Equilibrium. Quarterly Journal of Economics and Economic Policy
Volume 18 Issue 2 June 2023
p-ISSN 1689-765X, e-ISSN 2353-3293
www.economic-policy.pl

ORIGINAL ARTICLE

Citation: Karas, M., & Režňáková, M. (2023). A novel approach to estimating the debt capacity of European SMEs. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 18*(2), 551–581. doi: 10.24136/eq.2023.017

Contact to corresponding author: Michal Karas, michal.karas@vut.cz

Article history: Received: 25.02.2023; Accepted: 10.06.2023; Published online: 30.06.2023

Michal Karas
Brno University of Technology, Czechia
orcid.org/0000-0001-8824-1594

Mária Režňáková
Brno University of Technology, Czechia
orcid.org/0000-0002-7261-607X

A novel approach to estimating the debt capacity of European SMEs

JEL Classification: *G32; G33*

Keywords: *debt capacity; financial distress; macroeconomic factors; financial constraints*

Abstract

Research background: The concept of debt capacity assumes that a maximum value of debt ratio exists that when exceeded triggers unfavourable consequences, such as drop in market value, default or a change in the business' creditworthiness. With the current state of the art there is a priori no theoretical assurance that such a specific value exists, or rather it is represented by an interval of values. Beyond that, our understanding of debt capacity is often limited to a theoretical approximation by firm-specific factors, while the context of macroeconomic factors, especially those critical for SMEs, is neglected.
Purpose of the article: The aim of this paper is to present a novel approach to estimating SMEs' debt capacity. Further, the aim is to answer the question of what firm-level and macroeconomy conditions lead to exhausting the SMEs' debt capacity and under what conditions a specific value of maximum debt capacity could be estimated.

Methods: To estimate the debt capacity, we suggest a use of an information entropy minimising heuristic and the Minimal Description Length Principle. In this approach, the observed feature space is categorised into several regions. In this case, such a region represents a set of firm- and macroeconomy-specific conditions forming the debt capacity of the SMEs. To the best of our knowledge, such an approach has not yet been used in debt capacity applications.
Findings & value added: We found out that the debt ratio itself provides little explanation of exhausted debt capacity, suggesting that high debt levels are compensated for by other factors. By using the suggested approach, a set of more than 100 different regions was analysed. It was found that in case of five regions (sets of conditions) the debt capacity is exhausted, as the high level of debt has significant distress consequences.

Introduction

Debt capacity is an important term for many applications in various corporate finance topics, starting with capital structure theories, stock returns analysis and financial flexibility issues, while being crucial for the transfer pricing aspects of financial transactions. Despite the variety of potential applications, existing studies have failed to provide a measure of debt capacity that could be estimated on a corporate level and be applicable for small and medium enterprises (SMEs). Potential application to SMEs is important from several perspectives.

The role of SMEs in the economy has been widely recognised by many authors. SMEs are generally considered to be the backbone of the global economy (Gupta *et al*., 2015, Civelek *et al*., 2021; Ključnikov *et al*., 2021), or rather an economy's engine for sustainable growth and stable employment (De Moor *et al*., 2016; Tomášková & Kaňovská, 2022; León-Gómez *et al*., 2022). Beyond that, limited access to external financing sources has a significant impact on the capital structure of SMEs, which is consequently different from that of large business (see Jin *et al*., 2018 or Filipe *et al*., 2016). As a result, the factors that make up the debt capacity of SMEs could be considered as specific to this segment of business and deserve special attention.

Having a potential tool for estimating debt capacity would fill an important research gap. Debt capacity issues are commonly discussed throughout capital structure theories, while little has been said about the application of this issue to transfer pricing problems, even though a solution to this problem would be highly beneficial to tax authorities. Debt capacity might provide an important insight into the transfer pricing aspects of financial transactions, especially in the case of lending between associated companies to assess whether the conditions of financial transactions are consistent with the arm's-length principle. This issue is discussed in chapter 10 of the OECD guide to transfer pricing. The main issue is that in the case of independent companies the conditions of the loan will be the result of various commercial circumstances, while in case of intragroup lending the group has discretion when deciding on the loan conditions. In might happen that the balance of debt and equity funding of a borrowing entity which is part of a company group might differ from that which would exist if it were an independent entity operating under same or similar circumstances. In such a situation, the question arises of whether the interest on such a loan complies with the arm's length principle or rather, whether such a loan can be regarded as loan or should be seen as another kind of payment, in particular a contribution to equity capital. The second issue could be elegantly solved by estimating the debt capacity of the borrowing entity, assuming that the debt capacity takes into account the market conditions and other relevant features of the borrowing entity.

To the best of our knowledge, existing studies on debt capacity have in common that the debt capacity is either approximated by different firm-level features or is predicted as a theoretical value based on estimated model coefficients (e.g., Lee *et al*., 2021; Kjenstad & Kumar, 2022; Catherine *et al*., 2022). At the same time, none of the existing studies analysed debt capacity values strictly by exploring the firm's realised debt ratios under various conditions. The purpose of this article is to fill this gap.

The aim of this paper is to analyse the debt capacity of unlisted European SMEs, where the debt capacity was addressed as the maximum debt ratio that does not increase the distress probability. Above that, we argue that the debt capacity feature needs to be analysed as a special case under firm-, industry- and macroeconomy-specific conditions, rather than as a general case.

Methodologically, to estimate the debt capacity, we suggest a use of an information entropy minimising heuristic and the Minimal Description Length Principle. This approach directly utilises the realised and observed values of debt ratios, while the same applies for the resulting debt capacity values, which is contrary to theoretical estimates of debt capacity.

The article is organised as follows. The first section provides a review of the literature on the debt capacity issue, pointing out the research gap on the topic. The second section introduces the suggested methodological approach for estimating debt capacity at the firm level. The results of the conducted analysis are presented in the third section, while the fourth section provides a discussion of the results. Finally, the conclusion is provided in the fifth section.

The novelty of this paper lies in fact that a new approach is suggested for debt capacity analysis. The main advantage of the suggest approach is that it is strictly based on realised debt ratio observations, instead of predicted values. The suggested approach also does not pose limits to the characteristics of the data, such as a normal distribution or the non-presence of outlier values, which are otherwise factors limiting the use of traditional classification approaches. Beyond that, with this approach, the debt capacity is analysed as a conditional feature, while also reflecting macroeconomy-specific factors of the business environment, which decide the access of SMEs to external financing and thus effect their capital structure and debt capacity.

Literature review

The term 'debt capacity' was originally defined by Myers (1977) as the point at which an increase in debt use reduces the total market value of the firm's debt. For Brennan and Schwartz (1978) the larger the debt, the higher the tax savings on income tax to be enjoyed and the limit to further debt issue is given by the moment when it leads to harming the survival probability of the business. Hess and Immenkötter (2014) mentioned that debt capacity is commonly addressed as a critical amount of debt that a firm is willing to hold but it does not have to coincide with default threshold, where the default threshold is a critical debt ratio or a related financial figure which ends the existence of the firm if it is exceeded. Leary and Roberts (2010) understand debt capacity in relation to pecking order theory as a debt ratio that leads firms to issue equity. Lemmon and Zender (2010) connect debt capacity with a possibility for a firm, based on its underlying characteristics, to enter the public debt market. The possibility of entering the external debt market is seen by many authors (such as Whited, 1992 or Almeida *et al*., 2004) as being related to the existence of bond ratings. The reason, according to Lemmon and Zender (2010), is that a firm with high likelihood of entering public debt markets exhibits sufficiently stable cash flows, large collateral and sufficient information transparency. Respecting the existence of debt capacity sheds more light on several topics; e.g. from the perspective of capital structure theories, adding the debt capacity factor could shed more light on the results of testing the pecking order theory's validity (see Shyam-Sunder & Myears, 1999 or Lemmon & Zender, 2010).

