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# THE DOUBLE-EDGED SWORD OF SALES GROWTH: IMPLICATIONS FOR SMES INSOLVENCY RISK

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***Abstract***

*Research on SME insolvency is one of the most important areas in economy because it is crucial for economic growth which would not be possible without growing firms. These two phenomena - insolvency and growth are typically studied independently. This study brings them together by examining the interaction between sales growth and insolvency among small and medium enterprises (SMEs). On the dataset of financial ratios for Croatian SMEs by applying logistic regression with interaction effects, it is investigated how sales growth, leverage and liquidity affect the probability of insolvency. The results showed that sales growth decreases the risk of insolvency, but that it depends on the level of indebtedness of SMEs. The least risky are those SMEs whose sales growth is supported by an adequate level of capital. SMEs with high sales decline have the highest probability of insolvency even when leverage and liquidity are suitable.*

**Keywords***: SMEs growth, insolvency risk, sales growth, logistic regression with interaction effects*

**JEL classification:** *G3, G32, L26*

## 1. Introduction

One of the most relevant and most intriguing phenomenon in studies dealing with small and medium enterprises (SMEs) is insolvency. The reason is obvious – enterprises in insolvency cannot continue with their business activities and people are losing jobs. Therefore, understanding factors that influence insolvency is essential for improving SME resilience. Traditionally, research on enterprise insolvency has relied on models utilizing standard financial ratios such as liquidity, activity, leverage and profitability. In most studies, various financial ratios are observed statically, and less often the dynamic aspects of enterprise performance are investigated. One such indicator is sales growth. Although sales are used in the creation of various financial indicators, less attention is paid to understanding how sales growth affects insolvency risk. One of the reasons for this is that sales growth and insolvency are studied as two independent phenomena.

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It is known that sales growth is a driver of firm development. On the other hand, in order to achieve sales growth, financial resources are needed, which often implies borrowing, and this can create pressure on the liquidity of the company. This paradox according to which sales can have a positive, but at the same time negative effect on the company, makes it an important and relevant research topic. This is particularly significant because previous research rarely examines in which interactions with other financial indicators, sales growth has a positive and in which negative effect on enterprise insolvency.

Our research addresses this gap by examining whether and how sales growth affects insolvency, both directly and through interactions with other financial indicators. Unlike traditional models that treat financial indicators as they work independently, this study examines how they interact with one another. In particular, it explores how the effect of leverage on insolvency changes depending on liquidity and how liquidity matters under different levels of leverage. Initial modeling procedure included broader set of financial ratios, but three indicators consistently emerged as the most relevant in explaining insolvency risk among SMEs – sales growth, leverage and liquidity. So, the research ultimately focuses on these indicators which jointly capture enterprises' growth dynamics and financial structure. The aim is therefore not to build a comprehensive prediction model but to better understand how growth and financial stability combine to influence probability of insolvency.

The next section provides reviews of the theoretical mechanisms connecting growth and financial stability.

## 2. Theoretical foundation

This study brings together two streams of theory – those related to firm growth and those focusing on financing constraints and growth-related vulnerabilities.

One of the most influential theories of SME growth is Penrose's Theory of the Growth of the Firm (Penrose 1959). According to this theory, each firm is viewed as a unique combination of material, human, financial and managerial resources together with the services these resources provide. Growth originates primarily from the firm, through the use of managerial knowledge and capabilities that enable new ways of combining existing resources. As the firm grows and managers gain experience, they develop additional capacity which can stimulate further growth and innovation. However, Penrose points out that growth has its limits. If growth happens too quickly, management may struggle to coordinate new resources and processes effectively, creating inefficiencies and organizational tension. This situation, often called Penrose trap, occurs when rapid growth undermines internal coordination and financial stability. Fast growth usually requires substantial external financial resources which can cause liquidity pressures or financial distress if cash flows or operational efficiency fail to keep pace. In this sense, although growth is generally seen as a sign of success, it can also become a source of vulnerability when it exceeds the firm's managerial or financial capacities.

While Penrose focused on resources and internal capacities, Greiner (1972) emphasized the organizational and managerial dimensions of growth. His model describes firm development through a sequence of predictable phases of growth each followed by a period of crises that moves organization into the next stage. According to Greiner, firms typically begin with 'growth through creativity' when innovation and informality dominate. As they expand, the need for clearer direction and structure emerges leading to a crisis of leadership. The next phase 'growth through direction', introduces hierarchy, specialization and formal control systems. As managers seek greater independence, this leads to crisis of autonomy. The next phase is 'growth through delegation' where decision making becomes decentralized, but this can create a crisis of control due to coordination weakening. The subsequent phase 'growth through coordination' restores order through planning and systems. However, the emphasis on these structures of the generates bureaucracy that can ultimately result in a crisis of red tape. Finally, 'growth through collaboration' highlights teamwork, trust and adaptability, but firms may face a crisis of internal growth that calls for strategic renewal or partnerships.

From the perspective of insolvency risk, Greiner's model illustrates how each stage of growth brings new structural and managerial challenges that can affect financial stability. Periods of crisis are particularly critical as they often involve inefficiencies, rising costs and declining responsiveness, all of which can erode profitability and liquidity. If firms fail to adapt successfully these pressures can accumulate, increasing their exposure to financial distress and insolvency.

In the context of insolvency, the Pecking Order Theory (Myers and Majluf 1984) can be linked to growth theories. The theory suggests that firms follow a hierarchy of financing preferences. They first rely on internal funds such as retained earnings since this avoids the costs of external financing and reflects managerial confidence in the firm's profitability. The next preferred source is debt, used when internal funds are insufficient. Equity financing is least preferred as issuing new shares may be interpreted by investors as a sign of uncertainty about the firm's value. This theory is particularly relevant for SMEs which typically have limited access to external capital and rely heavily on funds and debt. As firms grow, they often increase their leverage which in turn can enhance their risk of insolvency.

Combining these theoretical perspectives provides a more complete understanding of how growth and financial instability interact in shaping insolvency risk. The Penrose theory indicates internal limitations to growth due to managerial capacities and efficient use of resources. Greiner's model connects organizational and managerial crises with different stages of growth. On the financial side, Pecking Order Theory explains external growth constraints such as limited access to capital, dependence on debt and increasing leverage.

