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

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Michal Karas

Brno University of Technology, Czech Republic

 orcid.org/0000-0001-8824-1594

Mária Režňáková

Brno University of Technology, Czech Republic

 orcid.org/0000-0002-7261-607X

The role of financial constraint factors in predicting SME default

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Abstract

Research background: SMEs face financial constraints in their development, which limits their access to external funds, tightens their investment possibilities, and limits their growth. Much research effort has been devoted to understanding the nature and sources of this phenomenon. In sharp contrast to this, very little has been said about the role of these factors in explaining the default probability of these types of enterprises. Understanding such interrelationships could help to adopt policies to alleviate the situation of constrained SMEs and lower their default rates.

Purpose of the article: This study analyses the role of financial constraint factors in SME defaults. This is done by utilising the financial constraint factors in a newly derived default prediction model. A comparison of the derived model and other SME default prediction models is carried out to assess the potential of financial constraints in the discrimination power of the model.

Methods: In this study, we use the Cox semiparametric model, while leaving the baseline hazard rate unspecified and employing macroeconomic variables as explanatory variables. The discrimination power was addressed in terms of the area under the curve (AUC), resulting in out-of-sample testing. The DeLong test was used to compare the AUC of the created and analysed models. The model was estimated on a set of over 213,731 SMEs from 28 counties, covering the period 2014–2019.

Findings & value added: It was found that adopting the financial constraint measures can explain the default of small and medium enterprises with high accuracy; however, they do not explain the default of micro enterprises.

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Introduction

Small and medium enterprises (SMEs) are considered the backbone of the global economy, as an engine for sustainable growth and stable employment, innovation, and hopefully an important route to recovery in the aftermath of the COVID pandemic. A better understanding of the factors that limit the growth of SMEs or are related to their default could help in adopting a more efficient policy and support the recovery of the economy. The nature of the problem is that SMEs are considered as riskier clients by credit providers and that SMEs face limited access to finance, which further makes them highly vulnerable in times of environmental change. Credit providers often adopt the same measures for credit application of SMEs and large businesses, and predict debt repayment ability. Unlike large businesses, they must face financial constraints, which impact their capital structure and investment decisions, and influence business performance, which means that the same measures cannot be effectively adopted for SMEs and large businesses. Financial constraints limit firms' optimal investment and growth opportunities and consequently their competitiveness from a long-term perspective. Such constraints increase the vulnerability of SMEs in times of economic downturns. Limited competitiveness could impact firm survival or, rather, its default probability and its manifestation in a firm's financial statement, compared to large businesses.

This constraint originates partly from firm-specific factors (such as limited availability of internal funds) and partly from external factors which can alleviate or aggravate the situation (such as the level of stock market development, legal system efficiency, etc.). Financial constraints can drive the financial difficulties of SMEs and, consequently, the risk of their default.

Considering the amount of attention paid over recent decades to understand the default of large and listed businesses, and the default of SMEs, makes the situation even worse, as the research on SME defaults could be viewed as very limited compared to research on large business defaults. The issue is further complicated by the fact that the majority of default prediction models rely on employing idiosyncratic factors. Prior research has shown that environmental factors also play a significant role in default prediction. Above that, the role of financial constraint factors in the risk of default in general has been little investigated. However, it can be argued that the factors driving the default of SMEs are different from the factors driving the default of large businesses. The main question behind this research is: what role do the financial constraints factors play in the risk of default of SMEs? We use the firm-level manifestations of financial con-

straints (e.g., internal funds availability) and environmental factors, which alleviate or aggravate the situation of a constrained firm (e.g., level of financial market development or corruption level), and use them as explanatory variables of a default prediction model. To reach sufficient data variability, especially of environmental factors, a panel of countries, instead of a single country data, were analysed. To assess the influence of the created model, the results of the model accuracy were compared with the Altman and Sabato model results (both with original settings and re-estimated coefficients).

To the best of our knowledge, this context has not yet been addressed in the literature. This study aims to analyse the extent to which financial constraint factors can explain the risk of default for SMEs. For this purpose, we directly construct a default prediction model that incorporates factors that are considered internal or external manifestations of the financial constraint situation. The factors were initially analysed on a univariate basis, and a multivariate model was derived. The analysed financial constraint factors served as explanatory variables and were utilised by the Cox proportional hazard model, which allows us to capture the multiperiod nature of the analysed phenomenon. The discrimination power was addressed in terms of the area under the curve (AUC), resulting in out-of-sample testing.

The remainder of this paper is organised as follows. A review of the literature provides a discussion of financially constrained factors and their potential influence on firm default probability and ways of utilising such factors while predicting default. The next section describes the methodology adopted, research sample, and the research question. The results and discussion section presents the outcomes of the research, and the conclusion section suggests several issues to be addressed in future research.

Literature review

Financial constraint factors

The financial constraint issue was first addressed by Fazzari *et al.* (1988), who showed that the investment decisions of financially constrained firms are more sensitive to the availability of internal cash flows, than they are in the case of unconstrained firms. The definition of financially constrained business could be found in Beck *et al.* (2006), according whom, a business is considered as being financially constrained, “*if a windfall increase in the supply of internal funds results in a higher level of investment spending*”. The consequences of the financially constrained situation from the business

financial perspective are highly negative, because such businesses are more dependent on external funds and thus, more sensitive to fluctuations in credit markets (Jin *et al.*, 2018). The growth potential of such businesses is highly limited, as they have to rely on limited internal funds, which in turn constrains their ability to invest (Erdogan, 2018). In addition, access to external sources shapes, not only firm growth, but also the default (Musso & Schiavo, 2008).