Azofra *et al*. (2020) pointed out that a lot of research into capital structure is primally concerned with understanding the different characteristics that explain how firms shape their capital structures over time, with macroeconomic factors having received comparatively little attention. Gungoraydinoglu and Öztekin (2011) analysed the determinants of capital structure and found that firm-level covariates drive two-thirds of the variation in capital structure across countries, while the country-level covariates explain the remaining one-third.

Debt capacity could also explain some cross-sectional stock returns, especially in case of financially constrained firms (see Almeida & Campallo, 2007 or Hahn & Lee, 2009). Debt capacity is often regarded as a term in theoretical models providing and explanation to more complex issues (see the works of Almeida & Campallo, 2007; Hahn & Lee, 2009). For the theoretical framework of Almeida and Campallo (2007), the debt capacity issue is considered as a borrowing constraint of their model. Such constraints are given by the interaction between the asset tangibility function and new investment value. Almeida and Campallo (2007), in line with this, argue that the holding of pledgeable assets supports more borrowing, which turns into further investment in pledgeable assets, while providing an empirical measure of a firm's tangibility as a proxy of asset pledgeability.

Hahn and Lee (2009) used the firm's tangibility measure of Almeida and Campallo, 2007 as an approximation of the firm's debt capacity. Based on this, the author showed that such a debt capacity significantly affects the cross-sectional stock returns of financially constrained firms. Debt capacity has also been looked at in terms of spare debt capacity. Marchica and Mura (2010) estimated spare debt capacity as the difference between observable debt levels and predicted debt levels. Hess and Immenkötter (2014) argue that neither study provides a measure of debt capacity, which might serve as guidance on how to identify unused debt capacity. Hess and Immenkötter (2014) suggest a novel debt capacity measure, represented by the critical debt ratio that triggers a downgrade in the creditworthiness of the firm. Their approach is based on the change in the credit rating of the firm.

Examining the debt capacity issue specifically for the conditions of SMEs poses a greater challenge than in the case of large companies. As noted by Beck *et al*. (2006) SMEs are often dependent on bank credit financing. However, from the perspective of commercial banks, SMEs are perceived as riskier clients than large corporations (see North *et al*., 2010, Dietsch & Petey, 2004). The external financing option is then made up of the trade credit and its terms (McGuinness *et al*., 2018).

Subsequently, when financing investments, SMEs must rely on limited internal funds, which in turn constrains their ability to invest (Erdogan, 2018). This has significantly negative additional consequences for debt capacity, as investment in pledgeable assets and the debt capacity of a business are closely related (e.g., Almeida & Campallo, 2007, Hahn & Lee, 2009).

With respect to the methodological aspect of the problem, as noted by Hess and Immenkötter (2014), studies do not provide a debt capacity measure at the corporate level. The approach of Hess and Immenkötter (2014) is a rare example of a study aimed at specifying debt capacity at this level. The limitation of their approach is that it requires businesses with assigned rating evaluations, which is usually not the case for SMEs. From this perspective, the identification of a debt capacity measure applicable for SMEs is lacking. To contribute to the topic, we suggest and test a novel approach for solving the problem which applies a nonparametric methodology, and is in addition immune to the negative influence of the presence of extreme values.

Research methods

The research sample consists of 212,834 SMEs operating in one of 27 European countries (EU–27). SMEs were defined in terms of sales value, which was limited to range from 2 to 50 mil. EUR. The research sample covers the period from 2012 to 2021 and thus a data set of 2,128,340 firm-year observations was initially collected. Data on companies were drawn from the Orbis database, while data on macroeconomic factors were collected from the Eurostat database and matched with financial data based on country-year specification.

We addressed the corporate-level debt capacity as the maximum debt ratio that does not increase the probability of distress. We use the distress definition of Tinoco and Wilson (2013), which is a situation occurring whenever the firm's EBITDA is lower than its financial expenses for two consecutive years. For Tinoco and Wilson (2013) the business is also considered as being in distress in the case of negative growth of market value for two consecutive years.

As the focus of this paper is on unlisted businesses, negative growth of market value is an unobservable factor: thus we limited the recognition of the distress situation to the relationship between EBITDA and financial expenses. Such a definition of debt capacity, where the debt capacity is linked to distress rather than default, offers more flexibility from a modelling perspective. Unlike the default of a business, distress does not represent a terminal condition but rather a temporary one. Beyond that, default is not a sudden event but rather the culmination of several years of adverse performance (as noted by Agarwal & Taffler, 2008).

The relationship between default and debt level is spread over time. On the other hand, the relationship between levels of debt and financial expenses is more direct and to a greater extent under management control. The distress condition was assessed with a dummy variable (status), which reached a value of 1 if EBITDA was lower for two consecutive years than interest payments and 0 otherwise. This dummy variable was calculated only when there was a valid observation of EBITDA for both assessed periods, thus significantly lowering the number of observations. Furthermore, the values of debt-equity ratio were limited to positive values only, as negative values are caused by negative equity values. Companies with negative equity cannot with high probability draw on any additional loans and thus their debt capacity is exhausted.

One of the analysed variables (dividend pay-out) requires two periods for calculation. For this reason, the number of periods for which complete observation were available was limited to 9. Beyond that, the number of observations where the information about industry classification was available for was 1,450,168.

Suggested methodology for identifying a critical debt ratio value

The idea behind debt capacity is an assumption that there exists a critical value of debt ratio, which could be described as a sharp border, which when exceeded triggers financial distress. Currently, the question of whether debt capacity takes the form of a specific point or is rather represented by an interval of values remains unanswered. From this perspective, debt capacity analysis should be accompanied with discriminant ability analysis, which would add information about distress severity when debt capacity reaches its limits. The suggested approach to identifying debt capacity is based on the following assumptions.

The first step is analysing the extent to which the debt ratio can serve as a classifier for discriminating between distressed and non-distressed businesses. Initial analysis of this discrimination ability was carried out on a full sample (i.e., across all groups). During this analysis, the debt ratio was assessed as a potential distress classifier, while the discrimination ability was evaluated by ROC analysis with the application of a trapezoidal approach. Although the initial results might be misleading due to the possible consequences of Simpson's paradox (e.g., Kennedy, 2005), such initial analysis could provide an insight into the phenomenon and justify the need to analyse the various conditions. This is in particular when the estimated discrimination probability is poor, which would contradict theoretical expectation, as debt ratio is generally considered a very strong default predictor (Cathcart *et al*., 2020; Zavgren, 1985 or Stiglitz, 1972).

The next step is splitting the sample into regions exhibiting different probabilities of distress. The idea behind this step is that the critical values of debt ratios that trigger distress would depend on other company-specific or rather environment-specific conditions. It could be assumed that debt capacity will be different for high-profit and low-profit SMEs, as such businesses will differ in terms of internal funds generating ability. On the other hand, the relationship between profitability and capital structure in the presence of distress risk is a more complex issue and has not yet been completely solved (Bongini *et al*., 2021). A similar assumption could be made when it comes to macroeconomic factors such as interest rates. Low interest rates are incentives for firms' investment, and the expected return on investment is higher when interest rates are low than in where they are high. Such a situation would imply a higher demand for debt issuance. On the other hand, high interest rates cause rising costs on debt capital; firms must pay more to their lenders (Tinoco & Wilson, 2010). Thus, higher interest rates are expected to increase the probability of firm distress. For an effective split identification, which would transform analysed continuous features such as business profitability into category variables, a method of minimising information entropy was adopted, while applying the Minimal Description Length (MDL) principle. This procedure represents supervised optimal binning methods, where the discretisation of continuous variables (such as interest rates or business profitability) was carried out with respect to dummy variables, which reach 1 for a distress business observation and

0 otherwise. In such an approach, the continuous variables representing the conditions potentially influencing distress probability are binned to define a subsample, under which the debt ratio will be conditionally analysed. Minimising information entropy should achieve the minimum possible loss of information content of the binned variable. Under this procedure, a set of five factors representing potentially relevant company- and macroeconomy-specific factors was discretised into five dummy variables, giving five categories in which the debt ratio was analysed. Furthermore, the literature on business default shows that industry specifics play a significant role when analysing factors triggering default (Chava & Jarrow, 2004 or Gupta *et al*., 2015). Initially, there were 21 industry sections analysed (according to the NACE rev. 2 classification). But this was too smooth a differentiation, so instead of that we group the industries section into four categories (for detail see Table 1), where the grouping was inspired by Chava and Jarrow (2004).

