.1 Descriptive Statistics Results

During the study period, almost half of the companies observed (mean of 434.60 or 45.01%) did not settle their obligations within the legally prescribed 60-day period, while an average of 531 companies or 54.99% settled their obligations to other companies within 60 days (Table 2).

Table 2*:* Descriptive statistics - results for the dependent variable

Variable	Mean	Std Dev	Median	Skewness	Kurtosis
0	531	40.55243	525	0.38709	-1.66425
1	434.6	12.66096	435	-0.45335	-1.10259

Note. Abbreviations used in the table are as follows: Std Dev: standard deviation.

The results of the descriptive statistics for the independent variables are shown in Tables 3 and 4. It can be seen that some indicators have high values for skewness and kurtosis, which indicates the presence of extreme values (outliers). Logistic regression models can be sensitive to such asymmetries and outliers, as these conditions can lead to biased parameter estimates. Winsorisation was therefore used as a suitable transformation technique. The extreme values (outliers) were replaced by the values corresponding to the 1st and 99th percentile of the respective distributions (see Table 4).

Table 3*:* Descriptive statistics - results for the independent variables

Variable	Mean	Std Dev	Skewness	Kurtosis
CFI_CCInt	13713.99	216811.74	32.9688537	1264.26
CFI_CCLib	0.5100898	2.0401074	9.6818754	393.6876999
CFI_CCTLib	0.4163739	1.6482997	20.9214410	688.9451455
CFI_QPro	0.7900150	48.0763361	3.4428921	522.7399837
CFI_CInv	-2252.65	121844.08	-48.7252756	2729.39
CFI_CFin	-0.5099392	13.1080908	23.8421450	1095.69
CFI_CRoa	0.1076756	0.1659395	2.0791854	41.2532194
CFI_CRoce	0.0913901	0.1625811	2.0922993	44.1710361
CFI_CRoe	925.1415214	22256.34	25.9916463	816.1548371
CFI_CF_I	963030.97	7014598.98	-2.6670534	119.9890120
CFI_CF_II	3390384.15	12739775.28	7.9934492	139.9631016

Note. Abbreviations used in the table are as follows: Std Dev: standard deviation.

Table 4: Descriptive statistics - results for transformed variables

Variable	Mean	Std Dev	Skewness	Kurtosis
REP_CFI_CCLib	0.4659478	0.9325866	3.0543251	12.6430419
REP_CFI_CCTLib	0.3659089	0.7535143	3.8968609	18.8588223
REP_CFI_CCInt	6782.49	37401.20	7.5021036	58.1127406
REP_CFI_CFin	-0.7265959	1.4661230	0.8363093	13.8908859
REP_CFI_CInv	-0.1429381	19.1504173	-2.9174861	29.4957804
REP_CFI_CRoe	119.3178172	430.8328858	4.4459347	24.4150680
REP_CFI_CF_II	3148256.83	6922384.27	3.7290742	18.1115113
REP_CFI_CRoa	0.1072728	0.1408080	0.6572948	3.0572514
REP_CFI_CRoce	0.0910216	0.1382331	0.5806808	3.2295247
REP_CFI_QPro	1.0478567	5.8644243	1.2273275	17.5785580
REP_CFI_CF_I	1035613.01	3724255.31	1.9713518	11.3565604

Note. Abbreviations used in the table are as follows: REP: variables transformed through winsorisation; Std Dev: standard deviation.

From the data presented, it can be seen that the skewness and kurtosis coefficients are significantly lower after the variable transformation and approach a normal distribution.

4.2 Logistic Regression Results

Table 5 shows the results of the logistic analyses, sorted by descending Gini coefficient (Somers' D). The Gini coefficient is a measure of the inequality of distribution and is used as an indicator in various contexts, including for the assessment of model suitability in predictive analytics. In practice, an acceptable level of model discriminatory power implies Gini coefficient values greater than 0.4 (Grebenar, 2018, cited in Baesens et al, 2016).

Table 5: Results of logistic analyses ranked by descending Gini coefficient (Somers' D)

Variable	Somers' D	Estimate	Wald Chi-Square	Pr > Chi-Square
REP_ CFI_CCLib*	0.228	-0.4965	106.7824	<.0001
REP_CFI_CCTLib*	0.228	-0.6888	101.9547	<.0001
REP_CFI_CCInt*	0.154	-3.25E-6	10.5175	0.0012
REP_ CFI_CRoa*	0.102	-1.0177	18.7187	<.0001
REP_ CFI_CRoce*	0.094	-0.9487	15.7640	<.0001
REP_ CFI_ CF I**	0.058	-1.6E-8	3.2946	0.0695
REP_ CFI_CFin	0.030	-0.0130	0.3422	0.5585
REP_CFI_CRoe	0.028	-0.00002	0.0801	0.7772
REP_ CFI_QPro	0.002	0.00264	0.2277	0.6332
REP_CFI_CF II	-0.022	5.09E-10	0.0118	0.9136
REP_CFI_CInv	-0.076	0.000098	0.0034	0.9538

Note. * - significant at the 5 % level; ** significant at the 10 % level.