When a firm grows rapidly, these internal and external pressures can reinforce one another. Limited managerial capacities and a weak coordination system combined with limited access to financing and growing debt can significantly increase the exposure to insolvency. In this way, growth, which is normally a sign of business prosperity, can actually become a source of fragility if it is not accompanied by adequate resource management and a sustainable financial structure. The theoretical framework created in this way can serve as a basis for understanding the interaction between growth and insolvency and serve as a conceptual basis for the empirical analysis made in this paper.

## 3. Previous research

### 3.1. Insolvency prediction models in SMEs

***Models Based on Financial Indicators***

Most studies on SME default prediction rely predominantly on quantitative variables, particularly financial ratios. Since the introduction of the Altman Z-score (Altman 1968), such models have consistently included financial indicators that capture liquidity, profitability, leverage, solvency and activity. Numerous studies have employed the original Altman Z-score variables to predict financial distress (Sulub 2014; Celli 2015; Tung and Phung 2019; Bogdan, Bareša, and Hađina 2019; Cindik and Armutlulu 2021). There are also studies that develop models to find a combination of financial ratios that provide good predictions. Although many studies have shown excellent predictive power, the perfect combination of financial ratios has not yet been found. Researchers typically aim to select variables that are both statistically significant and economically meaningful, acknowledging that model accuracy depends on factors such as sample characteristics, data availability, data quality and the analytical method applied.

Wang, Ma, and Yang (2014) point out that special attention should be paid to the selection of variables. Hernandez and Wilson (2013) reported that when developing robust insolvency prediction model, it is necessary to test different combinations of financial ratios in order to achieve optimal predictive performance. Chen and Shimerda (1981) reviewed 26 articles that classified 65 financial ratios incorporated in predictive studies between 1966 and 1975 and reported 41 financial ratios that were considered to be important in one or more of the 26 articles. More recently, Cheraghali and Molnar (2024) analyzed 145 studies dealing with default models and found that as many as 120 studies used financial ratios. Their analysis showed that the most commonly used were current ratio, quick ratio, cash to total assets, working capital to total assets, net income to total assets, retained earnings to total assets and net income to equity. Karas and Reznakova (2020) pointed to the importance of cash flow indicators, among which they indicated that operating cash flow ratios combined with short-term debt metrics significantly improve distress prediction.

***Models Combining Financial and Non-Financial Variables***

Since financial indicators alone are often not sufficient to explain and predict insolvency, especially in SMEs, numerous studies combine them with non-financial indicators. Such indicators include macroeconomic, firm-related and market-related variables.

Altman et al. (2023) added variables related to payment behavior, employee structure and management board characteristics to financial indicators to test how this affects insolvency prediction for SMEs. They found that employee turnover, average employee tenure and changes in management significantly increase predictive accuracy. Lee, Choi, and Yoo (2023) also integrated traditional financial indicators and company characteristics. They showed that financial indicators are still significant for prediction, but that the quality of prediction increases when management and operational indicators, as well as technological and market-related variables, are included in the model.

Some researchers advocate the use of macroeconomic variables in insolvency prediction. This was confirmed by Bofim (2009), whose risk model performance improved by adding macroeconomic variables to financial indicators. Similarly, Beck, Jakubik, and Piloiu (2015) identified key macroeconomic indicators that influence default - GDP growth, exchange rates, leading rates and share prices. Filipe, Grammatikos, and Michala (2016) suggested that, in addition to accounting-based indicators, the models should be enriched by adding macroeconomic indicators and firm location, which significantly affects bankruptcy rates among European SMEs. They showed that as SMEs grow in size, their sensitivity to macroeconomic fluctuations is lower. In addition, they emphasized that it is necessary to use economic models that are precisely calibrated for specific regional and local conditions.

Campbell, Hilscher and Szilagyi (2008) and Maffett, Owens, and Srinivasan (2017) explored the integration of accounting and equity market variables to increase predictive accuracy. In their comprehensive analysis of 145 reviewed studies, Cheraghali and Molnár (2024) showed that 109 of them included at least one category of non-financial variables. Non-financial characteristics refer to the owner and the company, credit records and relational data, and macroeconomic indicators. Among them, the most frequently used are firm size, firm age and managerial attributes, and GDP growth as a macroeconomic indicator.

Ciampi et al. (2021) also analyzed over 100 studies published between 1986 and 2019. They concluded that SME default prediction models should be regularly calibrated to take into account changes related to the weighting of predictive variables in order to emphasize the importance of forward-looking and qualitative variables in times of financial distress. They also investigated the survival of SMEs in the post-COVID period and came to the conclusion that it increasingly depends on innovation capacity and human and relational capital. Based on the analysis, they gave guidelines for future research, among which they emphasize the expansion of the set of qualitative variables, the integration of innovation-based indicators, credit-relationship measures, the implementation of cross-county studies and the use of big data.

Overall, it can be concluded that combining financial and non-financial variables significantly improves the quality of the model for assessing the insolvency of SMEs and increases the explanatory and predictive power. However, there are still challenges related to the availability of data, methods of measuring qualitative constructs such as innovation capacity or quality of management, and data collection, as well as mutual comparability of models. This opens up space for future research that could contribute to the integration of multidimensional databases and the application of artificial intelligence in discovering hidden patterns in data.

***Models Based on Non-Financial Variables***

Recently, there have been studies in which models are developed exclusively on qualitative information and non-financial variables. Such an approach is particularly interesting for SMEs that often do not have audited financial statements, which can result in poor quality accounting data. Berzani and Shema Zlatokrilov (2024) developed an insolvency prediction model for SMEs where they used firm characteristics and macroeconomic data. In their model, it was shown that the age of the company, multiple banking relationships and sectoral insolvency rates increase the risk of insolvency, while operating as a chain business reduced it. Of the macroeconomic variables, the inflation rate, which is negatively related to insolvency, proved to be significant.

Lee, Choi, and Yoo (2020) developed an SME insolvency prediction model that is based on non-financial data from technological feasibility assessments. According to their model, the key indicators that most influence the prediction of insolvency are factors of management and business feasibility, including management ability, financing and competitive position.

