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The Hazard Model for European SMEs: Combining Accounting and Macroeconomic Variables

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Abstract

Predicting the default of small and medium-sized businesses (SMEs) using the hazard model approach represents an area relatively neglected by mainstream literature. On the one hand, SMEs are regarded as the backbone of the economy; on the other hand, their specific features pose a challenge to the modelling process. This issue is further complicated by the fact that many modern structural approaches to default modelling are simply unsuitable for SMEs due to their limited size. Therefore, researchers only rely on accounting, non-financial, or macroeconomic data. The gap is especially noticeable in several studies on SME default prediction that employ the hazard model approach, which models the probability of default with respect to the time factor. A better understanding of the factors driving SMEs' default might help in adopting policies that strengthen their competitiveness. The aim of this study is to introduce a hazard model for EU-28 SMEs and analyse the contribution of macroeconomic indicators and proxies of external financial obstacle factors. This model was derived using the Cox semiparametric proportional model, leaving the baseline hazard unspecified and employing macroeconomic variables as explanatory variables. By analysing a sample of 202,209 European SMEs over the period 2014–2019, the results indicated that factors of employment rate, personal cost per employee, and interest rate play significant roles in determining the survival of SMEs. Adding these macroeconomic variables significantly increased the area under curve values compared to the situation where only accounting variables were used.

Keywords: SMEs, corporate default, Cox model, hazard model, competitiveness, baseline hazard rate.
JEL Classification: C14, G17, G33

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1. INTRODUCTION

The current literature on the prediction of corporate default, especially the default of large businesses, is quite extensive, with two dominating approaches to the prediction of defaults: Altman's (1968) approach utilising accounting ratios and Merton's (1974) structural approach based on the employment of market-driven variables. Despite the extensive number of papers published on the prediction of corporate default, only a small fraction focus on the default of small and medium-sized businesses (SMEs). A better understanding of the factors that cause the default of SMEs could help them adopt appropriate financial decisions and preserve or even enhance their market competitiveness (Kliestik et al., 2020).

This study aims to derive a hazard model for European SMEs and analyse the contribution of added macroeconomic variables to the model. Unlike previous studies, the Cox proportional model (Cox, 1972) was employed, while the baseline hazard rate was left undefined and macroeconomic variables were employed as explanatory variables. This approach makes it possible to employ more than one macroeconomic indicator, as would be the case when such a variable is used to specify the baseline hazard rate. A further difference lies in the analysis of EU-28 data and the focus on the SME segment, as most hazard studies focus solely on national data (commonly the US and the UK) and few consider the SME segment rather than listed businesses.

2. THEORETICAL BACKGROUND

The specifics of SMEs pose serious challenges to credit risk modelling (Karas & Režňáková, 2021; Kramoliš & Dobeš, 2020; Dankiewicz et al., 2020), as highlighted by Filipe et al. (2016) who noted that other contemporary credit risk modelling approaches such as Merton's (1974) structural approach or the latest approach of modelling based on credit default swap (CDS) spreads (Trujillo-Ponce et al., 2013) could not be used for SMEs.

This is because Merton's approach requires daily stock price data to estimate the asset volatility of the company. At the same time, most European SMEs are small and do not satisfy the entry requirements of stock exchanges, and market data are simply not available.

Furthermore, the CDS spreads approach is not applicable to SMEs, as these businesses do not have CDS information and do not issue bonds, as their main funding sources are their own resources and bank debt (Filipe et al., 2016). From this perspective, accounting data are the main source of usable information. It is worth mentioning that the accounting-based approach is criticised for the historic nature of the information it uses as input and does not consider the volatility of a firm's assets when estimating the risk of default (Vassalou & Xing, 2004). In contrast, Agarwal & Taffler (2008) provide three arguments in favour of the accounting-based approach. According to their study, corporate distress is not a sudden event; there is a low probability that a firm with good profitability and a strong balance sheet will file for bankruptcy due to a sudden change in the economic environment. Furthermore, corporate failure is the culmination of several years of adverse performance and is generally recognised in the firm's accounting statements. Moreover, the double-entry system of accounting ensures that window-dressing accounts or changing accounting policies will have a minimal effect on a measure that combines different facets of accounting information in financial ratios.