The final step in estimating the critical debt ratio is applying the information entropy minimising discretisation to the value of debt ratio separately for each of the possible scenarios. The MDL principal utilised will lead to finding the optimal split only where it will split the subgroup into otherwise homogeneous subregions. If such a split cannot be achieved, it would mean that debt capacity does not take the form of a single point, but rather is represented by an interval of values. In such a case, only information about the subgroup median value of debt ratio, as a central characteristic describing the analysed region, will be provided.

Potential firm- and macroeconomy-specific factors influencing debt capacity

In the course of analysing the influence of factors driving the debt capacity of SMEs, we need to analyse whether the potential factors significantly influence capital structure and through that might provide some further insight into debt capacity issues. We address the factors of independence of the business, financial constraints aspects and internal funds generation ability.

1. *Independence of the business:* the situation of an independent firm could be much different from that of one which is part of an alliance (group of firms), as being part of an alliance could compensate, at the firm level for the consequences of market imperfections (such as financial constraints) and ease access to finance (Ellouze & Mnasri, 2020). For control for compa-

ny independence, we use the *Indep* categorial variable, which takes value of 1 for companies with known shareholders, each of them having less than 25 % of direct or total ownership of the company, while for other cases the variable takes a value of 0.

2. *Financial constraints aspects:* the specific value of debt ratio that triggers the default threshold needs to be analysed separately for each industry and separately for financially constrained and unconstrained businesses, as there is a significant relationship between the level of financial constraints faced by a business and its probability of default (Karas & Režňáková, 2021). The lack of financial resources of SMEs make them face high financial risk (Virglerova *et al.*, 2021; Ključnikov *et al.*, 2022; Civelek *et al.*, 2023), whereas the given level of constraints depends on the development of the economy of the given country (Civelek & Krajčík, 2022). In order to distinguish between constrained and unconstrained business, the methodology of Hahn and Lee (2009) was adopted. Originally, Hahn and Lee (2009) adopted four classifications — asset size, pay-out ratio, bond rating and commercial paper rating. As the focus of this paper deals with situation of SMEs, only two the classifications of Hahn and Lee (2009) are applicable to the SME segment — asset size (*TA*) and pay-out ratio (*div*). The asset size (TA) serves as a proxy for business size and also can provide some information on potential collateral (based on the tangibility of the assets). Considering these two factors is important in explaining debt capacity, as they are interrelated. As shown by Fazzari *et al.* (1988), the investment decisions of financially constrained firms are more sensitive to the availability of internal cash flows than in the case of unconstrained firms. Beyond that, a constrained business cannot follow optimal investment and growth trajectories (Carreira & Silva, 2010), which affects the credit multiplier. It can be assumed that for a constrained business it is more difficult to increase its pledgeable assets and by that increase its debt capacity. This supports the need to analyse the situation of a constrained business separately. Dividend pay-out (Div) is being considered as a proxy for financial constraint levels, as financially constrained firms choose lower dividend pay-out ratios (see Cleary, 2006; Musso & Schiavo, 2008; Fazzari *et al.*, 1988; Gilchrist & Himmelberg, 1995), while a high dividend pay-out ratio is considered a sign of the absence of financial constraints (Musso & Schiavo, 2008). Hahn and Lee (2009) summarise that "*dividends and investment are a competing use of funds*".

Karas and Režňáková (2021) analysed the relationship between firm-specific and macroeconomic measures of financial constraints on the probability of SME default, concluding that the level of corruption and GDP per capita play a significant role in explaining cross-country differences in default probability. To control for the differences in economic development the GDP per capita (GDPpc) as a factor influencing the level of financial obstacles at the environment level, was included in the analysis. Interest rates (INT) influence a firm's distress through the capital structure, low interest rates are incentives for firms' investments, and the expected return on investment is higher when interest rates are low than when they are high. On the other hand, high interest rates lead to rising costs on debt capital and thus firms have to pay more to their lenders (see Tinoco & Wilson, 2010). Thus, higher interest rates are expected to increase the probability of firm failure. In this study, the yield on government bonds with a maturity of ten years was adopted as the interest rate variable, and such interest rates are used to define the Maastricht criterion on long-term interest rates.

3. *Internal funds generation capacity* — as a proxy for internal funds generating ability, we adopted the EBITDA over total assets indicator. Very similar ratios, namely EBIT over total assets ratio represent the most common profitability ratios among studies on distress prediction, such as for example, Li and Sun (2009), Psillaki *et al.* (2009). For Shumway (2001), profitability and debt ratio are the only robust default predictors, even when considering the dynamic nature of default process. However, we prefer the EBITDA measure, as EBITDA is often applied as a simplified surrogate of operating cash flows (see Mulford & Comsikey, 2002). A comparison of the power of EBITDA versus cash flow in distress prediction is discussed in detail in Welc (2017). As already shown by Beaver (1996), cash flow in relation to debt provides very strong information about the threat of financial distress. Extreme values were truncated and replaced by either the 1st or 99th percentile as appropriate. A linear mixed-effects model was estimated to verify the importance of analysing the debt ratio level under the subgroups defined by the specific conditions of the mentioned factors.

Linear mixed-effect model

To analyse the relationship among selected factors (in their original continuous form) and debt ratio, we employed a linear mixed effect model

(LMER). LMER is an extension of the simple linear regression model, which allows us to model both fixed and random effects, which is the main advantage of this method. This allows us to apply the model for analysis of the panel data, which is the case of data being analysed in this research, without violating the model's assumptions (for details see West *et al*., 2014):

$$D/E_{it} = \alpha + \beta X_{it} + \gamma IND_j + b_0 + \varepsilon_{it} + v_i \tag{1}$$

where:

D/E_{it}	debt ratio for the i-th company at time (t),
α	the intercept, β *and* γ are regression coefficients,
X_{it}	analysed variables that could influence the debt ratio,
IND_j	industry dummy, where j = 1,2,3,4,
b_0	random intercept,
ε_{it}	residual term,
v_i	effects of individuals.

Receiver operating characteristics (ROC) and area under curve (AUC) methodology

A receiver operating characteristic curve, or ROC curve, is a tool used to assess the discrimination power of a binary classifier. The area under curve (AUC) is a measure that is used as a summary of the ROC curve. There are several ways to estimate AUC values; Bradley (1997), among others mentioned that it is possible to calculate AUC by assuming that the underlying probabilities of predicting negative or positive are Gaussian and the AUC can be fitted by maximum likelihood estimation. Another way to calculate the AUC is to use a trapezoidal approach, which does not make any assumptions on the underlying probability distribution. Trapezoidal integration can be applied by the following formula (see Bradley, 1997):

$$AUC = \sum_i \left\{(1 - \beta_i \cdot \Delta\alpha) + \tfrac{1}{2}[\Delta(1 - \beta) \cdot \Delta\alpha]\right\} \tag{2}$$

where:

$$\Delta(1 - \beta) = (1 - \beta_i) - (1 - \beta_{i-1}) \tag{3}$$

$$\Delta\alpha = \alpha_i - \alpha_{i-1} \tag{4}$$

where:
1-β the sensitivity,
1-α the specificity.

