Predictive Capabilities of Working Capital as an Indicator of Impending Insolvency of a Company in the Czech Republic#

Vít Pečonka[1], Petr Jablonský[2]

Abstract: The aim of the study is to analyze the predictive capabilities of changes in working capital as an indicator of impending insolvency of companies in the Czech Republic. The research uses empirical data from the financial statements of companies that entered insolvency proceedings between 2019 and 2024 and compares them with a control sample of financially stable entities. The analysis was performed using logistic regression and additionally verified using ROC analysis. The results confirm that selected working capital indicators, in particular current liquidity and the ratio of working capital to total assets, have a significant ability to predict financial instability. The findings highlight the practical importance of effective working capital management for the early identification of insolvency risk and provide a basis for the development of early warning models in the corporate sector.

Keywords: working capital, insolvency, predictive models, liquidity, Czech companies
JEL Classification: G32, G33, C35

1 Introduction

The financial stability of companies is a key determinant of sustainable economic growth and competitiveness. Corporate insolvency is not just an individual problem for a single entity, but has systemic impacts on the broader economic environment, including employment, supply chains, and capital markets. Identifying warning signs of impending financial instability is therefore an important topic in corporate finance and public policy.

Traditional insolvency prediction models, starting with Altman's Z-score, rely primarily on static ratios that capture the financial situation of a company at a given point in time. While these approaches have provided a basic framework for estimating bankruptcy risk, their ability to capture dynamic changes in a company's financial health is limited. In response, research over the past two decades has focused on dynamic indicators that better capture operating liquidity and the management of short-term assets and liabilities, particularly working capital.

Working capital is the difference between current assets and current liabilities and is an indicator of a company's operating liquidity. Changes in working capital reflect a company's ability to effectively manage its inventories, receivables, and payables, and thus its flexibility in generating cash flows. A rapid deterioration in these areas may signal a transition from a phase of financial equilibrium to a phase of stress, which often precedes insolvency proceedings.

Empirical studies (Gavurová et al., 2022; Kim et al., 2024) confirm that selected working capital indicators can have significant predictive power. However, in the Czech context, this relationship remains relatively unexplored. The Czech economy is characterized by a high proportion of small and medium-sized enterprises, which are often sensitive to changes in liquidity, while the availability of short-term financing is more limited than in advanced Western economies. These factors make the analysis of working capital in the context of insolvency particularly relevant.

The aim of this study is to empirically verify whether selected working capital indicators can serve as early indicators of impending insolvency of companies in the Czech Republic. The study combines an econometric approach based on logistic regression with descriptive analysis to ensure the robustness of the findings. The results contribute to the literature on corporate financial health and also have practical implications for corporate management, banks, and investors.

This article is one of the outputs of a research project conducted by the Faculty of Finance and Accounting at the University of Economics, Prague, which is being implemented as part of institutional support IP100040.
[1] Prague University of Economics and Business, Faculty of Finance and Accounting, Department of Corporate Finance, nám. W. Churchilla 1938/4 130 67 Praha 3, Czech Republic
[2] Prague University of Economics and Business, Faculty of Finance and Accounting, Department of Corporate Finance, nám. W. Churchilla 1938/4 130 67 Praha 3, Czech Republic, Petr.Jablonsky@vse.cz.

2 Methods

2.1 Data set

The empirical analysis is based on financial data from companies registered in the Czech Republic that entered insolvency proceedings under Act No. 182/2006 Coll. on Bankruptcy and Methods of its Resolution between 2019 and 2024. The data comes from the specialized forensic agency Surveilligence, s.r.o., from the Justice.cz, ARES, and Albertina databases.

The data was limited to medium-sized companies with an annual turnover of between CZK 15 and 300 million.

For the purposes of descriptive analysis, a total of 155 companies were used that entered insolvency during the period under review and for which financial statements existed for the three accounting periods prior to the commencement of insolvency proceedings.

For the purposes of the insolvency model, a total of 366 companies were used, half of which were companies that entered insolvency during the period under review and for which financial statements were available for one accounting period prior to the commencement of insolvency proceedings. The other half consisted of a control sample of financially healthy comparable companies. Extreme values (1% of the highest and 1% of the lowest values) were removed from the set. This created a balanced data set that allowed for a fair comparison of both groups.

2.2 Variables and their construction

The empirical model used variables that reflect the individual components of working capital and the basic characteristics of financial stability. These are listed in Table 1 below.