The financial constraint issue is most often related to the situation of SMEs. The reason for this is twofold: first, the main source of external finance to SMEs is commercial banks; second, from the perspective of commercial banks, SMEs are perceived as riskier clients than large corporations (see North *et al.*, 2010, Dietsch & Petey, 2004; Saurina & Trucharte, 2004). Due to the dependency on bank credit financing (as noted by Beck *et al.*, 2008 or Stiglitz & Weiss, 1981), the vulnerability of SMEs is magnified in times of crisis, whereas survival often relies on the extension of additional trade credit and/or relaxed payment terms by their unconstrained creditors (as shown by McGuinness *et al.*, 2018).

The question is: what factors affect the level of financial constraints that SMEs must face in their development? There is a consensus that the factors are both internal and external. The internal factors are related to resource availability and strategic choices, while external factors are given by the carrying capacity of the environment or the level of competition (Eniola & Entebang, 2015).

Beck *et al.* (2006) investigated the determinants of the business's financial constraints, while the obstacles were perceived by the businesses themselves, where older, larger, and foreign-owned firms reported lower financing obstacles. Beck *et al.* (2006) further addressed the extent to which financial and economic development helps alleviate financing obstacles, concluding that the most important characteristics explaining cross-country differences in firms' financing obstacles are levels of financial intermediary development, stock market development, legal system efficiency, and higher GDP per capita. The level of financial development was measured as claims of financial institutions in the private sector as a share of GDP, while stock market development was evaluated in terms of the total volume traded on stock exchanges relative to GDP. Ullah (2020) further analysed this issue and concluded that businesses in countries with higher levels of GDP per capita, stock market development, legal systems, property rights, and lower levels of corruption face lower levels of financial constraints.

The level to which businesses experience financial constraints further depends on internal factors, such as liquidity, which serves as an approximation of the availability of internal funds (Fauceglia, 2015), business age,

ownership structure, and size, where the smallest firms are most adversely affected by these obstacles (Beck *et al.*, 2006). Firm growth constraints also differ between privatised firms and originally private firms, where private firms experience significantly higher financial corruption and legal obstacles than privatised firms (D'Souza *et al.*, 2017). Additional factors are asset tangibility, where businesses with more tangible assets have less difficulty obtaining loans through mortgage financing (Jin *et al.*, 2018). There is also evidence that the investment activities of firms with high pay-out ratios are more sensitive to internal cash flow availability (Cleary, 2006).

Potential link between financial constraints and firms' default probability

Limited access to loan financing, in the case of financially constrained businesses, causes such a business to not exhibit a typical sign of financially distressed business, signs like a high proportion of debt in capital structure, which is often mentioned in the case of distressed businesses (see Zavgren, 1985; Stiglitz, 1972; Shumway, 2001). However, limited access to external sources means that the business cannot follow optimal investment and growth trajectories (Carreira & Silva, 2010), which limits the business competitiveness from a long-term perspective and the probability of survival.

The reliance on internal sources of finance, typical for constrained businesses (Erdogan, 2018), results in the need to cut dividends. Firms cutting dividends can also exhibit, among others, higher debt ratios, lower interest coverage, and lower net income margins (Cleary, 2006). In other words, firms that cut dividends also exhibit signs of financially distressed businesses. The availability of internal sources is often approximated through liquidity factors (Fauceglia, 2015). Low liquidity also means a lack of capital needed to manage the business and problems in meeting shorter-term obligations, which is one of the most common causes of financial distress (Chen & Hsiao, 2008).

Predicting the default of SMEs based on a combination of firm-specific and external environmental factors

The default prediction models commonly employ firm-specific variables (such as financial ratios) to assess the probability of default by utilising different classification methods (e.g., Altman, 1968, 1983; Ohlson, 1980; Zmijewski, 1984). Some authors argue that financial ratios, based on accounting information, report past business performance. Hence, they support the use of market data and the structural model approach, which is

capable of taking advantage of forward-looking information carried by market prices and investor expectations about future development (see e.g., Trujillo-Ponce *et al.*, 2014). From the perspective of SMEs, the structural model approach seems to be practically inapplicable, as most SMEs do not meet the requirement to enter stock exchanges; thus, market data are not available in their case.

A substantial amount of work has been done to explore the usefulness of macroeconomic factors in combination with firm-specific factors in predicting default. Factors such as interest rates (Christidis & Gregory, 2010; Tinoco & Wilson, 2013; Holmes *et al.*, 2010; Nouri & Soltani, 2016; Hillegeist *et al.*, 2004), exchange rate (Holmes *et al.*, 2010 or Nam *et al.*, 2008), inflation rate (Christidis & Gregory, 2010; Nouri & Soltani, 2016; Tinoco & Wilson, 2013), employment rate (Holmes *et al.*, 2010) and GDP annual growth rate (Simons & Rolwes, 2009; or Nouri & Soltani, 2016). Some studies that addressed this issue in the context of SMEs, such as Gupta *et al.* (2015), used the hazard model to model the probability of bankruptcy of SMEs, while using the logarithm of company age, insolvency rate, and industry “the weight of evidence,” variables to control for both default time and macroeconomic conditions. There have been several attempts to utilise external factors in default prediction; however, none of these were primarily considered as factors representing financial constraint issues. The only exception found in the literature was the study by Zhang *et al.* (2019), who first addressed, with respect to Chinese business, the relationship between corruption level and firm likelihood of survival.