From a general perspective, SMEs can be viewed as a rather specific segment of businesses. However, they play a highly significant role in the economy (Civelek et al., 2021; Ključnikov et al., 2021; Virglerova et al., 2021). Gupta et al. (2015), among others, point out that SMEs are considered the backbone of the global economy and are viewed as an important route to recovery in the aftermath of the global financial crisis of 2008–2009. De Moor et al. (2016) added that SMEs are regarded as an economy's engine for sustainable growth and stable employment. According to Eniola et al. (2015), 'the importance of SMEs in the evolution of the economy, reduction in poverty, increase in employment, output, innovation in technology, and boost in social position and standard is globally proven and acknowledged in emerging as well as in developed economies'. The importance of SMEs in the economy is underlined by their numbers. By 2015, regarding the EU-28's non-financial business, the vast majority (92.8%) of businesses employed fewer than 10 individuals. Conversely, just 0.2% of all enterprises had 250 or more employees and were therefore classified as large enterprises. Large businesses have greater weight in terms of value-added and work provided, as large businesses provided work to more than one third (33.7%) of the EU-28's non-financial business economy workforce and generated 43.5% of its value added (Key figures on Europe, 2018).

A review of the literature on predicting the default of SMEs shows that only a fraction of the studies focuses on default prediction issues in SMEs. However, there are several arguments highlighting the necessity of treating SME default risk specifically and separately from the risk related to large businesses (Virglerova et al., 2020). First, studies suggest that SMEs are more vulnerable to changes in economic conditions and financing and face more obstacles than larger and older businesses (Virglerova et al., 2021). According to Ullah (2019), financial constraints are the most significant obstacle that SMEs must face during their growth. The given level of constraints depends on the economic development of a given country (Gavurova et al., 2020). The more liquid the stock market, the more efficient the legal system, and the higher the GDP per capita, the lower the obstacles reported (Beck et al., 2006). Second, the importance of treating SME defaults separately from the defaults of large businesses was later accented by the change to the Basel regulatory framework (i.e., the Basel II Accord).

Edmister (1972) published the first study on default prediction in SMEs, although his study did not highlight the need to treat the SME segment separately. Altman & Sabato (2007) showed that deriving a default prediction model specifically for SMEs may result in significantly higher accuracy than that achieved using a generic model. Altman et al. (2010) later addressed this problem by exploring the importance of adding non-financial data while predicting SME distress. Goncalves et al. (2016) and Belas et al. (2018) addressed the importance of non-financial data in the credit risk of SMEs.

From the modelling perspective, there are several studies criticising the current approach, in which the significance of the predictors is proven for one period of time only as being static because the time factor is ignored. Grice & Dugan (2001) investigated Ohlson's (1980) and Zmijewski's (1984) models and concluded that the precision of both models degraded significantly when they were applied to different data samples. They postulated that the relationship between financial figures and bankruptcy might change over time.

Only a limited number of studies, such as those by Holmes et al. (2010), Gupta et al. (2015), El Kalak & Hudson (2016), and Gupta et al. (2018), have addressed the application of hazard models for SME default modelling. Gupta et al. (2015) argued that the SME segment is not homogenous, with huge diversity in terms of capital structure, company size, access to external finance, management style, and the number of employees. Gupta et al. (2015) further highlighted that heterogeneity has been neglected in empirical studies on SME credit risk. The authors applied the discrete-time duration-dependent hazard rate to a large sample of non-financial UK SMEs during the period 2000–2009 while adopting the European Union definition of SMEs.