Table 1 Definition of variables in the insolvency model

Abbreviation	Indicator	Calculation
DIO	Days Inventory Outstanding – inventory management efficiency	(Inventory / Sales) × 365
DSO	Days Sales Outstanding - speed of converting sales into cash	(Receivables / Sales) × 365
DPO	Days Payables Outstanding - ability to defer payments	(Liabilities / Sales) × 365
CCC	Cash Conversion Cycle - measure of operational efficiency	DIO + DSO − DPO
CR	Current Ratio - short-term solvency	Current Assets / Short-Term Liabilities
WC/TA	Working Capital to Total Assets - structural stability	Working capital / Total assets
WC/E	Working Capital to Equity - ratio of operating funds to equity	Working Capital / Equity

Source: Own processing

2.3 Econometric Specification

Logistic regression was chosen for the empirical analysis, which models the probability of a company's insolvency $P(Y_i = 1)$ based on selected financial indicators. The general form of the model is:

$$\text{logit}(P_i) = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i \quad (1)$$

where X_{ki} represent individual working capital indicators and control variables. The dependent variable $P(Y_i = 1)$ takes on a binary value of 1 (if the company has entered into insolvency) or 0 (healthy company).

A model diagnosis was performed, specifically Pearson's test, which identified possible problems with the model specification (Almquist, 2023). Based on these findings, robust testing was performed to verify whether the identified problems could affect the statistical significance of individual predictors.

For the purposes of robust testing, White's robust standard errors in the HC0 variant (Long and Ervin, 2000) were used, which take into account the possible presence of heteroscedasticity in the residuals.

Taking heteroscedasticity into account affects the accuracy of the statistical evaluation of some variables. For this reason, the use of robust standard errors can be considered an important step towards increasing the reliability of the results of the corporate insolvency prediction model.

To ensure even greater reliability of the derived conclusions, the bootstrap inference method was applied. This approach does not require assumptions about the shape of the error distribution and allows for empirical estimation of the variability of the model coefficients based on repeated sampling from the original training data (Zivot, 2021). The method verifies whether the coefficient estimates are stable across different sampling conditions, thereby providing additional support for their interpretation and practical application.

2.4 Model validation

To ensure predictive reliability, the data was divided into a training (80%) and testing (20%) sample. The predictive ability of the model was evaluated on the testing sample using:

- Confusion matrix to determine classification accuracy,
- Receiver Operating Characteristic Curve („ROC“ curve),
- Area Under the Curve („AUC“) and
- Precision, Recall, and F1-Score for sensitivity and specificity balance.

3 Research results

3.1 Descriptive statistics

Table 2 summarizes the basic statistical characteristics of the variables in the sample of 155 insolvent companies. The results show that insolvent companies exhibit a significant deterioration in cash conversion cycle (CCC) and days payable outstanding (DPO) one year prior to insolvency, and conversely, an improvement in days inventory outstanding (DIO). All these factors reflect a lack of cash in the company and confirm that the effectiveness of working capital management can be significantly related to the financial stability of the company. Although these trends are clearly observable one year before insolvency, it can also be observed that the deterioration in working capital begins to occur one year earlier (i.e., two years before insolvency). The deterioration in liquidity is also indicated by the development of the current liquidity ratio (CR).

The WC/TA and WC/E indicators then paint a picture of a disrupted financial structure. Declining WC/TA medians indicate a gradual decline into structurally unsustainable ratios between working capital and assets. The growth of the WC/E indicator can be explained by the negative values of working capital and equity capital, which arose as a result of deepening losses. In such a situation, the indicator grows numerically, but its development must be interpreted in the broader context of other financial indicators, because on its own it can no longer reliably indicate the actual financial stability of the company.

Table 2 Descriptive characteristics of the sample of insolvent companies

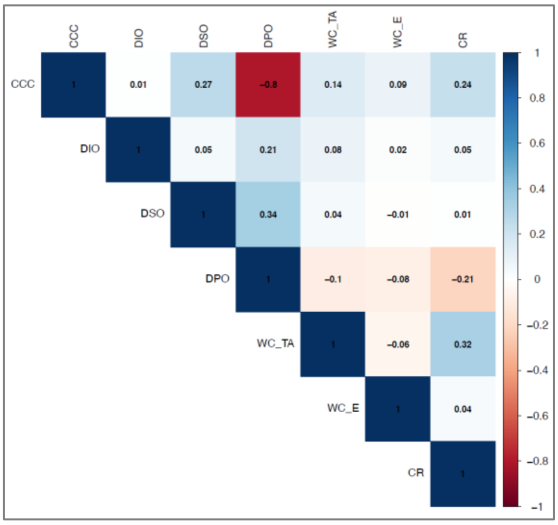
Median values	3 years before insolvency	2 years before insolvency	1 year before insolvency
DIO	11.8	11.6	7.7
DSO	65.8	66.3	66.1
DPO	132.2	147.1	215.8
CCC	-21.1	-31.3	-82.9
CR	1.14	1.07	0.77
WC/TA	8%	4%	-13%
WC/E	66%	83%	87%

Source: Own processing

3.2 Correlation analysis

As can be seen in Figure 1, the correlation matrix reveals the expected relationships between individual variables. Most variables are not strongly correlated with each other and are therefore suitable for inclusion in the model. Based on these results, it was decided to leave the individual variables in the regression model separately and to exclude only CCC as a composite indicator.