Research methodology

Research sample

The sample consists of 213,731 SMEs from EU–28 countries covering the period 2014–2019. Among these, 23,731 went legally bankrupt within one year. Financial statements, for the year preceding bankruptcy, were used for the analysis. Data at the firm level were drawn from the Amadeus database, while data on macroeconomic variables were obtained from the EUROSTAT and the Transparency International databases (corruption level data). The number of observations per SME segment and per year is shown in Table 1. The need to focus on a panel of countries lies in two facts. First, there are significant differences in GDP per capita, value traded on stock exchange, corruption, and other proxies of environmental level financial constraint factors among EU 28 countries. Second, because of such hetero-

generality, a focus on such a panel of countries is expected to result in high variability of the observation and better possibilities of estimating the effect of the analysed factors. In this study, the EU definition of SMEs given by the EU recommendation 2003/361 was adopted. We worked with the term default definition in terms of a judicial decision declaring a company insolvent. The sample was randomly divided into a learning part (70% of all observations) and a testing part (30%), the holdout sample.

The control for industry effect is managed by adding an industry dummy variable (“IND”). Primarily, the NACE Rev. 2 main section industry classification, which is a European industry classification, was employed. There are 21 main sections under this classification. From the modelling perspective, this is too smooth differentiation, which is why the industries were grouped into four industry groups (a procedure similar to that adopted by Chava & Jarrow, 2004).

The preliminary results of the data analysis showed that several variables clearly exhibit extreme outlier values; the variables under analysis were winsorised at the 1 or 99 percentile level to ensure that the results or the estimated parameters were not negatively influenced by this effect. Usually, the literature on credit risk or hazard models (e.g., Shumway, 2001; Altman *et al.*, 2010; Gupta *et al.*, 2015) tends to exclude financial businesses from the sample, although there are studies that have aimed to derive a model that also includes financial businesses (e.g., Chava & Jarrow, 2004).

Methods

The Cox semiparametric proportional model approach was employed to derive the model, it was first adopted by Lando (1998), who was the first to model default using the Cox model. Shumway (2001), Chava and Jarrow (2004), and Berent *et al.* (2017) demonstrated the superiority of the hazard model approach in predicting business defaults over other approaches. Berent *et al.* (2017) highlighted the need for treating the default as a multiperiod process, which advocates the employment of Cox’s hazard model approach. According to Gupta *et al.* (2015), the discrete hazard modelling technique is well suited for analysing bankruptcy data as it consists of binary dependent variables and exhibits both, time-series and cross-sectional characteristics.

The model was originally developed by Cox (1972), with the general formula of the Cox model as follows:

$$\lambda(t; z) = \exp(z\beta) \lambda_0(t) \quad (1)$$

The main disadvantage of the Cox model is the relationship between the distribution of failure time (t) and variables z . β is the parameter vector and $\lambda_0(t)$ is the baseline hazard function for the standard set of conditions $z=0$, while $\lambda_0(t)$ might be replaced by any known function $h(z\beta)$ (Cox, 1972). The Cox proportional hazard model can also be expressed in the logged form (Landau & Everitt, 2004):

$$\ln[h(t)] = \ln[h_0(t)] + \beta_1 X_1 \dots + \beta_q X_q \quad (2)$$

where: β_1, \dots, β_q are regression coefficients; X_1, \dots, X_q are the model's explanatory variables; $h_0(t)$ is the baseline hazard function; “*being the hazard rate for individuals with all explanatory variables equal to zero, this function is left unspecified. The estimated cumulative baseline hazard can be estimated from sample data and is often useful*” (Landau & Everitt, 2004).

The advantage of the Cox semiparametric hazard model is that its estimation is possible even when the baseline hazard function is left unspecified, which offers a considerable advantage when a reasonable assumption about the shape of the hazard cannot be made (see Cleves *et al.*, 2008, p. 129).

Generally, there are two main approaches to specification of the baseline hazard rate. The first is to use time dummies, as shown by Beck *et al.* (1998), and the second is to employ macroeconomic variables, as suggested by Nam *et al.* (2008), who argue that indirect measures, such as time dummies, are less effective in capturing time-varying macro dependencies. Gupta *et al.* (2015) followed the suggestion of Nam *et al.* (2008) and constructed the baseline hazard rate, including the insolvency risk variable, according to El Kalak and Hudson (2016), to accommodate the macroeconomic impact the firm has to face, which distorts the idea of the baseline hazard rate.

In this study, we use the Cox semiparametric model, while leaving the baseline hazard rate unspecified and employ macroeconomic variables as explanatory variables. Therefore, this approach is different from other studies (e.g., Nam *et al.*, 2008). The main difference is that with this approach, the macroeconomic variables influence the hazard rate through a shift of baseline hazard (as other explanatory variables) to control for cross-country differences.