Their model was separately developed for micro, small, and medium-sized businesses, while a comparison of the model's version results suggests that the segment of micro-businesses should be treated separately from the rest of the SME segment. Gupta et al. (2015) used the logarithm of company age, insolvency rate, and industry 'weight of evidence' variables to control the survival time and macroeconomic conditions. El Kalak & Hudson (2016) applied the same approach as Gupta et al. (2015) to a sample of SMEs in the USA during the period 1980–2013, when the Small Business Administration (SBA) was in operation. El Kalak & Hudson (2016) confirmed the conclusion reached by Gupta et al. (2015) regarding the necessity of treating micro-businesses separately from the rest of the SME segment due to different (i.e., lower) survival probabilities. However, El Kalak & Hudson (2016) also pointed out that Gupta et al.'s (2015) approach of utilising an insolvency rate variable as a baseline hazard rate distorts the baseline hazard idea.

3. RESEARCH OBJECTIVE, METHODOLOGY AND DATA

The sample consists of 202,209 SMEs from EU-28 countries, covering 2014–2019. Of these SMEs, 59,709 went legally bankrupt within one year, while financial statements from the pre-final period (a year prior to bankruptcy) were analysed. In this study, a business is considered a small company if its operating revenue is less than 1 million EUR, its total asset value does not exceed 2 million EUR, and the number of employees is less than 15. A business is considered a medium-sized company if its operating revenue does not exceed 10 million EUR, its total asset value does not exceed 20 million EUR and the number of employees is less than 150.

The sample was randomly divided into a learning part (70% of all observations) and a testing part (30%), and later adopted receiver operating characteristic (ROC) curve methods; this approach was also employed in relation to the hazard model by Gupta et al. (2015).

In line with Gupta et al. (2015), I tend to differentiate between small and medium-sized businesses, as the SME segment is not homogenous, and the reason behind treating small businesses separately from medium-sized businesses is based on their lower expected survival probability. A dummy variable (called the category of a company) was added to control for this.

Further, I employ an industry dummy ('IND') to control the industry effect for two reasons. First, the analysed data comes from businesses in different industries. Second, it has been shown that industry specifics play a significant role in bankruptcy prediction (specifically in the case of a hazard model, see Chava & Jarrow, 2004 or, for a more general perspective, Grice & Dugan, 2001).

In line with Chava & Jarrow (2004), the following industry grouping was employed: IND 1 – Miscellaneous industries, IND 2 – Manufacturing and mineral industries, IND 3 – Transportation, communications, and utilities, IND 4 – Finance, insurance, and real estate.

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.

3.1 Potential company-specific variables

Empirical studies dealing with the hazard approach and SMEs were reviewed and a list of potential variables was collected (see Table 1). Information on the expected variable sign was also drawn from these studies; in several cases, the authors explicitly stated the expected sign, while in other cases, the sign was drawn from the final model details (i.e. parameter estimates published in the studies).

Tab. 1 – List of analysed ratios. Source: 1 – Altman et al. (2010); 2 – Campbell et al. (2008); 3 – El Kalak & Hudson (2016); 4 – Gupta et al. (2015); 5 – Gupta et al. (2018); 6 – Hillegeist et al. (2004); 7 – Chava & Jarrow (2004); 8 – Shumway (2001)