Krasniqi, Kotorri, and Aliu (2023) examined the impact of bank relationships, collateral requirements, and banking sector characteristics on the probability of default. Although stronger relationship between the firm and the bank reduced default risk, and higher collateral and interest rates increased it, this effect disappeared after market concentration and bank profitability were taken into account. This suggests that the importance of bank relationships is expressed mainly in competitive markets.

This research shows that it is possible to estimate insolvencies based solely on non-financial variables, using variables related to managerial quality, but also those related to technological capabilities and contextual factors. However, as already pointed out, challenges related to measurement and data collection need to be addressed.

## 3.2. The role of sales growth in insolvency prediction models

The central part of this research relates to the relationship between sales growth and insolvency, which is complex and very often non-linear. Penrose (1959) in the Theory of the Growth of the Firm explained that the growth of a firm brings advantages in efficiency and market position, but it inevitably creates pressures in management and finance that can threaten its survival. This paradox, which we also deal with in our research, is especially present in SMEs that face the above-mentioned limitations. This mechanism aligns with the Pecking Order Theory (Myers and Majluf 1984), according to which growing firms often seek debt financing when they no longer have internal sources, which can lead to an increase in indebtedness and the risk of insolvency. Growth, therefore, generates both opportunities and risks, and previous research has shown diverse evidence. Some research has shown a positive impact of sales growth on insolvency risk, some a negative one, while there are also those that have shown that sales growth does not have a significant impact on insolvency.

Amaral (2008) showed that fast-growing small firms face higher failure risk due to overextension and limited adaptive capacity. Kanani, Moradi, and Valipour (2013) assessed real and sustainable growth concerning financial and business risk, defining sustainable growth as the maximum attainable sales growth rate without amortizing resources. Their research indicated a significant link between the discrepancy in firms' real and sustainable growth and financial risk, but no such relationship with business risk. Lin, Ansell, and Andreeva (2012) explore the impact of four different default definitions on the choice of financial predictors and the model's accuracy. They find that profit, growth and employee efficiency are prevalent in all default definitions and that growth in profitability, annual sales and operating revenue are always key variables to predict SME default.

Bonaccorsi di Patti et al. (2015) highlighted that a decline in sales, combined with high leverage, raises the probability of default and reduces firm resilience. Furthermore, the effect of sales growth on insolvency is influenced by liquidity. Higher liquidity at the same level of sales is associated with a lower probability of insolvency. Hussain et al. (2020) investigated growth opportunities' role in insolvency within a mediating framework encompassing capital structure and debt maturity decisions. They demonstrated a negative correlation between growth opportunities and insolvency risk, with growth opportunities adversely impacting capital structure but positively affecting debt maturity. Šarlija, Šimić, and Đanković (2023) identified sales growth as one of the most significant predictors of insolvency risk for SMEs, in addition to total assets turnover and the ratio of liabilities to equity.

Nordal and Næs (2010) modeled future sales growth by using insolvency risk as a predictor. They discovered a positive correlation between sales growth and bankruptcy risk. Namely, companies that have a high risk of bankruptcy are similar to those companies that expect to achieve a large increase in sales in the future. Specifically, smaller firms and those with low equity, profitability, and sales per unit of capital showed higher anticipated growth rates, suggesting a trade-off between upside potential and downside insolvency risk.

There are other studies where no significant relationship between insolvency and growth was found. Putri and Arifin (2021) investigated the impact of liquidity, leverage, institutional ownership and sales growth on financial distress, finding that sales growth did not influence financial distress, unlike liquidity, leverage and institutional ownership. Similarly, Nazaruddin and Daulay (2019) and Pindado and Rodrigues (2004) showed that variables related to sales and production in their insolvency models were not statistically significant. A recent study conducted on Moroccan SMEs (Lahcen and Amgar 2025) also tested sales growth among 27 financial indicators related to liquidity, efficiency and profitability. Sales growth was not identified as a key indicator either. Instead, three important ratios were economic profitability, commercial profitability and inventory turnover. Cheraghali and Molnár (2024) conducted a comprehensive survey of predictors used in SME default and insolvency models. They made an interesting discovery related to sales growth. Namely, although sales-related ratios are among the most frequently used ratios, especially the sales to assets ratio and the logarithm of sales, the sales growth indicator itself was not included in any of the studies they reviewed. This is important because it shows that researchers are relying more on a static sales measure rather than trying to use a dynamic sales approach.

In summary, the presented theories show the importance of growth and indicate a pattern of connection between growth and insolvency. Empirical research sometimes shows a positive and sometimes a negative relationship, while some research does not confirm any relationship. All this opens space for new research that can contribute to understanding the relationship between growth and insolvency. Although our research initially covered 31 financial ratios, through modeling it was shown that sales growth consistently appears as a key determinant in explaining insolvency, either independently or in combination with liquidity and leverage. Therefore, this research will try to contribute to the understanding of how growth dynamics affects financial vulnerability in the interplay between liquidity and indebtedness.

### 3.3. Methods used in insolvency prediction studies

In addition to the different selection of variables used, the success of insolvency prediction is also influenced by the applied modeling methodology. Classification methods are mostly used in predicting SME insolvency. Early studies relied mainly on statistical techniques, with discriminant analysis (Altman 1968) as the pioneering method, later followed by logistic and probit regression (Tabachnick and Fidell 1996; Tinoco and Wilson 2013). Among the new methods of machine learning and artificial intelligence, neural networks, decision trees, support vector machines, random forests and XGBoost stand out. Regardless of the development of new methods and approaches to modeling, traditional statistical methods, among which logistic regression stands out, are still most often used. (Shi and Li 2019; Kuizinienė et al., 2022). According to Cheraghali and Molnár (2024), neural networks and discriminant analysis were applied in 14 studies, support vectors machines in 13, random forest in 11 and logistic regression in 77 studies.

Recently researchers have investigated hybrid and non-linear approaches to integrate multiple data sources and improve predictive power, such as fuzzy clustering, cognitive mapping, multi-criteria decision making, non-linear programming, decision tree-based models using the Harmonic Support and Confidence (HSC) rule selection method (Corazza, Funari, and Gusso 2016; Oliveira et al. 2017.; Lee, Choi, and Yoo 2023).