As noted by Hanley and McNeil (1982), the trapezoidal approach systematically underestimates the AUC, because all points of the ROC are connected with a straight line instead of smooth concave curves. However, in the case of a reasonable number of points, the underestimation should not be too severe. Hand and Till (2001) build on the work of Bradley (1997) and present a different approach to calculate AUC, which is equivalent to Wilcoxon's statistical rank test. Under this approach, the AUC for a G classifier is given by:

$$A = \frac{S_0 - \frac{n_0(n_0+1)}{2}}{n_0 n_1} \tag{5}$$

where:
n_0 and n_1 the numbers of positive and negative examples, respectively, and

$$S_0 = \sum r_i \tag{6}$$

where:
r_i the rank of the i-th positive example in the ranked list.

Ling and Zhang (2002) showed that if we build a classifier, which maximises AUC, instead of accuracy, such a classifier would produce not only higher AUC but also higher accuracy than would be achieved in the opposite case (i.e., building a classifier which maximizes accuracy in the first place), which is an important point when addressing debt capacity.

The information entropy minimising heuristic and the minimal description length principle

Debt capacity by its nature represents a specific value of a firm-specific measure, which means that it must be addressed as a specific value of a business observation, rather than a model's variable. We suggest that estimating debt capacity could be carried out by supervised binary discretisation of the continuous values of debt ratio with respect to distress conditions. This supervised binary discretisation can be carried out by using information entropy minimising heuristics, which was presented by Fayyad and Irani (1993). This supervised algorithm uses the class information entropy of candidate partitions to select bin boundaries for discretisation (see Dougherty *et al.*, 1995). Such a heuristic is adopted in classification tree methods, such as CART (for details see Frydman *et al.*, 1985 or Hastie *et al.*, 2009). Binning offers several advantages from a modelling perspective. As, for example, the resulting classification rule is easy to interpret (Brezingar-Masten & Masten, 2012). Second, it is a nonparametric method, which is also able to capture complex relationships between variables (Brezingar-Masten & Masten, 2012), and three, the method is very robust with regard to the existence of outliers in the sample (Di Marco & Nieddu, 2014). However, the biggest advantage of this method for the purposes of the presented research is that the values observed in the sample are considered as possible splits, allowing us to find the maximum debt ratio realised by a specific business and we do not need to rely on a theoretical value based on an estimated model. The idea behind the entropy minimising discretisation method is as follows (see Dougherty *et al.*, 1995). Let us assume a set of instances S, a feature A, and a partition boundary T, the entropy of class information of the partition induced by T, denoted E (A; T; S) is given by:

$$E(A;T;S) = \frac{|S_1|}{|S|} Ent(S_1) + \frac{|S_2|}{|S|} Ent(S_2) \tag{7}$$

For a given feature A (in the case presented with the debt ratio), the boundary T_{min} which minimises the entropy function over all possible partition boundaries is selected as a binary discretisation boundary. This method can then be applied recursively to both partitions induced by T_{min} until some stopping condition is achieved, thus creating multiple intervals on feature A (see Dougherty *et al.*, 1995). Often, the minimal description length principle (MDL) is used to determine a stopping criterion (see Fayyad & Irani, 1993), and the recursive partitioning within a set of values S stops if:

$$Gain(A,T;S) < \frac{log_2(N-1)}{N} + \frac{\Delta(A,T;S)}{N} \tag{8}$$

where:

N the number of instances in the set S,

$$Gain(A,T;S) = Ent(S) - E(A,T;S) \tag{9}$$

and

$$\Delta(A,T;S) = log_2(3^k - 2) - [k \cdot Ent(S) - k_1 \cdot Ent(S_1) - k_2 \cdot Ent(S_2)] \tag{10}$$

where:
k_i the number of class labels represented in the set S_i.

Results

The initial analysis of the discrimination power of the debt ratio was carried out on a full sample and separately for each of the analysed industry groups and for independent and non-independent businesses. The discrimination power of debt ratio, at this initial phase, is rather weak, as the maximum AUC reached is 0.645 (for details, see Table 2), which is below the generally considered threshold of 0.7 for which the discrimination power is considered acceptable (see Hosmer & Lemeshow, 2000, p. 162).

Initial results clearly show the need to analyse levels of debt ratio in a deeper context. For this purpose, the LMER model was estimated in the form (1) while only the results for fixed-effects estimation are presented. The results for fixed-effects estimation are presented in Table 3.

The debt ratio is significantly different between industries, which is in line with expectations. For non-independent SMEs the debt ratio is significantly higher than for independent ones. Regarding the rest of the firm-specific factors, the higher the asset size, the higher the debt ratio, where the asset size serves as a proxy for pledgeable assets. A similar conclusion applies for dividend pay-out (DIV); companies which can afford higher dividend pay-outs (and potentially have a better access to external financing) exhibit a higher proportion of debt in their capital structure. Conversely, companies with high profitability or rather high cash flow generating ability (ROA) tend to have lower debt levels. Regarding macroeconomic factors, for economies with higher economic development approximated by GDP per capita (GDPpc) levels, a higher debt ratio could be observed, and the same applies for long-term interest rates (Int). All the mentioned effects are significant at a 1% level and thus will be utilised as factors defining the subgroups under which the debt ratio level will be further analysed.

In the next step, these variables were discretised with respect to the probability of distress. The split for the analysed variables is formulated for every industry group separately to account for the industry effect and separately for independent and non-independent companies, as we assume significantly different situations for these two types of company. The resulting splits of the analysed variables are presented in Table 4. The corresponding entropy levels are shown in parentheses, where the lower the entropy is, the more efficient the discretisation.

Among the analysed variables, the lowest information loss in explaining the relationship between the analysed variables and distress was seen in the case of the ROA variable. A similar conclusion can be applied to independent companies, as the entropy levels of the same variables are lower for this group. In the case presented, in several cases the algorithm utilised does not identify a split, which means that further splitting of the subspace by using the given variable would lead to weak discrimination with respect to distress probability. Using these splits, we were able to analyse 138 combinations of firm- and macroeconomy-specific conditions (referred to as regions). We further analysed the realised values of debt ratios under specific conditions of these regions, finding that only in 36 of them, significant estimates of AUC were identified, where the AUC value is at least 0.6 and the number of firm-year observations is at least 100. For each such a region the debt ratio values were binarily discretised with respect to distress probability in order to identify a possible critical value of the debt ratio that could be assigned as debt capacity. The given region is identified by industry category (IND) and independence (Indep) membership and further by bins of analysed discretised variables — values lower than the specific split value (see Table 4) are assigned as 1, while larger values are assigned as 2. The results of all 36 analysed regions are presented in Table 5. The results should be interpreted in the following way. For example, companies in Region 1 met simultaneously the following features:

1. Operate in various industries (IND = 1),
2. are not independent (Indep = 0),
3. their assets size is lower than 4,524.73 th. EUR,
4. their dividend pay-out ratio is greater than 0.011% (i.e., they are probably not financially constrained),
5. their profitability is lower than 8.14% (i.e. they could be considered as low-profit companies).

6. They are operating in countries where GDP per capita is higher than 97% of the EU average and the long-term interest rates on government bonds are lower than 1.49%.

For such companies it was possible to identify a critical debt ratio that triggers distress and its specific value is 2.0782 (which is equivalent to a debt-to-asset ratio of 67.51%). The severity of the distress threat, measured by AUC is 0.686. The existing splits in the debt ratio are equal to the median values of the debt ratio for given subgroups. As the range of the analysed values of debt ratios is generally very wide, we focus on the quartile borders. The interval formed by the quartile borders covers 50% of the values centred around the median value.