The extent to which financial constraint factors are related to the probability of SME default is addressed in terms of discrimination power, measured in terms of AUC. For this purpose, a default prediction model was derived, while its uniqueness lies in fact, which mainly employs factors that are hypothesised as measures of financial constraints. There is no specific

cut-off value for AUC which would be distinguished as a weak and strong discrimination power. There is, however, a general rule (e.g., as mentioned by Hosmer and Lemeshow, 2000, p. 162), which can be summarized as follows: $AUC = 0.5$ suggests no discrimination power, $0.7 < AUC < 0.8$ suggests acceptable discrimination, $0.8 < AUC < 0.9$ suggests excellent discrimination, and $AUC > 0.9$ is considered as outstanding discrimination. As the AUC is suggested to treat relatively, a comparison with the selected default prediction model for SMEs was conducted.

The initial step in deriving the model was testing the differences in the survival curves of different subgroups in the sample by employing the log-rank test. Subgroups are commonly distinguished using dummy variables. Special focus was paid to differentiate between micro, small, and medium enterprises, whereas the prior expectation predicts a different survival probability (as noted by Gupta *et al.*, 2015 or El Kalak & Hudson, 2016), above that smaller firms tend to face a higher level of financial constraints (see e.g., the study of Devereux & Schiantarelli, 1990; Beck *et al.*, 2006; Ullah, 2020; D'Souza *et al.*, 2017; or Musso & Schiavo, 2008). To meet this assumption, the model will be estimated for each of the groups separately, as this seems to be the most flexible approach for dealing with this issue.

The next step in creating the model lies in the initial discrimination analysis, under which a univariate model is estimated for each of the analysed variables while meeting the expected sign of the estimated check along with the estimate significance. The univariate model was derived using the same methodology as the final multivariate model, that is, the Cox proportional hazard model. However, in the case of the univariate procedure, the model is derived for each of the analysed variables separately. Such a procedure is commonly employed in the process of selecting variables of default prediction models (see e.g., Brezigar-Masten & Masten, 2012; El Kalak & Hudson, 2016; Altman *et al.*, 2010; Gupta *et al.*, 2015; Nam *et al.*, 2008).

After excluding non-significant variables or variables that do not meet the expected signs, a multivariate model might be estimated. In line with Balcean and Ooghe (2006), who stressed that the logit models are highly sensitive to the presence of multicollinearity phenomenon, it might be expected that Cox hazard models could be also sensitive to such phenomenon presence, the multicollinearity check has to be done prior the multivariate model estimation. For this purpose, Pearson's correlation coefficient and variance inflation factor procedure was conducted. The final multivariate model was derived in a stepwise manner (forward selection).

Once the model is created, out-of-sample testing may be conducted. The AUC methodology was chosen as a suitable measure of model discrimination power, as its outcome was not based on the current setting of the model cut-off score. The AUC values should be assessed in an absolute manner (based on the general rule mentioned by Hosmer & Lemeshow, 2000) and in a relative manner, that is, compared with AUC values reached by a selected SME default prediction model. For this purpose, the model of Altman and Sabato (2007) was selected, as it is specially derived for SMEs and can be applied to the analysed sample. The model is applied to the holdout samples in its original setting (specific value of coefficients) and in re-estimated form, where the re-estimation is performed on the learning sample on which the created model is derived. Estimated AUC values are compared using the methodology of DeLong *et al.* (1988), which assesses the significance of the difference between two AUC values. The Altman and Sabato (2007) model version with unlogged predictors was employed, and the model takes the following form:

$$\begin{aligned} \log PD / (1 - PD) = & 4.28 + 0.18 \cdot EBITDA/TA - 0.01 \cdot CL/E + \\ & + 0.08 \cdot RE/TA + 0.02 \cdot C/TA + \\ & + 0.19 \cdot EBITDA/IE \end{aligned} \quad (3)$$

where:

PD	the probability of default, while the modelled probability is the probability that a business will default within one year,
EBITDA	Earnings before interest taxes, depreciation, and amortization,
TA	total assets,
CL	short-term debt,
E	book value of equity,
RE	retained earnings,
C	cash,
IE	interest expenses.

For comparison purposes, the coefficients of the Altman and Sabato (2007) model were re-estimated on the learning sample to ensure that the coefficient setting was not adversely affected by the influence of different periods or business environment conditions. The original methodology was used to re-estimate the model, that is, the logistic regression procedure. The model with re-estimated coefficients takes the following form:

$$\begin{aligned} \frac{\log PD}{1 - PD} = & 2.425 + 2.048 \cdot \frac{EBITDA}{TA} + \\ & + 0.0000044 \cdot CL/E + 0.629 \cdot RE/TA + 1.992 \cdot C/TA + 0.0000002 \cdot \\ & \cdot EBITDA/IE \end{aligned} \quad (4)$$

Model potential variables

From a general perspective, lower financial constraints or easier access to external finance lower the probability of a firm exiting the market (as shown by Musso & Schiavo, 2008), and financial constraints are expected to negatively influence the firm's survival or increase the risk of default.

The expected relationship between the selected signs and the risk of default is as follows: first, external factors. Beck *et al.* (2006) showed that countries with higher levels of financial intermediary development and stock market development report lower financing obstacles, and the same applies to countries with higher economic development (e.g., Ullah, 2020). The variables of *private credit* and *value traded* are used as proxies for the level of financial intermediary development in each country, while *GDP per capita* is a proxy for the economic development of countries. A potential drawback of *private credit* measures is that it only captures the actual volume of credit from financial institutions, while excluding non-bank credit such as debt financing on securities markets (e.g., Fauceglia, 2015). Higher levels of *private credit*, *traded*, and *GDP per capita* are expected to lower the probability of default. However, the negative influence of financial constraints on the business is magnified by *corruption* and lower *law reinforcement* levels (e.g., Beck *et al.*, 2005).