### 3.4. Formulation of hypotheses

Building on Penrose's (1959) theory of firm growth and Greiner's (1972) growth model, we conceptualize growth as a dynamic process that simultaneously generates opportunities and constraints for SMEs. Penrose views firm expansion as a function of internal resource utilization and managerial capabilities, emphasizing that rapid growth can stretch these resources and create organizational inefficiencies. Similarly, Greiner's model assumes that each stage of firm growth brings specific managerial and organizational challenges, which, if not effectively managed, can lead to crisis or decline. Additionally, the Pecking Order Theory (Myers & Majluf, 1984) emphasizes that growth increases the need for external financing, which can then increase the risk of financial distress. In this context, sales growth captures both the firm's capacity to exploit market opportunities and the financial pressures that arise from expansion. Sales growth can initiate opportunities through revenue expansion and strengthening the market position, but it can simultaneously create vulnerability through increased needs for financing and organizational pressure. Conversely, a sales decline disturbs revenue stability and increases insolvency risk through profitability loss. Thus, growth should be understood not only as a performance indicator but also as a potential source of financial vulnerability.

Accordingly, we formulate two key hypotheses:

H1: Sales growth significantly influences the probability of insolvency among SMEs.

H2: The effect of sales growth on insolvency is moderated by financial conditions, specifically leverage and liquidity in a way that the risk of insolvency is heightened when firms combine rapid growth with financial constraints.

To empirically test these hypotheses, a logistic regression model including both main and interaction effects of sales growth and key financial ratios is developed.

## 4. Data variables and methodology

### 4.1. Data and sample selection

The empirical research is based on Croatian SMEs. has been an EU member since 2013 and has the population of 3.88 million (Census, 2021), GDP per capita of 12410 EUR, exports of goods and services of 42.1% (as % of GDP), external debt of 79.8% (as % of GDP) and unemployment rate of 7.5 (Croatian National Bank 2021). Croatian economy is characterized by high external debt where the main sources of SMEs financing are bank loans and leasing while equity funding as well as other funding sources are poorly represented (CEPOR 2020). We believe that this research could be relevant for economies characterized by dependence on external financing and its structural exposure to liquidity and leverage pressures.

All financial statements of SMEs in Croatia were available for sample creation. First, all SMEs that were insolvent in 2019 were selected, resulting in 3207 cases. After that, the same number of solvent SMEs was randomly selected. For this total number of 6414 SMEs, sales growth was calculated for the period 2018 and 2019. 4271 SMEs that had complete data on insolvency and growth were retained in the sample. After that, an additional 613 cases were dropped due to missing data for the calculation of key financial ratios. Therefore, the final modeling sample contained a total of 3658 SMEs, 1924 solvent and 1734 insolvent. Listwise deletion was applied due to incomplete reporting for some firms. While this step was technically necessary, it may have introduced bias if firms with missing statements systematically differ from those with complete data. Given that the standard practice in modeling defaults is to have a balanced sample, such a methodological approach was also applied in this research. Although such a design does not reflect the actual distribution of defaults, the balanced sample ensures that the model captures characteristics of insolvent firms that are relatively rare in the entire population. In addition, in this research, the goal was not to calibrate the probability of default, but to examine the relationship between various financial indicators and insolvency, so the balanced design deemed appropriate for the stated goal.

## 4.2. Description of variables

Financial indicators were calculated for the year 2018. An SME is classified as insolvent if it failed to meet its obligations for a period exceeding 90 days at any point during 2019. Given that financial indicators precede the observed outcome, the design enabled the analysis of financial characteristics as determinants of insolvency. Focusing on a one-year prediction horizon allows for a clear temporal link between financial conditions and subsequent insolvency, reducing endogeneity concerns and ensuring that predictor variables are strictly prior to the outcome. However, this approach also introduces temporal limitations, as it captures short-term dynamics rather than long-term patterns of financial deterioration. Future research could extend this framework by applying multi-year horizons or panel-based approaches to examine the persistence of growth and financial structure effects on insolvency risk over time.

Sales growth is defined as the year-over-year percentage increase in sales revenue, comparing sales figures from 2018 to those from 2019:

$$sg = \frac{sales_t - sales_{t-1}}{sales_{t-1}}$$

Sales growth is grouped into 4 categories: (i) sales growth ≤ -1 (high decline); (ii) sales growth>-1 and <=0 (moderate decline); (iii) sales growth>0 and ≤1 (moderate growth); (iv) sales growth>1 (high growth).

During the data preparation stage, several financial ratios were excluded from the modelling process to ensure statistical stability since they contained outliers (total debt over EBITDA, cash over debt, operating cash flow over equity). Finally, 31 financial ratios used in this research are divided into eight groups: (1) Profitability ratios: ROA, ROE, PM, EBIT margin, EBITDA margin, retained earnings over total assets; (2) Liquidity ratios: current ratio, quick ratio, cash ratio, cash over sales; (3) Leverage ratios: total debt ratio, debt-equity ratio, equity to assets, current liabilities over assets, current liabilities over equity, equity over fixed assets, (equity + long-term debt)/fixed assets; (4) Turnover ratios: total asset turnover, fixed asset turnover, inventory turnover, days' sales in inventory, receivables turnover, days' sales in receivables; (5) Sales growth; (6) R&D indicators: nontangible assets/total assets, R&D expenditures over total assets, goodwill over total assets; (7) Investment indicators: investment over total assets, investment over total revenue; (8) Export indicators: export over sales, export over import.

Although a broader set of 31 financial ratios was initially considered, the final model retained only sales growth, leverage and liquidity. This parsimonious specification reflects the aim to analyze the interaction between growth dynamics and financial structure, rather than to optimize predictive performance. When sampling SMEs from the total base of all Croatian SMEs, random sampling was used, which ensured representativeness across different sectors and regions, which mitigates the potential bias raising due to not including indicators for the regional and sectoral affiliation of SMEs. Nevertheless, incorporating industry and regional controls could further enhance predictive accuracy and capture structural heterogeneity in future research.

## 4.3. Logistic regression with interaction effects

To address the research objectives outlined in the introduction, we employ logistic regression as the primary analytical method. This approach enables us to examine the relationship between financial indicators and insolvency while also exploring the interaction effects among financial indicators. By incorporating interactions, the model provides deeper insights into how these factors jointly influence insolvency risk.