A specific value of debt capacity, which has the potential to distinguish between distressed and non-distressed companies under the given region, was identified in the case of 12 regions. These specific values meet the requirements of the debt capacity metric. The identified debt capacity values range from 1.5376 to 4.2978, which is equivalent to debt-to-asset values between 60.59 and 81.12%. The discrimination power of the debt ratios in these 12 regions, measured by AUC, ranges between 0.605 and 0.686.

Furthermore, the results also suggest that the discrimination power of the debt ratio in explaining the distress probability is significantly dependent on other idiosyncratic and macroeconomic conditions, which contribute to the information value carried by the debt ratio. For several regions, debt capacity values have very strong potential in explaining distress probability, as the corresponding AUC value exceeds 0.9 and is statistically significant, namely for regions 8, 11, 16, 32 and 34. In all cases, these regions contain observations of high-profit companies. And in the majority, these companies are not independent and are not financially constrained (exhibit higher dividend pay-out ratios). Although there was a high discrimination ability of the debt ratio under these regions, no specific value of debt ratio, which would distinguish between distressed and non-distressed companies, was identified.

Discussion

In the current state of the art, debt capacity is treated as a specific value of the debt ratio, although there is no guarantee provided that such a sharp border exists, and the debt capacity is not rather an interval value. Existing approaches to estimating the debt capacity rely on approximation of debt capacity by other firm-specific characteristic, especially asset tangibility, or else the debt capacity is predicted based on regression function estimates.

The approach to debt capacity estimation respects the fact that the debt capacity might be an interval of values, rather than existing as a specific value.

The basic assumption of the existence of debt capacity in terms of a critical debt ratio is that the debt ratio is strongly related to financial distress. This assumption is strongly underpinned in the existing literature (e.g., Traczynski, 2017 or Cathcart *et al*., 2020), according to which this feature of debt capacity is valid across all industries. The results of the initial analysis of debt ratio showed that the discrimination capacity of debt capacity at the univariate level is rather weak (reaching a maximum AUC of 0.645), even when the independence character of the business and its industry classification are considered. This result suggests that there is a missing context of other relevant factors that might potentially enhance the information content of the debt ratio factor. Many studies showed that the capital structure of SMEs, which is the subject of this research, is shaped to a large extent by a limited ability to gain external financing (Beck *et al*., 2006; Ullah, 2020 or North *et al*., 2010). The result of LMAR model estimation showed that factors like assets size, dividend pay-out and assets profitability have a significant impact on debt ratio levels. However, when using these ratios as a potential split for defining the regions, we have found that no scheme is shared across different industries and dependent and independent companies. This is most obvious in the case of total assets and interest rate factors. For dependent companies, these factors produce a significant split across all industries (with the exception of the case of financial companies). In contrast, these factors do not produce any separation for independent companies. For non-independent firms which are part of an alliance (group of firms), the alliance could compensate, at the firm level, for the consequences of market imperfections (such as financial constraints) and ease access to finance (Ellouze & Mnasri, 2020).

Such a potential easing of access to finance, through the alliance, could also explain why the interest rate (as a macroeconomic factor) was identified as a split only in the case of non-independent companies. Through the easier access to debt finance, the increasing interest rate might be a stronger incentive for issuing higher debt levels and by that enjoying higher tax savings, in line with the postulate of Brennan and Schwartz (1978).

The final step in the conducted analysis was to split the debt ratio in each of the analysed regions. The results, at first glance, seem ambivalent. The debt ratio was identified for only those regions for which a weak discrimination power of the debt ratios was identified. Compared to that, some regions were identified for which the discrimination power of debt ratios was very high, while no specific split of debt ratio was identified, whereas this discrimination power was much higher than in the case of initial discrimination analysis, when only the factors of independence and industry classification were addressed. These results suggest that debt capacity is being exhausted under specific firm-level and macroeconomy-level conditions, as an increasing debt value triggering default for the majority of the companies. The factor that these companies have in common that they are highly profitable, where majority of these companies are not independent and are not financially constrained (exhibit higher dividend pay-out ratios). At first sight, this contradicts the theoretical assumptions, according to which the higher the profitability, the higher the internal funds generating ability, which should result in lower probability of distress, as distress occurs when the supply of liquid assets dries up (see Beaver, 1966). A possible explanation for that might be that for a high profit company, any distortions in EBITDA generating ability could result in volatility of debt ratios, through equity changes, in the presence of relatively high debt levels.

Regarding the methodological aspects of the conducted analysis. Our current understanding of debt capacity is limited to consequences when the capacity is exceeded, or the debt capacity is approximated by other factors. When considering the consequences, these could be a decline in market value (as for Myers, 1977), or additional equity issues (see Leary & Roberts, 2010), a change in credit rating (Hess & Immenkötter, 2014) or not entering the public debt market (e.g., see Whited, 1992). Hess and Immenkötter (2014) also mentioned a very common understanding of debt capacity, that is, a level of debt, which when exceeded leads to the business ceasing to exist, to its default. Some studies instead of that link the maximum borrowing available to the business with the liquidation value of business assets (e.g., Almeida & Campallo, 2007; Hahn & Lee, 2009). From the practical perspective of utilising the debt capacity concept, for example, for further insight and justification in transfer pricing issues, it is vital that such a concept would be applicable for the majority of businesses, i.e. not only for large and listed businesses but for SMEs as well. At this point, empirical estimation is more challenging, as SMEs are usually not publicly listed; thus a drop in market value is not directly observable, often they are financially constrained, which might limit the possibilities of raising additional equity, and they do not have assigned credit ratings. From this perspective, we suggest linking the debt capacity to financial distress condition, where distress is defined in terms of EBITDA and interest expenses (see Tinoco & Wilson, 2013). The option of linking debt capacity with the threat of default was also considered. The advantage of this approach is that such a condition is reliably measured for every business, distress is rather a temporary condition and is more frequent than default, which improves the modelling possibilities. Above that, default needs to be understood as the culmination of several years of adverse performance (see Agarwal & Taffler, 2008) and thus as a more severe condition than distress.

Concerning research limitations, the first limitation deals with the number of potential variables that might be employed for splitting feature variable space (of all observed values of debt capacity). An inevitable consequence of increasing the number of variables used for analysis (and for region definition) is lowering the number of observations that meet all the created conditions. Second, when analysing debt, the data do not allow us to control for intragroup lending and to effectively control for interest-carrying debt.

Conclusions

In this paper, we propose a novel methodology for estimating the debt capacity of SMEs, as the existing approaches are not suitable for this segment of businesses or are not capable of reflecting current macroeconomy conditions. Under the proposed approaches, the debt capacity is strictly analysed in terms of realised values of debt ratios on a large set of European SMEs. This is contrary to other approaches, under which the debt capacity is calculated as a theoretical value using the coefficient of the estimated model. For estimating debt capacity, we suggest the use of information entropy minimising heuristics and the minimal description length principle. To the best of our knowledge, we are not aware of the application of this approach in debt capacity estimation issues. Under this approach, the observed feature space is categorised into several regions. This has both advantages and limitations. The non-parametric nature of the method and its immunity to outlier values could be considered an advantage, especially when compared to traditional approaches. The conditional discretisation of the feature variable space, which is the basic principle of the method, leads to the definition of less and less populated regions, where the number of analysed variables increases. Although the sample contained more than 1.5 million observations, for some regions only a few were available.

From the perspective of practical implications, the obtained results might provide valuable guidance on some complicated transfer pricing issues, such as assessing whether a financial transaction, in the case of lending between associated companies, is consistent with the arm's-length principle. When the estimated debt capacity is exceeded, such a transaction might not be consistent with the mentioned principle. However, the effective practical application of this idea requires further research.

The result suggests that there is still space for further splitting, as for many of the regions the discrimination power of the debt ratios was relatively low. This suggests that an unobserved factor is playing a significant role. For further research, the potential of factors approximating the financial obstacles of SMEs' external financing should be addressed in more detail.