Second, the firm-level factor, the problem with financial constraints is that it is directly unobservable; thus, the literature often relies on proxies such as size, age, or liquidity. In this section, we present firm-specific proxies for financial constraints that were subjected to analysis.

The firm's liquidity serves as a proxy for financing difficulties and is considered a valid approximation of credit constraints (see Fauceglia, 2015). However, the relationship between liquidity and default risk is not straightforward, as shown by Zhang *et al.* (2020): small businesses which are financially constrained and hold much cash are more likely to default in the future, whereas the cash is used "a buffer to absorb future losses" (Zhang *et al.*, 2020).

The factors of *leverage and repaying ability* represent on the one hand, factors influencing financial risk (e.g., Tinoco & Wilson, 2013) and on the other hand, a high leverage or/and poor repaying ability further mean a clear obstacle for a business to obtain additional external funds as the risk for a potential creditor is high. Thus, these factors are considered as factors of financial constraints and default risk and have been adopted in various studies (e.g., Berman & Héricourt, 2010; Fauceglia, 2015; Musso & Schiavo, 2008).

Regarding the *sales growth* factor, growth in sales generates higher operating cash flow and, thus, the business becomes more financially stable through this higher internal fund generation ability. Based on this, a higher growth rate could be related to lower financial constraints. Furthermore, sales growth is often regarded as an indicator of a firm's long-term financial viability (e.g. D'Souza *et al.*, 2017).

There is a body of literature regarding a firm's *size*, *age*, and *exporting orientation* as factors of financial constraints, whereas a consensus prevails that younger, smaller, and export-oriented firms are considered more constrained (see Devereux & Schiantarelli, 1990; Beck *et al.*, 2006; Ullah, 2020; D'Souza *et al.*, 2017 or Musso & Schiavo, 2008). By contrast, younger firms grow faster (Evans, 1987; Dunne *et al.*, 1988).

The extent to which a firm's growth is depending more on external financing than internal sources is addressed as *the firm's reliance on external capital*. This measure is often adopted in studies on financial constraints (see Kroszner *et al.*, 2007; Jin *et al.*, 2018). The high reliance on external financing could be viewed as a consequence of the insufficiency of internal sources for investment activities, which further implies a low *dividend pay-out ratio*. As shown by many studies, financially constrained firms choose lower dividend pay-out ratios (see Cleary, 2006; Musso & Schiavo, 2008; Fazzari *et al.*, 1988; Gilchrist & Himmelberg, 1995), while the high dividend pay-out ratio is considered a sign of the absence of financial constraints (Musso & Schiavo, 2008).

Carpenter and Petersen (2002) predicted that the growth of a small business facing constraints depending on its internal finance could be affected by a "leverage effect" when the firm's access to debt depends on collateral. We have added *an asset tangibility* indicator as a proxy of collateral that the firm could offer to control for the "leverage effect" which potentially alleviates financial constraints.

The situation of a stand-alone firm could be much different from the situation of a firm which is part of an alliance (group of firms), as a part of the alliance could compensate, at the firm level, the consequences of market imperfections (such as financial constraints) and ease access to finance (Ellouze & Mnasri, 2020).

The list of analysed variables along with the adopted definition is shown in Table 2. The expected sign is based on the assumption that the increase in a given indicator value is related to the increase in the default probability for which the (+) sign is assigned, and in the opposite situation, that is, the factor increase is assumed to lower the default risk, the (-) sign is assigned.

Results and discussion

The results of the log-rank test are presented in Table 3, which assesses the significance of the categorical variables. Next, the result of initial discrimination is shown in Table 4, presenting the results of univariate estimates of every variable. The most important results of multivariate model estimates are presented in Table 5, whereas the results of assessing the discrimination power of the financial constraint factors in predicting default are shown in Table 6.

The log-rank test results ($\chi^2=114,569.7$; $df=2$; $p \text{ value}=0.0000$) confirm that the survival curves for micro-, small-, and medium-sized enterprises significantly differ, which is in line with expectations (see Gupta *et al.*, 2015; or El Kalak & Hudson, 2016). This led us to derive the model for micro-, small-, and medium-sized enterprises separately, while the aim of doing this is to better address the heterogeneity of the SME group.

The log-rank test procedure was conducted for the test of categorical variables under analysis (see Table 3 for results), namely the variables of *group membership (GM)*, *industry (IND)*, and *export orientation (Exp)*. The test results showed that both *group membership* and *export orientation* are significant variables from the perspective of default risk throughout the SME segment, thus being incorporated into the model.

The next step was the derivation of a univariate model for each of the analysed variables; details of the estimation are listed in Table 4. The variables *CA/TA*, *TL/TA*, *E/TL*, *age*, and *value added* were excluded from the set of analysed variables because they were either not significant or did not meet the expected sign.