If the vector of predictor values for an enterprise is denoted by $x = (x_1, x_2, \ldots, x_k)$ and the regression parameter vector by $\beta = (\beta_1, \ldots, \beta_k)$, the model that describes conditional probability of insolvency $p(x)$ can be shown by the equation:

$$log\frac{p(\boldsymbol{x})}{1-p(\boldsymbol{x})}=\boldsymbol{x}'\beta. \quad (1)$$

This means that the predictor values $x$ and probability of insolvency are linked through the nonlinear equation:

$$p(x)=\frac{e^{x'\ \beta}}{1+e^{x'\ \beta}}. \quad (2)$$

The classical maximum likelihood theory was applied for estimation (see, for example Dobson and Barnett 2018). When choosing a model, several classical criteria and procedures were combined. For example, minimization of information criteria (Akaike and Bayesian), models' comparison based on deviance and the principle of parsimony. As the response variable is binary, a ROC (random operating characteristic) analysis was also performed. It means that several classification measures (AUC, sensitivity, specificity, Kolmogorov-Smirnov statistic) were calculated to compare models.

In logistic regression, it is common practice to interpret the contribution of predictors to the response variable on the log-odds scale. Specifically, each parameter reflects the impact of the corresponding predictor on the log-odds of the outcome, which can be interpreted through the odds ratio. It is crucial to understand that odds ratios are frequently misinterpreted as relative risks. Unlike odds ratios, relative risk refers to the ratio of probabilities, not the ratio of odds.

As the relationship between probability of insolvency and predictors is nonlinear, the interpretation of the contribution of each variable to the response (probability of insolvency) should be discussed conditionally on the other variables involved in the predictor $\boldsymbol{x'\beta}$. This is even more important if there are interactions in models.

Accordingly, the modeling process places significant emphasis on marginal effects, which measure the relationship between changes in predictors and corresponding changes in the outcome (Williams 2012; Cameron and Trivedi 2010).

To be more specific, let us suppose that the predictor $x_1$ is continuous. The marginal effect of $x_1$ on the response $p=(x_1,\dots,x_k)$ is the partial derivative of the function $p$ with respect to $x_1$. For the logistic regression model, it is:

$$\frac{\partial p}{\partial x_1}=\beta_1\frac{e^{\boldsymbol{x}'\boldsymbol{\beta}}}{\left(1+e^{x'\ \boldsymbol{\beta}}\right)^2} \quad (3)$$

As the derivative of a function is a measure of the rate at which the value $p$ changes with respect to the change of the variable $x_1$, it is evident that this change is highly dependent on the values of all predictors. Also, it is important to notice that a marginal effect is no longer for a unit change but for a small change in the continuous predictor.

For categorical predictor, the marginal effect corresponds to the difference in $p$ for the two different categories. For example, let us assume that the second predictor $x_2$ is a dummy variable related to the predictor with two values.

Then, the marginal effect

$$p(x_1,1,\dots,x_k)-p(x_1,0,\dots,x_k)=$$

$$\frac{e^{(x_1,1,\dots,x_k)'\ \boldsymbol{\beta}}}{1+e^{(x_1,1,\dots,x_k)'\ \boldsymbol{\beta}}}-\frac{e^{(x_1,0,\dots,x_k)'\ \boldsymbol{\beta}}}{1+e^{(x_1,0,\dots,x_k)'\ \boldsymbol{\beta}}} \quad (4)$$

also depends on other predictor values.

Incorporating marginal effects into the model-building process is not straightforward, as they are primarily intended for interpretation. However, average marginal effects (AMEs), calculated as the average of observation-specific marginal effects, provide additional insights and can be used to compare models when selecting one for interpretation. Accordingly, we computed and compared AMEs across several selected models to aid in this decision-making process.

For all computations we used R language and environment for statistical computing and graphics and packages ROCR (Sing et al. 2005), margins (Leeper 2021) and marginal effects (Arel-Bundock 2022).

Applying the described methodology to the dataset, we developed a model presented in Table 5.

Before interpreting the model, a detailed analysis of the predictors is presented.

Table 1 shows the relative frequencies of sales growth categories for the full sample and by solvency status. Among solvent SMEs, 42.15% experienced a sales decline, compared to 73.59% of insolvent ones.

Leverage is measured as the ratio of current liabilities to equity. Since equity can be negative in the Croatian accounting system when liabilities exceed assets, the ratio was categorized. Table 2 shows that most solvent SMEs are moderately leveraged, while most insolvent SMEs have liabilities exceeding their assets.

**Table 1. Relative frequencies of sales growth**

| Sales growth | Sales growth description | % in whole sample | % among solvent SMEs | % among insolvent SMEs |
|---|---|---|---|---|
| ≤ -1 | High decline | 10.11 | 3.53 | 17.42 |
| >-1 and <=0 | Moderate decline | 46.94 | 38.62 | 56.17 |
| >0 and ≤1 | Moderate growth | 32.09 | 44.65 | 18.17 |
| >1 | High growth | 10.85 | 13.2 | 8.25 |
| Total | | 100 | 100 | 100 |

Source: Authors' own work

**Table 2. Relative frequencies of leverage ratio**

| Current liabilities/ equity | Current liabilities/ equity description | % in whole sample | % among solvent SMEs | % among insolvent SMEs |
|---|---|---|---|---|
| <0 | negative | 41.42 | 25.68 | 58.88 |
| ≥0 and ≤5 | moderate leverage | 47.38 | 62.01 | 31.14 |
| >5 | high leverage | 11.21 | 12.32 | 9.98 |
| Total | | 100 | 100 | 100 |

Source: Authors' own work

Because quick ratio and leverage were found to be associated with sales growth, Tables 3 and 4 present their distributions by sales growth category.

The Kruskal–Wallis test confirms significant differences in liquidity across sales growth levels ($p < 10^{-15}$). SMEs with moderate sales growth show the highest liquidity, whereas those with large sales declines show the lowest. Similarly, Pearson's Chi-squared test confirms a strong dependence between leverage and sales growth ($p < 10^{-15}$). SMEs with substantial sales declines most often have negative leverage. Interestingly, among high-growth SMEs, both negative and high leverage are more frequent compared to the moderately growing group.