To summarise the results, we found that the debt ratio itself provides little explanation on exhausted debt capacity, suggesting that high debt levels are compensated for by other factors. By using the suggested approach, a set of more than 100 different regions was analysed. It was found that in the case of five regions (sets of conditions) the debt capacity is exhausted, and the high level of debt has significant distress consequences.

References

Agarwal, V., & Taffler, R. (2008). Comparison of the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking and Finance*, *32*(8), 1541–1551. doi: 10.1016/j.jbankfin.2007.07.014.

Almeida, H., & Campallo, M. (2007). Financial constraints, asset tangibility, and corporate investment. *Review of Financial Studies*, *20*(5), 1429–1460. doi: 10.1093/rfs/hhm019.

Almeida, H., Campello, M., & Weisbach, M. S. (2004). The cash flow sensitivity of cash. *Journal of Finance*, *59*, 1777–1804. doi: 10.1111/j.1540-6261.2004.00679.x.

Azofra, V., Rodríguez-Sanz, J. A., & Velasco, P. (2020). The role of macroeconomic factors in the capital structure of European firms: How influential is bank debt? *International Review of Economics and Finance*, *69*, 494–514. doi: 10.1016/j.iref.2020.06.001.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, *4*, 71–111. doi: 10.2307/2490171.

Beck, T., Demirguc-Kunt, A., Laeven, L., & Maksimovic, V. (2006). The determinants of financing obstacles. *Journal of International Money and Finance*, *25*(6), 932–952. doi: 10.1016/j.jimonfin.2006.07.005.

Bongini, P. Ferrando, A., Rossi, E., & Rossolini, M. (2021). SME access to market-based finance across Eurozone countries. *Small Business Economics*, *56*, 1667–1697. doi: 10.1007/s11187-019-00285-z.

Bradley, A. P. (1997). The use of the area under the roc curve in the evaluation of machine learning algorithms. *Pattern Recognition*, *30*(7), 1145–1159. doi: 10.1016/S0031-3203(96)00142-2.

Brennan, M., & Schwartz, E. (1978). Corporate income taxes, valuation, and the problem of optimal capital structure. *Journal of Business*, *51*, 103–114. doi: 10.1086/295987.

Brezingar-Masten, A., & Masten, I. (2012). CART-based selection of bankruptcy predictors for the logit model. *Expert Systems with Applications*, *39*(11), 10153–10159. doi: 10.1016/j.eswa.2012.02.125.

Carreira, C., & Silva, F. (2010). No deep pockets: Some stylized empirical results on firms' financial constraints. *Journal of Economic Surveys*, *24*, 731–753. doi: 10.1111/j.1467-6419.2009.00619.x.

Cathcart, L., Dufour, A., Rossi, L., &. Varotto, S. (2020). The differential impact of leverage on the default risk of small and large firms. *Journal of Corporate Finance*, *60*, 101541. doi: 10.1016/j.jcorpfin.2019.101541.

Catherine, S., Chaney, T., Huang, Z., Sraer, D., & Thesmar, D. (2022). Quantifying reduced-form evidence on collateral constraints. *Journal of Finance*, *77*, 2143–2181. doi: 10.1111/jofi.13158.

Chava, S., & Jarrow, R. A. (2004). Bankruptcy prediction with industry effects. *Review of Finance*, 8, 537–569. doi: 10.1093/rof/8.4.537.

Civelek, M., Ključnikov, A., Fialova, V., Folvarčná, A., & Stoch, M. (2021). How innovativeness of family-owned SMEs differ depending on their characteristics?. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *16*(2), 413–428. doi: 10.24136/eq.2021.015.

Civelek, M., & Krajčík, V. (2022). How do SMEs from different countries perceive export impediments depending on their firm-level characteristics? System approach. *Oeconomia Copernicana*, *13*(1), 55–78. doi: 10.24136/oc.2022.002.

Civelek, M., Krajčík, V., & Fialova, V. (2023). The impacts of innovative and competitive abilities of SMEs on their different financial risk concerns: System approach. *Oeconomia Copernicana*, *14*(1), 327–354. doi: 10.24136/oc.2023.009.

Cleary, S. (2006). International corporate investment and the relationships between financial constraint measures. *Journal of Banking & Finance*, *30*, 1559–1580. doi: 10.1016/j.jbankfin.2005.03.023.

De Moor, L., Wieczorek-Kosmala, M., & Blach, J. (2016). SME debt financing gap: The case of Poland. *Transformations in Business & Economics*, *15*(39), 274–291.

Di Marco, L., & Nieddu, L. (2014). Trigger factors that influence bankruptcy: A comparative and exploratory study. *Rivista Italiana di Economia Demografia e Statistica*, *68*(3/4), 191–198.

Dietsch, M., & Petey, J. (2004). Should SME exposures be treated as retail or corporate exposure? A comparative analysis of default probabilities and asset correlations in French and German SMEs. *Journal of Banking & Finance*, *28*, 773–788. doi: 10.1016/j.jbankfin.2003.10.006.

Dougherty, J., Kohavi, R., & Sahami, M. (1995). Supervised and unsupervised discretization of continuous features. In A. Prieditis & S. Russell (Eds.). *Machine learning: Proceedings of the twelfth international conference*. San Francisco: Morgan Kaufmann Publishers.

Ellouze, D., & Mnasri, K. (2020). Business group diversification, financial constraints, and firm performance: The case of Tunisian group affiliated firms. *Journal of Management and Governance*, *24*, 273–301. doi: 10.1007/s10997-019-0945 4-4.

Erdogan, A. I. (2018). Factors affecting SME access to bank financing: An inter-view study with Turkish bankers. *Small Enterprise Research*, *25*, 23–35. doi: 10.1080/13 215906.2018.1428911.

Fayyad, U. M., & Irani, K. B. (1993). Multi-interval discretization of continuous-valued attributes for classification learning. In R. Bajcsy (Ed.). *International joint conference on artificial intelligence*. San Francisco: Morgan Kaufmann.

Fazzari, S., Hubbard, R., & Petersen, B. (1988). Financing constraints and corporate investment. *Brookings Papers on Economic Activity*, *1*, 141–195. doi: 10.2307/253 4426.

Filipe, S. F., Grammatikos, T., & Michala, D. (2016). Forecasting distress in European SME portfolios. *Journal of Banking & Finance*, *64*, 112–135. doi: 10.1016/j.jbankf in.2015.12.007.

Frydman, H., Altman, E. I., & Kao, D. L. (1985). Introduction recursive partitioning for financial classification: The case of financial distress. *Journal of Finance*, *40*(1), 269–291. doi: 10.1111/j.1540-6261.1985.tb 04949.x.

Gilchrist, S., & Himmelberg, C. P. (1995). Evidence on the role of cash flow in investment. *Journal of Monetary Economics*, *36*, 541–572. doi: 10.1016/0304-3932 (95)01223-0.

Gungoraydinoglu, A., & Öztekin, Ö. (2011). Firm- and country-level determinants of corporate leverage: Some new international evidence. *Journal of Corporate Finance*, *17*(5), 1457–1474. doi: 10.1016/j.jcorpfin.2011.08.004.

Gupta, J., Gregoriou, A., & Healy, J. (2015). Forecasting bankruptcy for SMEs using hazard function: To what extent does size matter? *Review of Quantitative Finance and Accounting*, *45*(4), 845–869. doi: 10.1007/s11156-014-0458-0.

Hahn, J., & Lee, H. (2005). Financial constraints, debt capacity, and the cross section of stock returns. *Working paper, University of Washington and Korea Development Institute*.

Hand, D. J., & Till, R. J. (2001). A simple generalisation of the area under the ROC curve for multiple class classification problems. *Machine Learning*, *45*, 171–186. doi: 10.1023/A:1010920819831.