Furthermore, the initial results showed that the *corruption (Corr)* and *law* variables exhibited high VIF values (specifically, Corruption VIF = 22.740, Law VIF = 17.338), with a Pearson correlation coefficient of 0.932 ($p=0.0000$). After comparing the Wald statistics of both indicators, they reached comparable values; however, the *corruption* indicator is more frequently mentioned in the literature, thus remaining for further analysis. After excluding the *law* indicator, none of the variables exhibited a VIF exceeding 4 or 10, so the multicollinearity presence was regarded as non-significant and the multivariate model could be estimated.

Details of the estimated multivariate model are shown in Table 5. At the firm level, financial constraint measures of *liquidity (CA/CL)*, *sales growth (S(gr.))*, *size (in terms of log of sales value)*, *reliance on external financing (REF)*, *dividend pay-out ratio (Div./EBIT)* and *group membership (GM)*, are significantly related to the probability of SME default, regardless of the given SME segment; that is, these indicators apply for micro-, small-, and

medium-sized enterprises. The dependency of SMEs on external sources (especially trade credit) is in line with expectations (McGuinness *et al.*, 2018), while the same applies for the significance of the effect shared by all segments of SMEs (Gupta *et al.*, 2015). However, the significance of the liquidity factor in the case of micro enterprises contradicts expectations (Gupta *et al.*, 2015).

The dividend pay-out ratio (Div./EBIT) play is significantly related to the default, regardless of the given SME segment. In the meaning suggested by Fazzari *et al.* (1988) and Musso Schiavo (2008), a reason for a firm to choose a low dividend payment could be to save internal sources for profitable investment opportunities to maximise profit, while perceiving the dividend pay-out as a residual decision. However, this does not explain firms' default behaviour. Cleary (2006) mentioned that firms cutting dividends can also exhibit, among others, higher debt ratios, lower interest coverage, and lower net income margins.

The rest of the firm-level financial constraint measures are SME segment-specific; for example, the factor of financial debt repaying ability (FD/CF), plays a significant role in the case of micro businesses, while it is not significant in the case of small or medium businesses.

Environmental factors are considered a measure of financial constraints. The level of financial intermediaries' development in the economy (*private credit* indicator) and the level of corruption are significantly related to the default probability of all SME segments. A unique change in the *private credit* indicator seems to affect all SME segments with the same magnitude. The level of corruption, as a factor of financial constraint, also affects all segments of SMEs; however, its unique change has a different impact on different SME segments. In the case of small and medium-sized enterprises, the impact is nearly twice as high as in the case of micro enterprises (B for micro enterprises = - 0.026, while B for small enterprises = -0.059, and B for medium enterprises = -0.064). The larger the enterprise, the more beneficial it is from the perspective of its survival, and the lower the corruption level. According to Beck *et al.* (2005), the smaller the business, the more significant the effect of corruption, and even the default probability is magnified. The first study to link corruption level with firm survival is the study of Zhang *et al.* (2019), according to whom (with respect to Chinese private companies, not limited to SMEs), corruption positively affects the firm likelihood of survival. Our results contradict this conclusion with respect to SMEs.

There is a consensus in the literature that a decrease in a country's GDP level triggers firms' defaults, whereas SMEs are considered especially vulnerable to such changes (Simons & Rolwes, 2009). We found that the level

of GDP capital also plays a significant role in the firm's default probability, however, only in the case of micro and small enterprises, while not affecting significantly the default risk of medium enterprises, which contradicts the general expectation.

Moreover, the industry effect (*IND*) plays a significant role in assessing the default risk of micro and small enterprises; however, it does not play a significant role in the case of a medium-sized enterprise segment. In the case of manufacturing and mineral industries (*IND 2*), the default risk faced by enterprises is higher than in the case of miscellaneous industries (*IND 1*).

The discrimination power of the created model was tested on both learning and testing samples. The testing was performed in terms of estimating the AUC value, which is a common approach in the case of the prediction model. The results were also compared to the results of testing the Altman and Sabato (2007) model, which is an SME default prediction model; that is, the results of testing this model will be utilised for benchmark purposes in this study. The discrimination power of the created model could be regarded in terms of Hosmer and Lemeshow (2000), as acceptable in the small-and medium-sized enterprises (AUC values of 0.853 and 0.793, respectively) which could be interpreted as a significant effect. We can conclude that the financial constraint factors play an important role in predicting the default probability of this size of enterprises. However, this effect is very weak for micro enterprises (AUC = 0.502).

For benchmarking purposes, the results were compared with the results of Altman and Sabato's (2007) model, which represents an accurate tool for predicting SMEs' default. It is worth mentioning that the model of Sabato (2007) considered only firm-level factors, unlike the created model, which also accounts for external environmental factors (for details, see Table 6).

The differences in the AUC values of the selected models were subjected to the DeLong *et al.* (1988) test, which assesses the significance of the difference between two AUC values (details are presented in Table 7). The Altman and Sabato (2007) model in the original setting reached AUC values from 0.739 to 0.764, while the AUC of our model ranged from 0.502 (for micro enterprises) to 0.853 (for small enterprises). In the case of small and enterprises, our model significantly outperforms the Altman and Sabato (2007) model, while in the case of small enterprises, the result holds even after the coefficients of the Altman and Sabato models are re-estimated. In the case of micro enterprises, the Altman and Sabato (2007) model outperforms our model.