**Table 3. Descriptive statistics of quick ratio according to sales growth**

| Measure | High sales decline | Moderate sales decline | Moderate sales growth | High sales growth |
|---|---|---|---|---|
| Mean | 0.7 | 1.05 | 1.28 | 1.05 |
| Standard deviation | 1.06 | 1.28 | 1.29 | 1.18 |
| Median | 0.25 | 0.58 | 0.84 | 0.72 |
| Lower quartile | 0.02 | 0.14 | 0.3 | 0.18 |
| Upper quartile | 0.99 | 1.4 | 1.78 | 1.38 |
| Min | 0 | 0 | 0 | 0 |
| Max | 5.53 | 6 | 5.96 | 5.97 |
| N | 370 | 1717 | 1174 | 397 |

Source: Authors' own work

**Table 4. Relative frequencies of leverage according to sales growth**

| Leverage | High sales decline (%) | Moderate sales decline (%) | Moderate sales growth (%) | High sales growth (%) |
|---|---|---|---|---|
| negative | 68.11 | 45.54 | 28.19 | 37.78 |
| moderate leverage | 24.05 | 44.09 | 60.31 | 45.09 |
| high leverage | 7.84 | 10.37 | 11.5 | 17.13 |
| Total | 100 | 100 | 100 | 100 |

Source: Authors' own work

## 5. Result

All 31 variables were included in the modeling process. Different modeling procedures and diagnostic tests, different selection procedures, multicollinearity testing were used to extract the variables that best contribute to the interpretation of insolvency. The most dominant indicators in different models were 3 ratios - sales growth, leverage and liquidity. These variables jointly capture the dynamic (growth), structural (leverage) and short-term stability (liquidity) aspects of SME performance thus aligning well with both theoretical reasoning and empirical robustness. The resulting model achieved an AUC of 0.76, indicating satisfactory discriminative ability despite its parsimonious specification. Table 5 presents the results of the logistic regression model ($\chi^2(15) = 184.76$, $p < .001$; AUC = 0.76).

As shown by the results, insolvency is impacted by the sales growth and leverage combined - with their main and interacting effect being statistically significant. Quick ratio has no significant main effect or interaction effect, but its average marginal effects show statistical significance. Main effects show that SMEs that have a strong drop in sales have a higher probability of insolvency compared to SMEs that have a moderate decline as well as any level of sales growth. SMEs with moderate growth have the lowest level of insolvency, followed by those with high growth, which confirms that balanced growth is much more sustainable than rapid growth or rapid decline in sales. From a financial structure perspective, SMEs with moderate leverage tend to face less insolvency risk than those operating with negative equity. However, once leverage becomes excessive, its risk profile converges with that of negative equity, implying that the advantages of growth may be neutralized by the burden of high debt. The interaction effects offer a more nuanced understanding of the relationship between growth and financial structure. Firms that achieve strong sales growth by maintaining moderate leverage exhibit the greatest resilience to insolvency, whereas those that experience high growth and high leverage also have reduced lower insolvency risk - but the effect is notably weaker. The abovementioned trend underscores that growth contributes to solvency only when it is supported by a well-balanced financial structure - one that aligns with the firm's stage of development and adheres to life-cycle and growth theory principles. (Penrose, 1959; Greiner, 1972).

**Table 5. Logistic regression model of insolvency**

| Effect | Estimate | SE | t value | p value |
|---|---|---|---|---|
| Intercept | 0.863 | 0.029 | 29.383 | <.001 |
| **Main effects*** | | | | |
| Quick ratio | -0.005 | 0.027 | -0.168 | 0.866 |
| Moderate sales decline | -0.150 | 0.034 | -4.458 | <.001 |
| Moderate sales growth | -0.364 | 0.039 | -9.45 | <.001 |
| High sales growth | -0.260 | 0.047 | -5.473 | <.001 |
| Moderate leverage | -0.158 | 0.069 | -2.299 | 0.021 |
| High leverage | -0.065 | 0.089 | -.735 | 0.462 |
| **Interaction effects** | | | | |
| Quick ratio x Moderate sales decline | -0.009 | 0.029 | -0.324 | 0.745 |
| Quick ratio x Moderate sales growth | -0.026 | 0.030 | -0.875 | 0.382 |
| Quick ratio x High sales growth | -0.004 | 0.036 | -0.105 | 0.916 |
| Moderate sales decline x Moderate leverage | -0.106 | 0.073 | -1.442 | 0.149 |
| Moderate sales growth x Moderate leverage | -0.118 | 0.077 | -1.544 | 0.122 |
| High sales growth x Moderate leverage | -0.207 | 0.091 | -2.265 | 0.023 |
| Moderate sales decline x High leverage | -0.070 | 0.010 | -0.728 | 0.466 |
| Moderate sales growth x High leverage | -0.147 | 0.100 | -1.466 | 0.142 |
| High sales growth x High leverage | -0.340 | 0.111 | -3.073 | 0.002 |

* base category for sales growth is high sales decline; base category for leverage is negative leverage

Source: Authors' own work

**Table 6. Average marginal effects (AME) of variables on predicted values of insolvency**

| Factor | AME | SE | Z | p | Confidence interval (95%) | |
|---|---|---|---|---|---|---|
| | | | | | lower | upper |
| Moderate leverage | -0.268 | 0.019 | -13.876 | <.001 | -0.306 | -0.230 |
| High leverage | -0.182 | 0.026 | -7.136 | <.001 | -0.232 | -0.132 |
| Quick ratio | -0.018 | 0.007 | -2.510 | 0.012 | -0.032 | -0.004 |
| Moderate sales decline | -0.219 | 0.029 | -7.525 | <.001 | -0.275 | -0.162 |
| Moderate sales growth | -0.465 | 0.030 | -15.406 | <.001 | -0.524 | -0.406 |
| High sales growth | -0.400 | 0.035 | -11.346 | <.001 | -0.469 | -0.331 |

Source: Authors' own work

Table 6 reports the average marginal effects (AME) which quantify the average change in the probability of insolvency associated with a one-unit change in each predictor.