Hanley, J. A., & McNeil, B. J. (1982). The meaning and use of the area under a receiver operating characteristic (ROC) curve. *Radiology*, *143*(1), 29–36. doi: 10.114 8/radiology.143.1.7063747.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction*. New York: Springer-Verlag. doi: 10.1007 /978-0-387-84858-7.

Hess, D., & Immenkötter, P. (2014). How much is too much? Debt capacity and financial flexibility. *CFR Working Paper, University of Cologne, Centre for Financial Research (CFR)*, *14-03*.

Hosmer, D. W., & Lemeshow, S. (2000). *Applied logistic regression*. Wiley.

Jin, Y., Luo, M., & Wan, C. (2018). Financial constraints, macro-financing environment, and post-crisis recovery of firms. *International Review of Economics and Finance*, *55*, 54–67. doi: 10.1016/j.iref.2018.01.007.

Karas, M., & Režňáková, M. (2021). The role of financial constraint factors in predicting SME default. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *16*(4), 865–889. doi: 10.24136/eq.2021.032.

Kennedy, P. (2005). Oh no! I Got the wrong sign! What should I do? *Journal of Economic Education*, *36*(1), 77–92. doi : 10.3200/JECE.36.1.77-92.

Ključnikov, A., Civelek, M., Fialova, V., & Folvarčná, A. (2021). Organizational, local, and global innovativeness of family-owned SMEs depending on firm-individual level characteristics: evidence from the Czech Republic. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *16*(1), 169–184. doi: 10.24136/ eq.2021.006.

Ključnikov, A., Civelek, M., Krajčík, V., Novák, P., & Červinka, M. (2022). Financial performance and bankruptcy concerns of SMEs in their export decision. *Oeconomia Copernicana*, *13*(3), 867–890. doi: 10.24136/oc.2022.025.

Kjenstad, E. C., & Kumar, A. (2022). The effect of real estate prices on peer firms. *Real Estate Economics*, *50*, 1022–1053. doi: 10.1111/1540-6229.12362.

Lee, C., Wang, C., Yin, C., & Choo, M. (2021). Do firm characteristics affect debt capacity? Evidence in CEO succession. *Applied Economics*, *53*(48), 5567–5583. doi: 10.1080/00036846.2021.1925626.

Leary, M., & Roberts, M. (2010). The pecking order, debt capacity, and information asymmetry. *Journal of Financial Economics*, *95*, 332–355. doi: 10.1016/j.jfineco. 2009.10.009.

Lemmon, M., & Roberts, M. (2010). The response of corporate financing and investment to changes in the supply of credit. *Journal of Financial and Quantitative Analysis*, *45*, 555–587. doi: 10.1017/S0022109010000256.

León-Gómez, A., Santos-Jaén, J. M., Ruiz-Palomo, D., & Palacios-Manzano, M. (2022). Disentangling the impact of ICT adoption on SMEs performance: The mediating roles of corporate social responsibility and innovation. *Oeconomia Copernicana*, *13*(3), 831–866. doi: 10.24136/oc.2022.024.

Li, H., & Sun, J. (2009). Predicting business failure using multiple case-based reasoning combines with support vector machine. *Expert Systems with Applications*, *36*(6), 10085–10096. doi: 10.1016/j.eswa.2009.01.013.

Ling, C. X., & Zhang, H. (2002). Toward Bayesian classifiers with accurate probabilities. In M. S. Chen, P. S. Yu, & B. Liu (Eds). *Advances in knowledge discovery and data mining. PAKDD 2002. Lecture notes in computer science*. Berlin, Heidelberg: Springer.

Marchica, M. T., & Mura, R. (2010). Financial flexibility, investment ability, and firm value: Evidence from firms with spare debt capacity. *Financial Management*, *39*(4), 1339–1365. doi: 10.2139/ssrn.891562.

McGuinness, G., Hogan, T., & Powell, R. (2018). European trade credit use and SME survival. *Journal of Corporate Finance*, *49*, 81–103. doi: 10.1016/j.jcorpfin.2017.12.005.

Mulford, C. W., & Comiskey, E. E. (2002). *The financial numbers game: Detecting creative accounting practices*. New York: John Wiley & Sons.

Musso, P., & Schiavo, S. (2008). The impact of financial constraints on firm survival and growth. *Journal of Evolutionary Economics*, *18*, 135–149. doi: 10.1007/s00191-007-0087-z.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, *5*, 147–175. doi: 10.1016/0304-405X(77)90015-0.

North, D., Baldock, R., & Ekanem, I. (2010). Is there a debt finance gap relating to Scottish SMEs? A demand-side perspective. *Venture Capital*, *12*(3), 173–192. doi: 10.1080/13691061003658670.

Psillaki, M., Tsolas, I. T., & Margaritis, M. (2010). Evaluation of credit risk based on firm performance. *European Journal of Operational Research*, *201*(3), 873–881. doi: 10.1016/j.ejor.2009.03.032.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business*, *74*(1), 101–124. doi: 10.1086/209665.

Shyam-Sunder, L., & Myears, S. C. (1999). Testing static tradeoff against pecking order models of capital structure. *Journal of Financial Economics*, *51*, 219–244. doi: 10.1016/S0304-405X(98)00051-8.

Stiglitz, J. E. (1972). Some aspects of the pure theory of corporate finance: Bankruptcies and takeovers. *Bell Journal of Economics and Management Science*, *3*(2), 458–482. doi: 10.2307/3003033.

Tinoco, M. H., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market, and macroeconomic variables. *International Review of Financial Analysis*, *30*, 394–419. doi: 10.1016/j.irfa.2013.02.013.

Tomášková, E., & Kaňovská, L. (2022). Impact of cooperation flexibility on innovation flexibility in SMEs. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *17*(2), 533–566. doi: 10.24136/eq.2022.019.

Traczynski, J. (2017). Firm default prediction: A Bayesian model-averaging approach. *Journal of Financial and Quantitative Analysis*, *52*(3), 1211–1245. doi: 10.1017/S002210901700031X.

Ullah, B. (2020). Financial constraints, corruption, and SME growth in transition economies. *Quarterly Review of Economics and Finance*, *75*, 120–132. doi: 10.1016/j.qref.2019.05.009.

Welc, J. (2017). EBITDA vs. cash flows in bankruptcy prediction on the Polish capital market. *European Financial and Accounting Journal*, *12*(2), 91–103. doi: 10.18267/j.efaj.183.

West, B. T., Welch, K. B., & Gałecki, A. T. (2014). *Linear mixed models. A practical guide using statistical software*. New York: CRC Press.

Whited, T. M. (1992). Debt, liquidity constraints, and corporate investment: Evidence from panel data. *Journal of Finance*, *47*, 1425–1460. doi: 10.1111/j.1540-6261.1992.tb04664.x.

Virglerova, Z., Ivanova, E., Dvorsky, J., Belas, J., & Krulický, T. (2021). Selected factors of internationalisation and their impact on the SME perception of the market risk. *Oeconomia Copernicana*, *12*(4), 1011–1032. doi: 10.24136/oc.2021.033.

Zavgren, C. V. (1985). Assessing the vulnerability to failure of American industrial firms: Logistic analysis. *Journal of Business Finance and Accounting*, *12*(1), 19–45. doi: 10.1111/j.1468-5957.1985.tb00077.x.

Acknowledgement

The paper was supported by the Technology Agency of the Czech Republic within project No. TL05000328 “Setting the market price for financial transactions while using the arm’s length principle”.

Ministry of Education and Science
Republic of Poland

The journal is co-financed in the years 2022–2024 by the Ministry of Education and Science of the Republic of Poland in the framework of the ministerial programme "Development of Scientific Journals" (RCN) on the basis of contract no. RCN/SN/0129/2021/1concluded on 29 September 2022 and being in force until 28 September 2024.