Based on the data presented, it can be concluded that five of the eleven observed cash flow indicators are statistically significantly associated with the probability of default in non-financial companies at the 5 % significance level ($p < 0.05$), with several showing very strong significance ($p < 0.0001$). These indicators are: CFI_CCLib; CFI_CCTLib; CFI_CCInt; CFI_CRoa and CFI_CRoce. In addition, one indicator is associated with a significance level of 10 %, namely CFI_CF I.

The findings of this study provide valuable insights into the role of cash flow indicators in credit risk assessment for non-financial companies in Bosnia and Herzegovina. The results show that six of the eleven observed cash flow indicators are significantly associated with credit risk. This suggests that cash flow indicators have information value in explaining fluctuations in credit risk for companies in the non-financial sectors and therefore provide an answer to the first research question.

The second research question in this paper assumes that cash flow indicators have predictive power in assessing the probability of default, i.e. credit risk in non-financial companies. According to the data presented and based on the Gini coefficient, none of the observed cash flow indicators have a satisfactory predictive power for the probability of default when used in stand-alone models. The value is less than 0.4 for all variables. The findings are consistent with those of Gupta et al (2013) and Piatti (2014), who conclude that, although cash flow ratios demonstrate discriminatory ability, do not have satisfactory predictive power in stand-alone models.

Accordingly, the results of this study suggest that, although cash flow indicators on their own lack robust predictive capacity, their explanatory power suggests that they should not be ignored when developing models to predict credit risk when combined with other indicators. This aligns with Bhandari et al (2019), who demonstrated that the strongest predictive power is achieved when accrual-based and cash flow indicators are combined. More broadly, these findings support recent calls in the literature (Litvinenko & Alver, 2023; Seretidou et al, 2025) to integrate cash flow measures into credit risk modelling, not as substitutes but as complements that enhance the comprehensiveness and robustness of default prediction frameworks.

5. Conclusion

Although cash flow indicators are not widely used in academic research, this study demonstrates that they provide valuable informative and explanatory value. The empirical analysis, conducted over a five-year period on a sample of 939 to 1017 large non-financial companies in Bosnia and Herzegovina, showed that indicators such as liquidity coverage of current liabilities, total liabilities and interest as well as liquidity return on total assets and liquidity return on capital and liabilities have informational value in explaining fluctuations in credit risk. On the other hand, their individual predictive power could not be proven. However, this does not mean that these indicators should be completely excluded from further analysis, especially when developing combined models with other variables.

This study contributes to the existing literature and improves the understanding of the impact of cash flow indicators on credit risk in non-financial companies. The number of available studies on the determinants of credit risk in non-financial companies remains limited compared to the extensive research focusing on banks.

Therefore, this study provides a solid basis for future research, especially because the results were obtained in a period of economic stability and using the international accounting standard IAS 39, which was replaced by IFRS 9 in 2018. From a broader perspective, exploring all factors that improve informed decision making is very important for effective corporate governance that is aligned with long-term sustainability goals. Therefore, the development of credit risk assessment models that incorporate all relevant information is essential, as only measurable factors can be properly analysed, monitored and managed.

This study has several limitations. The first limitation is that the analysis covers the pre-crisis period from 2015 to 2019. Future studies should therefore include the period from 2020 onwards to enable a comparative analysis of the findings of this study. The second limitation is that only large companies were included, so the conclusions may not be transferable to small and medium-sized enterprises (SMEs), whose characteristics and financial behaviour may differ significantly. The third limitation is that the method used is a univariate logistic regression analysis, which has limited ability to account for interactions between multiple variables. In future studies, it would be advantageous to expand the sample to include SMEs and to apply multivariate analysis approaches. The inclusion of additional data, such as accrual-based financial indicators and relevant non-financial information, could further improve the understanding of the determinants of credit risk in non-financial companies.

Ethics declaration: Ethical approval was not required for this research as it was based solely on publicly available financial and corporate governance data. The study did not involve human participants, personal data, or experimental procedures.

AI declaration: AI tools were not used in the preparation of this study.

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