The results confirm that sales growth has the strongest effect, followed by leverage. Compared to firms experiencing a sharp sales decline, SMEs with moderate growth show the largest reduction in insolvency probability, around 45% on average. Even high growth lowers insolvency risk by roughly 40%. The moderate sales decline also shows a significant reduction but of smaller magnitude.

Concerning financial structure, it can be noticed that moderate and high leverage both significantly reduce insolvency probability relative to negative equity, confirming that a positive capital base and sustainable debt levels strengthen resilience. Although liquid assets contribute to solvency, their influence is secondary to sales performance and capital structure. Collectively, the AME results affirm the core model findings; insolvency risk within SMEs is dependable mostly upon growth dynamics accompanied by the overall strength of the firm's balance sheet with the short-term liquidity playing a minor role.

Building on the average marginal effects reported in Table 6, it is useful to explore how different combinations of leverage and sales growth jointly shape insolvency probabilities. Table 7 presents the predicted probabilities for these combinations, holding liquidity constant at its mean value (1.09).

Table 7 shows that the risk of insolvency depends on the interaction between leverage and sales growth. The lowest probability of insolvency (below 0.3) is present in SMEs that have a combination of moderate or high growth with moderate or high leverage. The minimum predicted probability (≈0.19) appears in two groups: moderately leveraged firms with moderate growth and highly leveraged firms with high growth.

**Table 7. Probability of insolvency according to leverage and sales growth with liquidity held at mean value**

| Sales growth | Leverage | Predicted probability of insolvency | Confidence interval (95%) | |
|---|---|---|---|---|
| | | | lower | upper |
| High growth | Negative | 0.5936 | 0.5141 | 0.6731 |
| Moderate growth | Negative | 0.4648 | 0.4140 | 0.5156 |
| Moderate decline | Negative | 0.6972 | 0.6629 | 0.7315 |
| High decline | Negative | 0.8575 | 0.7879 | 0.9270 |
| High growth | Moderate | 0.2294 | 0.1564 | 0.3025 |
| Moderate growth | Moderate | 0.1889 | 0.1520 | 0.2258 |
| Moderate decline | Moderate | 0.4333 | 0.3982 | 0.4684 |
| High decline | Moderate | 0.6999 | 0.5997 | 0.8001 |
| High growth | High | 0.1879 | 0.0802 | 0.2956 |
| Moderate growth | High | 0.2527 | 0.1766 | 0.3289 |
| Moderate decline | High | 0.5616 | 0.4954 | 0.6278 |
| High decline | High | 0.7921 | 0.6289 | 0.9552 |

Source: Authors' own work

From this, it could be concluded that the most resilient are those SMEs where sales growth is supported by an adequate level of capital. SMEs with high sales decline have the highest probability of insolvency (0.7-0.9). In addition to them, the high-risk group includes those SMEs that have a moderate sales decline and negative leverage.

Interestingly, the effect of leverage reverses depending on growth intensity:

- For moderate growth, moderate leverage is safer than high leverage.
- For high growth, the opposite holds – high leverage becomes beneficial, likely because external financing supports the expansion.

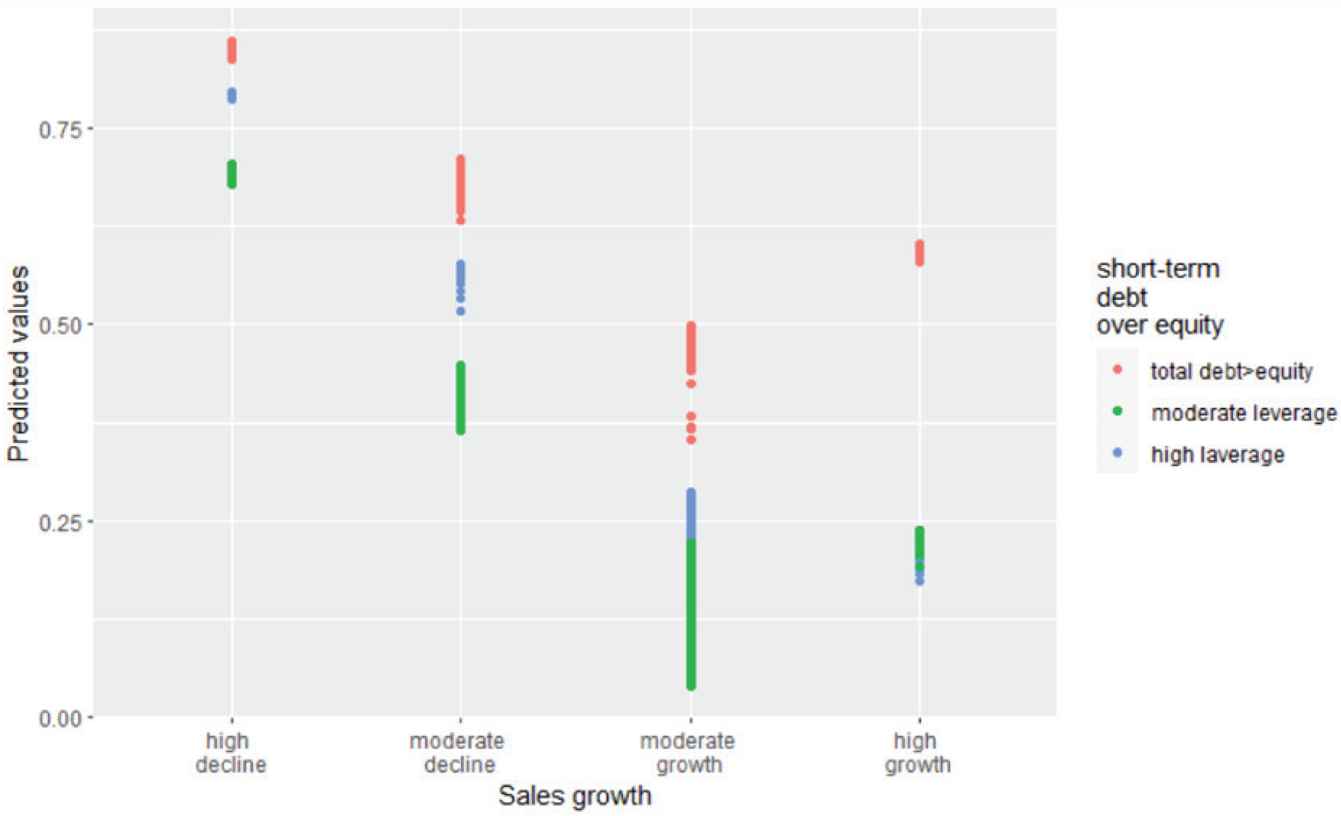
These patterns highlight the nonlinear relationship between financial structure and growth in determining insolvency risk. In other words, leverage can either mitigate or amplify insolvency risk depending on the firm's growth dynamics.