Abbr.	Description	Ex. sign.	Abbr.	Description	Ex. sign
C/TA	cash/total assets[3;4]	(-)	QA/TA	quick assets/total assets[4]	(-)
CA/CL	current assets/ current liabilities[1;7;3]	(-)	QR	quick ratio[3;5]	(-)
CA/S	current asset/ sales[3]	(+)	RE/TA	retained earnings/ total assets[8;7;6;4;3;5]	(-)
CashR	cash ratio[5]	(-)	S/TA	sales/total assets[8;7;6]	(+)
CE/TL	capital employed/ total liabilities[1;4;3;5]	(-)	S/TTA	sales/tangible assets[5]	(-)
CL/E	short-term debt/ equity[4;3;5]	(+)	SHP	stock holding period[5]	(+)
CL/TA	current liabilities /total assets[3]	(+)	size	ln(total assets/ GDP price level index)[6]	(-)
DCP	debtor collection period[5]	(+)	ST/TA	stock/total assets[4]	(+)
EBIT/CE	EBIT/capital employed[5]	(-)	St/WC	stock/working capital[1]	(+)
EBIT/S	EBIT/sales[5]	(-)	T/TA	taxes/total assets[4;5]	(-)
EBIT/TA	EBIT/ total assets [8;7;6]	(-)	TC/TA	trade creditors/total assets[4;3]	(+)
EBITDA/ IE	EBITDA/ interest expenses[4;3;5]	(-)	TC/TD	trade creditors/trade debtors[1]	(+)
EBITDA/ TA	EBITDA/total assets[4;3;5]	(-)	TC/TL	trade creditors/total liabilities[1;4]	(+)
FE/S	financial expenses/sales[5]	(+)	TCPP	trade creditors payment period[5]	(+)
FE/TA	financial expenses/ total assets[3;5]	(+)	TD/TA	trade debtors/total assets[4]	(+)
IA/TA	intangible assets/ total assets[4]	(+)	TL/NW	total liabilities/net worth[5]	(+)

Ln(age)	natural logarithm of age (number of days)[7]	(-)	TL/QA	total liabilities/quick assets[1]	(+)
log (CA/CL)	log (current assets/ current liabilities)[4]	(-)	TL/TA	total liabilities/total assets[8;7;2;3]	(+)
NI/E	net income/equity[3;5]	(-)	TL/TTA	total liabilities/ tangible total assets[5]	(+)
NI/S	net income/sales[3;5]	(-)	WC/S	working capital/sales[3]	(-)
NI/TA	net income/ total assets[8;7;6;2]	(-)	WC/TA	working capital/total assets[8;7;6;5]	(-)

3.2 Research methods

The Cox semiparametric proportional model approach was employed to derive the model, which was first adopted by Lando (1998), who was the first to model default with the Cox model. Further seminal work in this field was conducted by Shumway (2001), who demonstrated the superiority of the hazard model approach in predicting business defaults over the static approach model (i.e., not considering the multi-period nature of the data). The superiority of the hazard approach has also been confirmed by other authors, such as Chava & Jarrow (2004) and Berent et al. (2017). According to Gupta et al. (2015), 'the discrete hazard modelling technique is well suited to analyse data that consists of binary dependent variables and exhibits both time-series and cross-sectional characteristics, such as bankruptcy data'.

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 we cannot make a reasonable assumption about the shape of the hazard' (Cleves et al., 2008).

Applications of the hazard model are most often inspired by Shumway's (2001) seminal study, which showed that the discrete-time hazard model is equivalent to a multi-period logit model. In contrast, authors tend to specify the baseline hazard rate.

Generally, there are two main approaches to the specification of the baseline hazard rate. The first is to use time dummies, as shown by Beck et al. (1998), or employ macroeconomic variables, as suggested by Nam et al. (2008). They argue that indirect measures, such as time dummies, are less effective in capturing time-varying macro dependencies.

In this study, the Cox semiparametric model was used, leaving the baseline hazard rate unspecified and employing macroeconomic variables as explanatory variables. Therefore, this approach is different from that of 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), which seems to be useful as the analysis deals with panel data.

3.3 Selecting model variables

To select the variables, I employed the same two test procedures used by El Kalak & Hudson (2016). The starting point of the procedure was the derivation of a univariate model for each of the analysed variables, while the variables that exhibit significant estimates and had the expected sign were retained for further analysis. This approach has also been widely adopted by other authors (e.g. Altman et al., 2010; Gupta et al., 2015; Nam et al., 2008).