Figure 1 Correlation matrix of financial indicators



Source: Own processing

To verify that there was no strong interdependence between the explanatory variables, the Variance Inflation Factor (VIF) was also calculated. The results showed that none of the variables had a VIF value higher than 5. Multicollinearity was not identified, confirming the suitability of the data for logistic regression.

3.3 Logistic regression

The logistic model estimates the probability of insolvency as a function of selected working capital indicators on the training data set. The resulting coefficients, including White's robust standard errors, are shown in Table 3.

Table 3 Parameters of the insolvency prediction model

Variable	Coefficient estimate	Standard error	Z-value	P-value
(Intercept)	1.0037	0.6941	1.4460	0.1480
DIO	0.0005	0.0045	0.1190	0.9050
DSO	0.0088	0.0028	3.1830	0.0015**
DPO	0.0027	0.0014	1.9700	0.0488
WC/TA	-2.7182	1.0027	-2.7170	0.0066**
WC/E	-0.1164	0.0700	-1.6630	0.0962
CR	-1.4190	0.4964	-2.8580	0.0043**

Significance: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.1$
Source: Own processing

The subsequent application of the bootstrap inference method summarized in Table 4 confirmed the results of the previous robust analysis. However, it shows different degrees of stability of individual variables in the model.

Based on 95% confidence intervals, it can be stated that the variables DSO, WC/TA, and WC/E have intervals that exclude zero and can therefore be considered statistically significant and robust predictors. In addition, they retain a significant influence even at increased confidence levels (up to 99%), which further strengthens their credibility (Bobbitt, 2021).

In contrast, the variables DIO and DPO do not show significance at any of the tested levels, as their intervals contain zero, suggesting that their influence on the risk of bankruptcy is not statistically consistent and is likely to depend on the specific form of the data (Zivot, 2021).

The CR variable appears to be marginally significant in the bootstrap CI, while in the output with robust standard errors it was statistically significant, its bootstrap interval includes zero, which indicates greater uncertainty about its stability across samples. Its influence should be interpreted with caution, and any confirmation would warrant additional analysis.

Overall, bootstrap inference confirms the high quality of the basic model and contributes to a detailed understanding of which predictors can be considered reliable benchmarks in predicting corporate insolvency.

Table 4 Overview of bootstrap testing for 90%, 95%, and 99% confidence intervals

Variable	90% confidence interval	95% confidence interval	99% confidence interval	Significance
Intercept	[0.0622; 3.3416]	[-0.0980; 3.9783]	[-0.3787; 5.1974]	Only at the 90% level
DIO	[-0.0063; 0.0088]	[-0.0070; 0.0106]	[-0.0101; 0.0146]	Insignificant at all levels
DSO	[0.0052; 0.0167]	[0.0044; 0.0184]	[0.0033; 0.0228]	Stable and significant
DPO	[-0.0002; 0.0053]	[-0.0005; 0.0061]	[-0.0013; 0.0084]	Not significant
WC/TA	[-4.8092; -1.0004]	[-5.3413; -0.7103]	[-6.3131; -0.1867]	Highly significant
CR	[-0.2961; 0.1315]	[-0.3360; 0.1957]	[-0.4186 ; 0.3347]	Borderline significant
WC/E	[-3.4576; -0.9227]	[-4.0062; -0.8364]	[-5.4000; -0.6964]	Stable significance

Source: Own processing

3.4 Evaluation of the model on the test data set

After training the model on the training set and verifying its robustness, it was validated on independent test data. The aim was to verify how well the model can classify companies as healthy or insolvent and to assess its predictive capabilities outside the original sample. The main metrics for evaluating the model's performance were the confusion matrix and ROC curve together with the AUC value (Betinec, 2006).