Conclusions

Despite the attention paid over recent years to the topic of financial constraints faced by SMEs, very limited research has been conducted to analyse the role of these factors in the probability of SME default. Understanding such interrelationships could help to adopt policies to alleviate the situation of constrained SMEs and lower their default rates. Financial constraints are the result of market imperfection and therefore, limit the access to external funds, limiting not only the growth potential, but as shown in this paper, also negatively influencing the survival likelihood of SMEs.

At the firm level, the limited internal funds availability approximated by liquidity, reliance on external capital, and sales growth, size, and dividend pay-out ratio significantly affect the default probability of all segments of SMEs. On the contrary, there are some segment-specific ratios, such as financial debt repaying ability, which is specific for micro enterprises or leverage (in terms of trade credit over total assets ratio), which is specific for small and medium enterprises. At the environmental level, the level of corruption and level of financial intermediary development significantly influence the default probability of all segments of SMEs, while the level of economic development affects only the default probability of small enterprises.

Model utilizing the financial constraints measure, along with the repayment ability measures, can explain the difference between default and non-default SME with relatively high accuracy, especially in the case of small and medium enterprises. Our results show that models incorporating solely accounting ratios are insufficient for effective default prediction, while the need of incorporating other enterprise-level information and environment factors is clearly highlighted.

The results suggest that in the case of small and medium businesses, assessing the default probability from a wider context covering the financial constraint perspective could better explain the default probability of small and medium enterprises, while in the case of micro enterprises, the potential contribution seems to be limited.

As in any research, these results also have limitations. There are two main issues that deserve further research. First, the possible interaction between variables should be further investigated. The preliminary results showed that the variables describing the capital structure (e.g., TL/TA) interact with size factors (log of sales). Adding such interactions can significantly increase the AUC. Second, although the micro enterprises are considered as a segment, which experiences the financial constraints most significantly, the modelled financial constrained factors did not explain their

default probability. The link between default probability and financial constraint factors is less obvious than in the case of small or medium businesses.

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Annex

Table 1. Number of observations per segment in each analysed year

Segment/Year	2015	2016	2017	2018	2019	Total
Medium	123	1,972	7,356	84,545	5,171	99,167
Small	37	4,063	6,367	17,322	566	28,355
Micro	49	2,223	7,392	72,936	3,609	86,209
Total	209	8,258	21,115	174,803	9,346	213,731

Source: author's calculation based on the Amadeus database.

Table 2. Indicators commonly employed in studies on firm's constraints

Factor	Sign.	Description	Abbrev.
Private Credit	(-)	Credit volume of banks and other financial institutions extended to the domestic sector / GDP	PC
Value Traded	(-)	Total volume traded on stock exchanges / GDP	VT
Corruption	(-)	Corruption Perception Index by Transparency International (if highly corrupt = 0. If very clean = 100)	Corr
Law	(-)	Rule of Law from World Bank's WGI	Law
GDP per capita [in thousand USD]	(-)	Gross domestic product / total population	GDP pc
Profitability	(-)	EBITDA / total assets	EBITDA/TA
Liquidity	(-)	Current assets / total assets; Current assets / current liabilities	C/TA, CA/CL
Sales growth	(-)	The difference of log [sales (t-1)] and log [sales (t-3)]	S(gr.)
Leverage and repaying ability	(+)	Total debt / total assets; equity / total liabilities; trade credit / total assets; financial debt / operating cash flow	TL/TA, E/TL* TC/TA, FD/CF
Age	(-)	Firm actual age (log of the number of days from incorporation until the end of last year of statement)	age
Size	(-)	Log of the firm's sales at the end of the year (t - 1).	size
Export orientation	(-)	Dummy variable (1 if export revenue/operating revenues > 0.5; 0 otherwise)	Exp
Reliance on external financing	(+)	(Capital expenditures - operating cash flow) / capital expenditures	REF
Asset tangibility	(-)	Tangible assets / total assets	AT
Dividend pay-out ratio	(-)	Dividends / EBIT	Div/EBIT
Group membership	(-)	Dummy variable (1 if the firm is part of corporate group; 0 otherwise)	GM

*In the case of E/TL, a negative relationship was expected.

Source: author's compilation based on the literature review.

Table 3. Log-rank test results for GM, Exp, and IND variables

Variable/segment/statistics	Micro			Small			Medium		
	χ^2	df	p-val.	χ^2	df	p-val.	χ^2	df	p-val.
Exp.	103.667	1	0.000**	57.085	1	0.000**	20.844	1	0.000**
GM	1,994.151	1	0.000**	2,070.345	1	0.000**	321.126	1	0.000**
IND	111.929	2	0.000**	99.355	2	0.000**	10.094	2	0.006**

**significant at the 1% level, *significant at the 5% level.

Source: author's calculation based on the Amadeus database.