The categorical or dummy variable categories of company and industry were formed to control for the heterogeneity of the SME segment and the heterogeneity among the different industries. Before adding these variables to the otherwise univariate model or first-step model, the Kaplan-Meier procedure was run, together with a log-rank test, to test the equality of survival functions to gain insight into survival functions for all these categorical variables. In the case of unequal survival functions, the common approach of deriving the univariate model must be adjusted to control for differences between the groups. The next step was to run a multicollinearity check. If a highly correlated pair of variables was identified, the covariate with the lowest Wald statistic value was excluded from the final multivariate model.

3.4 Potential macroeconomic variables

In line with Nam et al. (2008), I employed macroeconomic variables to capture time-varying macro dependencies and, most importantly, as this study deals with panel data, to capture differences between European countries arising from different levels of economic development. The choice of potential macroeconomic variables was inspired by previous studies on hazard models or other studies dealing with default risk or SME financial constraints. These are expected to reflect the specific features to which SME survival is sensitive. The analysed macroeconomic variables are listed in Table 2, and the potential link to the survival probability of a business is discussed later. Data on macroeconomic variables were drawn from the EUROSTAT database.

Tab. 2 – Overview of hazard model literature employing macroeconomic variables. Source: own research

Macroeconomic variable	Literature	Ex. sign
Exchange rate	Holmes et al. (2010), Nam et al. (2008)	(+)
Interest rate	Christidis & Gregory (2010), Tinoco & Wilson (2013), Holmes et al. (2010), Nouri & Soltani (2016), Hillegeist et al. (2004)	(+)
Gross value added (GVA) per employee	Holmes et al. (2010)	(-)
Personal cost (PC) per employee	Holmes et al. (2010)	(+)
Inflation	Christidis & Gregory (2010), Nouri & Soltani (2016), Tinoco & Wilson (2013)	(+)
Employment	Holmes et al. (2010)	(-)

GDP annual growth rate	Simons & Rolwes (2009), Nouri & Soltani (2016)	(-)
GDP per capita	Beck et al. (2006)	(-)

According to Holmes et al. (2010), the exchange rate factor may be particularly important for SME survival, as they are more likely to 'face competition from abroad and be involved in exports and imports'. Exchange rate changes are expected to have an adverse effect on company survival as change 'implies a worsening of the competitive position relative to overseas competitors' (Holmes et al., 2010). The exchange rate from local currency to EUR was employed in this study, while the data were drawn from the Amadeus database, which quotes the exchange rate based on data from the International Monetary Fund (IMF) website; the exchange rates refer to the closing date of the statement.

Interest rates influence a company's survival probability through its capital structure; low-interest rates are incentives for companies to make investments, and the expected return on investments is higher when interest rates are lower than when interest rates are high. However, high interest causes rising costs of debt capital, with firms having to pay more to their lenders (Tinoco & Wilson, 2010). Higher interest rates are, for this reason, expected to increase the probability of a company's failure. In this study, the yield on government bonds with a maturity of 10 years was adopted as the interest rate variable; such interest rates are used to define the Maastricht criterion for long-term interest rates. Gross value (GVA) added is expected to have a positive influence on a company's survival (decreasing the probability of failure) since increasing GVA is associated with a growing market. In contrast, any wage increase (personal costs) means a rise in costs and is therefore expected to increase the probability of failure (Holmes et al., 2010).