Annex

Table 1. Industry classification adopted

Industry group adopted	NACE rev. 2 Main section
IND 1 - Miscellaneous industries	A, F, G, I, M, N, O, P, Q, R, S, T, U, J
IND 2 - Manufacturing and mineral industries	B, C
IND 3 - Transportation, communications and utilities	D, E, H
IND 4 - Finance, insurance, and real estate	K, L

Table 2. Results for the initial discrimination analysis of the debt ratio

IND	Indep	AUC	SE	p-val.	LB	UB
1	0	0.619	0.002	0.000	0.615	0.623
1	1	0.577	0.009	0.000	0.559	0.595
2	0	0.636	0.003	0.000	0.630	0.641
2	1	0.534	0.014	0.007	0.506	0.562
3	0	0.645	0.005	0.000	0.635	0.655
3	1	0.622	0.036	0.000	0.551	0.693
4	0	0.521	0.006	0.001	0.509	0.533
4	1	0.643	0.043	0.000	0.559	0.728

Note: AUC – area under the curve, SE – standard error, CI – 95 % confidence interval, LB – lower bound, UB-upper bound.

Source: own processing based on data from the Orbis database.

Table 3. LMER estimates of fixed effects

Parameter	Estimate	SE	t-stat.	p-val	CI	
					LB	UB
Intercept	2.109	0.150	14.014	0.000	1.814	2.404
[INDEP=0]	0.456	0.073	6.275	0.000	0.314	0.599
[IND=1]	-1.240	0.097	-12.762	0.000	-1.430	-1.049
[IND=2]	-2.291	0.099	-23.170	0.000	-2.485	-2.097
[IND=3]	-0.628	0.107	-5.844	0.000	-0.838	-0.417
TA	0.0000108	0.0000008	13.985	0.000	0.00000930	0.00001233
DIV	0.074	0.002	47.652	0.000	0.070	0.077
GDPpc	0.038	0.001	42.053	0.000	0.036	0.039
Int	0.358	0.005	73.708	0.000	0.348	0.367
ROA	-12.865	0.068	-188.465	0.000	-12.998	-12.731

Note: Estimate – estimated coefficient of the fixed effect, SE – standard error, CI – 95 % confidence interval, LB – lower bound, UB-upper bound.

Source: own processing based on data from the Orbis database.

Table 4. Split values and corresponding entropy levels of discretised variables

Category	**Independent (Indep =1)**				**Not independent (Indep = 0)**			
Variable/IND	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
ROA (%)	6.57 (0.176)	7.84 (0.126)	8.87 (0.096)	5.76 (0.186)	8.14 (0.191)	8.94 (0.167)	10.45 (0.170)	6.21 (0.279)
GDPpc		95 (0.142)			97 (0.227)		97 (0.200)	104 (0.339)
TA (th. EUR)					4524.73 (0.228)	6665.02 (0.198)		36768 (0.338)
DIV (%)	0.0017 (0.203)	0.0058 (0.147)			0.011 (0.226)	0.0038 (0.197)	0.088 (0.188)	11.6972 (0.336)
Int (%)					1.49 (0.228)	1.71 (0.197)	1.49 (0.201)	

Source: own processing based on data from the Orbis database.

Table 5. Debt capacity results

			Bins							Descriptive statistics			
R	IND	Indep	TA	DIV	ROA	GDP pc	Int	AUC	p-val	N	25%	50 %	75%
1	**1**	**0**	**1**	**2**	**1**	**2**	**1**	**0.686**	**0.000**	**13,838**	**1.065**	**2.078***	**4.235**
2	**1**	**0**	**1**	**2**	**1**	**2**	**2**	**0.635**	**0.000**	**16,407**	**1.802**	**4.297***	**11.03**
3	**1**	**0**	**1**	**2**	**1**	**1**	**1**	**0.626**	**0.000**	**11,212**	**0.876**	**1.993***	**4.581**
4	1	0	1	2	2	1	1	0.817	0.007	17,031	0.515	1.059	2.117
5	1	0	1	1	1			0.624	0.000	1,010	0.833	1.947	4.986
6	1	0	1	1	2	1	2	0.854	0.014	17,851	0.620	1.255	2.437
7	**1**	**0**	**1**	**2**	**1**	**1**	**2**	**0.608**	**0.000**	**14,748**	**0.854**	**1.847***	**3.950**
8	1	0	1	2	2	1	2	0.918	0.041	28,435	0.541	1.083	2.121
9	1	0	2	2	1			0.649	0.000	1,730	0.764	1.783	3.753
10	**1**	**0**	**2**	**2**	**1**	**1**	**1**	**0.639**	**0.000**	**16,052**	**0.675**	**1.695***	**3.822**
11	1	0	2	2	2	1	2	0.941	0.031	22,719	0.467	0.987	2.006
12	1	0	2	1	2	1	2	0.866	0.028	11,244	0.492	1.061	2.177
13	1	0	2	1	2	1	1	0.829	0.001	15,855	0.504	1.087	2.181
14	1	0	2	1	1			0.604	0.000	2,590	0.853	1.961	4.796
15	**1**	**0**	**2**	**2**	**1**	**1**	**2**	**0.605**	**0.000**	**16,276**	**0.622**	**1.537***	**3.442**
16	1	1		1	2			0.930	0.035	494	0.707	1.167	2.994
17	1	1			1			0.641	0.023	141	6.398	24.368	60.94
18	2	0	1	2	1			0.762	0.005	485	0.521	1.175	2.358
19	2	0	1	1	1			0.650	0.000	709	0.566	1.191	2.960
20	**2**	**0**	**1**	**2**	**1**		**1**	**0.635**	**0.000**	**16,666**	**0.813**	**1.719***	**3.724**
21	**2**	**0**	**2**	**2**	**1**		**1**	**0.682**	**0.000**	**21,806**	**0.712**	**1.571***	**3.181**
22	2	0	2	2	1			0.649	0.000	891	0.525	1.319	2.726
23	**2**	**0**	**2**	**2**	**1**		**2**	**0.645**	**0.000**	**17,994**	**0.826**	**1.807***	**3.801**
24	2	0	2		1		1	0.642	0.000	497	0.837	2.332	6.863
25	2	1		2	1			0.799	0.000	146	0.301	0.763	1.765
26	2	1		2	1	2		0.695	0.000	2,316	0.923	1.756	3.669
27	**3**	**0**		**2**	**1**	**2**	**1**	**0.676**	**0.000**	**6,196**	**1.033**	**2.201***	**4.673**
28	**3**	**0**		**2**	**1**	**2**	**2**	**0.675**	**0.000**	**5,404**	**1.406**	**3.193***	**7.409**
29	3	0		2	1			0.669	0.035	210	0.739	1.802	4.176

Table 5. Continued

R	IND	Indep	Bins					Descriptive statistics					
			TA	DIV	ROA	GDP pc	Int	AUC	p-val	N	25%	50 %	75%
30	**3**	**0**		**1**	**1**	**2**	**1**	**0.637**	**0.000**	**6,658**	**1.217**	**2.527***	**5.310**
31	3	0		2	1	1	1	0.631	0.000	4,235	0.800	1.844	4.391
32	4	0	1	2	2	2		0.945	0.008	4,167	0.888	2.095	5.459
33	4	0	1	2	1	1		0.632	0.000	880	0.574	1.680	5.356
34	4	0	2	2	2	1		0.929	0.010	1,214	0.414	1.347	3.346
35	4	0	2	2	1	1		0.613	0.000	1,466	0.244	0.976	3.075
36	4	1			1			0.610	0.007	751	0.457	1.343	3.203

Note: R-region, AUC - area under curve, LB / UB - 95 % lower/upper confidence interval bound under nonparametric specification, N – number of valid observations, 25 % /50 % / 75 % - 25th / median i.e. 50th / 75th percentile.

Source: own processing based on data from the Orbis database.