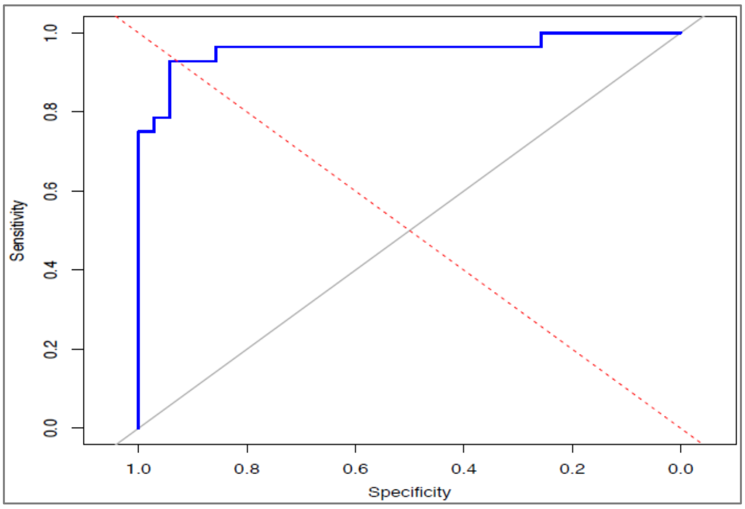
The confusion matrix allows the accuracy of the model's classification to be assessed. The model created on the training data sample was applied to the test sample with 90.48% accuracy. The model correctly classified 30 healthy and 27 insolvent companies, while it classified 5 healthy companies as insolvent and 1 insolvent company as healthy. This result indicates that the model is very good at identifying insolvent companies, but in some cases it mistakenly classifies healthy companies as insolvent, which can lead to false alarms.

To supplement the evaluation, a ROC curve was constructed, which shows the relationship between sensitivity and (1 - specificity) depending on the classification threshold used (Betinec, 2006). The results are presented in the Figure 2.

The AUC reached a value of 0.959, which indicates the model's excellent discriminatory ability. The curve shows a sharp increase in sensitivity while maintaining high specificity, which indicates that the model is very effective in separating the two classes.

An AUC approaching 1 is considered a sign of high predictive quality. The result of 0.959 confirms that the model created can be considered a reliable tool for predicting insolvency risk.

Figure 2 ROC curve



Source: Own processing

4 Conclusions

Working capital is not only an accounting category but also an important indicator of financial stability. Its management is a strategic tool for preventing insolvency and should be an integral part of modern approaches to financial management. The results show that:

- the effectiveness of working capital management is a key determinant of financial stability and
- current liquidity indicators and the ratio of working capital to assets have the highest predictive power.

These findings confirm the hypothesis that changes in working capital can serve as a reliable indicator of impending insolvency of companies in the Czech Republic.

Although the results show high robustness, the study faces several limitations. First, the data set used mainly includes companies that publicly disclose their financial statements, which may lead to selection bias.

Secondly, the model does not take into account macroeconomic variables such as interest rates, inflation, or GDP growth, which may affect companies' ability to maintain operational liquidity.

Thirdly, logistic regression only captures linear relationships between variables and the probability of insolvency, whereas non-linear effects (e.g., DSO or CR thresholds) may be significant.

Incorporating these factors into future models could increase the accuracy and usability of prediction systems in practice. It could also be interesting to analyze differences across various industries.

References

Almquist, Y. B. (2023). A guide to applied statistics with Stata. Online - viewed 2025-04-17. https://statsapplied.com/part-ii-regressionanalysis/logistic-regression/model-diagnostics-log-reg/link-test/.

Betinec, M. (2006). Using ROC curves to evaluate classifiers. *Robust* (pp.25-34). ISBN 80-7015-073-4.

Bobbitt, Z. (2021). How to Interpret a Confidence Interval that Contains Zero. *Statology*. Online - viewed 2025-04-20. https://www.statology.org/confidenceinterval-contains-zero/.

Gavurkova, B., Jencova, S., Bacik, R. & Miskufova, R., Letkovsky, S. (2022). Artificial intelligence in predicting the bankruptcy of nonfinancial corporations. *Oeconomia Copernicana,* 13(4), (pp. 1215–1251). ISSN 2353-1827, 2083-1277.

Kim, S. K., Kim, M. O. & Jung, H. R. (2024). U-shaped Relationship between Cash Conversion Cycle and Financial Distress: Evidence from Unlisted Companies in Korea. *Korean Accounting Review,* 49(5), (pp. 37–70). ISSN 1229-3288, 2508-7193.

Long, J. S. & Ervin, L. H. (2000). Using Heteroscedasticity Consistent Standard Errors in the Linear Regression Model. *The American Statistician,* 54(3), (pp. 217–224). ISSN 0003-1305.

Zivot, E. (2021). The Nonparametric Bootstrap, *Introduction to Computational Finance and Financial Econometrics with R*. Online - viewed 2025-04-19. https://bookdown.org/compfinezbook/introcompfinr/The-Nonparametric-Bootstrap.html.