Inflation is expected to indirectly affect the probability of a company's default by serving as an incentive to invest savings rather than seeing their purchasing power erode further in the future due to inflation. Inflation, therefore, increases investors' risk-taking capacity and, as a result, reduces the default probability (Tinoco & Wilson, 2013; Qu, 2008). However, as acknowledged by Qu (2008), the direction of the inflation effect on default probability has not been unequivocally established due to the complexity of the effect of inflation on the economy. Mare (2012) noted that a high inflation rate is a sign of weak macroeconomic conditions, during which there is also an elevated risk of a bank crisis. In this study, we adopted the Harmonised Index of Consumer Prices (HICP), specifically the annual average rate of change, as the inflation rate. Within this study, and based on the arguments above, it is expected that an increase in the inflation rate is related to a rise in a company's hazard probability. The employment rate is expected to lower the probability of failure. Employment is a proxy for demand; the higher the level of employment, the higher the expected demand (Holmes et al., 2010). The employment rate was drawn from the EUROSTAT database and referred to the percentage of employed individuals between the ages of 15 and 64, expressed as a proportion of the total population. Studies on SMEs often regard them as vulnerable to changes in the economic environment. Simons & Rolwes (2009) reported a significant negative relationship between GDP growth and company default rate. Beck et al. (2006) found that businesses in countries with a higher level of intermediary financial development, a more liquid stock market, a more efficient legal system, and a higher GDP per capita report fewer financing obstacles. Ullah (2020, p. 121) highlights that 'among all the business environment constraints affecting firm growth, financial constraints have been identified as one of the most detrimental growth obstacles'. GDP per capita might serve as a proxy for the financial obstacles a company has to face in its country; however, growth obstacles seem to affect survival probability indirectly. A negative relationship between GDP per capita and company survival may be expected for these reasons.

4. RESULTS AND DISCUSSION

According to the results of the log-rank test, there are significant ($p < 0.001$) differences between small and medium-sized businesses (SB variable), while there are also significant differences between businesses operating in different industries (IND variable). Initial discrimination analysis indicated that, of the 42 tested variables, only 25 exhibited significant coefficient estimates while also taking the expected sign. A similar procedure was followed for the macroeconomic factors under analysis. All the analysed macroeconomic variables are significant at the 1% level, except for the GDP annual growth rate. A possible explanation might be that the analysed period was a relatively stable period for EU SMEs, with only the Greek economy turning into recession in 2015 and 2016 and Croatia, Cyprus, Finland, and Serbia experiencing negative annual GDP growth in 2015. In terms of country-year GDP data, 99% of observation values were positive and did not, therefore, significantly trigger business defaults. For example, Nouri & Soltani (2016) analysed the impact of the GDP growth rate, interest rate, and inflation on the bankruptcy of businesses listed on the Cyprus stock exchange and found that these variables have no significant impact. However, it should be noted that their results were based on a different methodology. Regarding the expected sign of the analysed variables, only interest rates, personal cost (PC) per employee, and employment rate variables had the expected sign, which will be kept for further analysis.

The next step was to conduct a correlation check. Pearson's correlation coefficient and the variance inflation factor were used for this purpose. Four variables (NI/TA, CA/S, EBIT/S, and CashR) were excluded from further analysis for collinearity reasons.

4.1 Estimating the model coefficients

The model was estimated in two forms: Model 1, combining macroeconomic and accounting variables, and Model 2, employing only accounting variables (the same set as Model 1). Both models were tested using ROC curves, and area under curve (AUC) values were compared using the procedure suggested by DeLong et al. (1988).

Model 1 was estimated in a stepwise manner by employing a backward elimination procedure using conditional likelihood ratio statistics, which are considered the least prone to error measurement, as a criterion. As a result, the model was significant at the 1% level. Model 2 was derived using the same variables (except for macroeconomic variables) as Model 1. This model was also significant at the 1% level. The details of the estimated coefficients for Model 1 are presented in Table 3.

In Model 1, the stepwise procedure led to the exclusion of eight variables from the final model, while the residual chi-square was 9.910 (with df = 8), sig. = 0.271, which is not significant; therefore, forcing these variables into the model would not significantly contribute to the predictive power of the model.

The industry effect and the category of a company effect are significant variables in estimated Model 1, which is in line with expectations (Chava & Jarrow, 2004; Gupta et al., 2015).