Building on the predicted probabilities from Table 7, Figure 1 illustrates how insolvency risk varies across combinations of sales growth and leverage.

The highest insolvency probabilities are consistently found among SMEs experiencing high or moderate sales declines particularly in the case where total debt exceeds total equity. This risk gradually decreases with moderate and high leverage levels. However, the pattern changes in the case of high sales growth – while firms with negative leverage still face elevated risk, those with high leverage outperform their moderately leveraged counterparts, suggesting that leverage can become advantageous when rapid growth is supported by sufficient financing capacity.

These findings confirm the two central hypotheses of this study. First, sales growth significantly influences the probability of insolvency among SMEs, and second, this influence is conditioned by the firm's financial structure, particularly leverage and liquidity. The results underscore that moderate growth, supported by moderate leverage, represents the most resilient configuration, minimizing insolvency risk while maintaining financial stability.

**Figure 1. Predictions of probability of insolvency according to the levels of sales growth and leverage**




Source: Authors' own work

## 6. Discussion and conclusion

There are numerous studies dealing with the growth and insolvency of small and medium-sized enterprises. Most often, they are studied as two separate phenomena. Still, there are studies that try to reveal their connection. They give mixed results - some find positive, some negative, while others find no connection between insolvency and growth. This research aims to make a contribution in that field by giving another approach in studying their relationship. Specifically, the interconnectedness between growth and insolvency was analyzed both directly and through interactions with other financial indicators. Unlike traditional models that do not consider the mutual interaction of financial ratios, this approach with interaction effects enables a deeper understanding of how sales growth, leverage and liquidity together shape the probability of insolvency. Through interactions, it is possible to discover sophisticated patterns that would otherwise remain hidden in models that take into account only main effects.

This research has generated five key conclusions. First, although sales growth has been confirmed as an important phenomenon from a theoretical perspective, it has been understudied in insolvency research. Previous research has taken various measures of liquidity, leverage, turnover and profitability, but rarely captures the paradox of growth - as both an opportunity and a potential source of financial distress. Our results are consistent with the theories of Penrose and Greiner, which emphasize growth dynamics and distress. Secondly, in predicting insolvency, three variables stand out, which together, in interaction, affect the risk of insolvency - sales growth, leverage ratio (current assets/equity) and quick ratio (current assets-inventories/current liabilities). Thirdly, sales growth affects the reduction of insolvency risk, but this effect depends on the financial structure. In particular, SMEs where liabilities are greater than assets have a higher probability of default even when sales are growing, which shows that a very high level of indebtedness cancels out the positive effect of sales growth. The pattern of highly indebted SMEs with high sales growth is very interesting - they have a lower insolvency risk than equally indebted SMEs with moderate growth. It can be concluded that when SMEs are highly indebted, growth must be strong enough to maintain solvency. Fourth, the most exposed to insolvency are those SMEs that have a strong decline in sales, regardless of liquidity and leverage. Even those SMEs that have high liquidity are not protected from a high risk of insolvency if they have a strong decline in sales. Fifth, the research showed that it is important to include the interaction between financial indicators. Quick ratio alone, as a direct effect, did not show significance. However, in interaction with sales growth, it was shown to have a statistically significant effect. From this, it can be concluded that liquidity has become important when viewed in the context of growth intensity – SMEs that achieve strong growth can better absorb financial stress if they maintain a sufficient level of liquidity. Accordingly, SMEs that achieve a decline in sales and at the same time have a low level of liquidity have an even greater risk of insolvency.

The research also holds practical implications within the Croatian institutional and financial context, where SMEs represent over 99% of active enterprises and account for the majority of employment. For policymakers, given that growing firms are extremely important for every economy, and this research has shown that sustainable growth reduces the risk of insolvency, the state should provide access to finance through its programs for those firms that have the potential for growth. In addition, the simplification of the financing approval procedure and the creation of programs that encourage and reward responsible leverage management would contribute to growth. As far as bankers and investors are concerned, sales growth should be considered as a key indicator in assessing defaults. As the results show, the least risky SMEs clients are those who achieve growth with sustainable leverage. On the other hand, a drop in sales can be considered an early warning sign, even among those firms that have good liquidity. By strategically financing growth-oriented SMEs, financial institutions can simultaneously support economic development and mitigate portfolio risk exposure.

This research has several limitations related to data, variables and methodology. First, the research is based on observational financial data and as such it identifies statistical associations rather than causal mechanisms. Future work could employ longitudinal or quasi-experimental designs to explore the causal dynamics linking growth, liquidity and leverage with insolvency outcomes. Second, the analysis relied on financial statements of SMEs for two consecutive years, which constrains temporal generalization. Future research could extend this framework using panel data to assess how the persistence of growth and financial structure affects insolvency over time. Third, some financial ratios (total debt over EBITDA, operating cash flow over equity, cash over debt) were excluded due to outliers. Although this approach ensured model stability, it may have omitted potentially informative indicators. Future studies could apply robust statistical techniques (e.g., winsorization) to address this limitation. Fourth, listwise deletion was applied to handle missing data. This approach may have introduced bias if SMEs with incomplete reporting differ systematically from those with complete statements. Future research could use multiple imputation or alternative techniques to test the robustness of the results.

In addition, future research could expand in four directions: (1) incorporating industry-specific factors to test whether the growth and insolvency relationship differs across sectors; (2) including variables reflecting the SMEs' life-cycle stage, given its influence on capital structure and growth strategies; (3) integrating qualitative dimensions such as entrepreneur characteristics, human capital, R&D intensity and innovation; and (4) applying advanced analytical techniques, including neural networks or support vector machines in order to capture nonlinear patterns that traditional regression models might overlook.

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