Table 4. Univariate model estimation results

Variable/segment/statistics	Sign	Micro		Small		Medium	
		B	p-val.	B	p-val.	B	p-val.
EBITDA/TA	(-)	-0.002	0.010**	-0.357	0.000**	-0.103	0.000**
CA/TA	(-)	-0.561	0.000**	-1.256	0.000**	0.500	0.059
CA/CL	(-)	-0.039	0.000**	-0.395	0.000**	-1.495	0.000**
S(gr.)	(-)	-0.202	0.000**	-0.161	0.009**	-0.719	0.000**
TL/TA	(+)	-0.007	0.392	0.833	0.000**	0.823	0.000**
E/TL	(-)	-0.006	0.000**	0.010	0.000**	0.010	0.000**
TC/TA	(+)	0.266	0.000**	1.64	0.000**	2.854	0.000**
FD/CF	(+)	0.002	0.001**	0.010	0.000**	0.011	0.000**
age	(-)	3.201	0.000**	13.722	0.000**	11.007	0.000**
size	(-)	-0.309	0.000**	-2.011	0.000**	-2.151	0.000**
Exp	(-)	-1.248	0.000**	-2.625	0.000**	-1.462	0.012*
REF	(+)	0.019	0.000**	0.049	0.000**	0.064	0.000**
AT	(-)	-0.082	0.029*	1.238	0.000**	-0.435	0.121
Div./EBIT	(-)	-0.033	0.000**	-0.115	0.000**	-0.064	0.001**
GM	(-)	-0.503	0.000**	-1.264	0.000**	-1.175	0.000**
PC	(-)	-0.003	0.000**	-0.004	0.000**	-0.0001	0.914
VT	(-)	-0.00002	0.973	0.008	0.000**	0.007	0.010**
Law	(-)	-0.029	0.000**	-0.065	0.000**	-0.077	0.000**
Corr	(-)	-0.098	0.000**	-0.111	0.000**	-0.030	0.000**
GDP pc	(-)	-0.025	0.000**	-0.081	0.000**	-0.095	0.000**

**significant at 1% level, *significant at 5% level.

Source: author's calculation based on the Amadeus, Eurostat, and Transparency International databases.

Table 5. Estimation of model coefficients

Variable/segment/statistics	Sign	Micro		Small		Medium	
		B	p-val.	B	p-val.	B	p-val.
CA/CL	(-)	-0.018	0.000**	-0.088	0.000**	-0.647	0.000**
S(gr.)	(-)	0.111	0.000**	0.151	0.001**	-0.318	0.012*
TC/TA ^a	(+)	-	-	0.290	0.001**	1.275	0.000**
FD/CF ^a	(+)	-0.002	0.000**	-	-	-	-
size	(-)	-0.378	0.000**	-1.659	0.000**	-1.503	0.000**
Exp ^a	(-)	0.740	0.000**	1.568	0.027*	-	-
REF	(+)	0.011	0.000**	0.027	0.000**	0.051	0.000**
Div./EBIT	(-)	-0.016	0.000**	-0.023	0.018*	-0.064	0.002**
GM	(-)	0.424	0.000**	0.796	0.000**	0.620	0.000**
PC	(-)	-0.004	0.000**	-0.006	0.000**	-0.004	0.004**
Corr	(-)	-0.026	0.000**	-0.059	0.000**	-0.064	0.000**
GDP pc ^a	(-)	0.013	0.000**	0.029	0.000**	-	-
IND ^{a,b}	(-)	-	0.001**	-	0.016*	-	-
IND (=1) ^a	(-)	-0.057	0.001**	-0.128	0.004**	-	-
IND (=2) ^a	(-)	0.044	0.042*	-0.051	0.307	-	-

Note: a – Models were estimated for each of the subsamples separately; blank spaces mean that the variable did not enter the model for the given subsample. b – In case of dichotomous variables, the p-value is estimated for the variable, while the coefficient is estimated separately for each realisation of the value.

**significant at 1% level, *significant at 5% level

Source: author's calculation based on the Amadeus, Eurostat, and Transparency International databases.

Table 6. Results of model testing — test sample results

Model/segment / statistics	Micro			Small			Medium		
	AUC	SE ^a	95% CI ^b	AUC	SE ^a	95% CI ^b	AUC	SE ^a	95% CI ^b
Derived model	0.502	0.0078	0.489-0.516	0.853	0.00555	0.850-0.857	0.793	0.0146	0.790-0.797
AS orig.	0.739	0.00695	0.727-0.750	0.764	0.0059	0.760-0.768	0.749	0.0136	0.745-0.753
AS re_est.	0.743	0.00672	0.731-0.754	0.796	0.00566	0.792-0.800	0.805	0.0125	0.802-0.809

Note: a – standard error estimated based on the procedure of Delong et al. (1988), b – exact binomial confidence intervals, AUC – area under curve, AS orig. – Altman and Sabato (2007) model with original coefficient setting, AS re-rest – Altman and Sabato (2007) model with re-estimated (on the learning sample) coefficient setting, SE – standard error, CI – confidence interval.

Source: author's calculation based on the Amadeus, Eurostat, and Transparency International databases.

Table 7. Results of DeLong *et al.* (1988) test application

Model/segment/ statistics	AS orig.			AS re-est.		
	Micro	Small	Medium	Micro	Small	Medium
Difference between areas	0.236	0.0892	0.0449	0.24	0.0568	0.0121
SE ^c	0.00993	0.00777	0.0181	0.00982	0.00716	0.0154
z statistic	23.796	11.475	2.478	24.496	7.931	0.785
p-val.	P <	P <	P =	P <	P < 0.0001	P =
	0.0001	0.0001	0.0132	0.0001		0.4325

Note: c – standard error estimated based on the procedure of DeLong *et al.* (1988). AS orig. – Altman and Sabato (2007) model with original coefficient setting, AS re-est – Altman and Sabato (2007) model with re-estimated (on the learning sample) coefficient setting. SE – standard error.

Source: author's calculation based on the Amadeus, Eurostat, and Transparency International databases.