Regarding the details of Model 1, there are three macroeconomic variables included in the model: the interest rate, PC per employee, and employment rate. They all have the expected signs. The company-specific financial ratios in the final model describe the working capital management level (SHP) and its structure (C/TA, QA/TA). Further significant indicators are measures of business solvency (EBITDA/IE, CL/E, TL/NW, or CE/TL) or the relative size of financial expenses (FE/S) and net profit margin (NI/S). El Kalak & Hudson (2016) found that the net profit margin (NI/S) is a significant profitability measure for SMEs, although this measure is insignificant when focusing solely on small businesses. Gupta et al. (2018) reported varying (insignificant) explanatory powers across different time periods, while the same applies for the EBITDA/IE and CL/E indicators.

After the first derivation of the model, the quick ratio (QR) and net profit margin (NI/S) changed their sign to positive, contrary to prior expectations. According to Kennedy (2005), possible explanations for such a phenomenon could be the presence of multicollinearity, outliers, or missing interaction terms. As the data were winsorised and multicollinearity checked, the explanation that remained was a missing interaction term, resulting primarily from data aggregation. The variable interactions between industry group, category of company, and OENEG (dummy) were analysed as potential missing interactions. Only the interaction between the QR (or rather NI/S) variable and the category of a company indicator are included in the model, leading to a change in the main effect estimate sign.

Tab. 3 – Variables in Model 1. Source: own research

Variables		B	SE	Wald	p-val.
Macroe	Interest rate**	1.067	0.021	2,631.976	0.000
	PC per employee**	0.010	0.002	38.962	0.000
	Employment rate**	-0.036	0.005	61.928	0.000
Firm specific	C/TA**	-1.953	0.164	141.968	0.000
	CL/E**	0.006	0.001	46.443	0.000
	EBITDA/IE**	0.000	0.000	8.797	0.003
	FE/S**	1.617	0.171	89.381	0.000
	ln(age)**	-0.069	0.017	16.674	0.000
	NI/S**	-0.207	0.019	116.354	0.000
	QA/TA**	-0.172	0.064	7.240	0.007
	QR**	-0.131	0.031	17.411	0.000
	SHP**	0.000	0.000	19.310	0.000

Firm specific	size**	-1.147	0.042	738.019	0.000
	T/TA**	-2.749	0.699	15.470	0.000
	TL/NW**	0.006	0.002	7.520	0.006
Categorical (dummy)	SB**	1.236	0.064	371.831	0.000
	IND**			2,095.415	0.000
	IND = n/a**	3.068	0.113	740.366	0.000
	IND = 1**	-0.416	0.087	23.132	0.000
	IND = 2**	-0.356	0.091	15.261	0.000
	IND = 3**	-0.517	0.106	23.568	0.000
	OENEG**	-0.170	0.048	12.865	0.000
Interaction terms	SB x NI/S**	0.306	0.022	199.008	0.000
	SB x QR**	0.187	0.032	34.116	0.000

Note: *significant at 5% level; **significant at 1% level. B: coefficient estimate; SE: standard error.

The aim of this study was also to analyse the significance of macroeconomic variables in predicting the default of European SMEs by deriving a second version of the model (referred to as Model 2). The details of the estimated coefficients are shown in Table 4. This version of the model contains only accounting variables and dummy variables for industry and the category of a company. All the re-estimated coefficients have the expected sign, except for the relative size of quick assets (QA/TA), which changes its sign to positive, which may be the result of a missing interaction due to a change in the variable set. Furthermore, indicators TL/NW and EBITDA/IE were not significant in the model.

Tab. 4 – Variables in Model 2. Source: own research

Variables		B	SE	Wald	p-val.
Firm specific	C/TA**	-1.590	0.110	210.389	0.000
	CL/E**	0.009	0.001	166.900	0.000
	EBITDA/IE	0.000	0.000	1.640	0.200
	FE/S**	1.012	0.122	69.065	0.000
	ln(age)**	-0.174	0.010	323.096	0.000
	NI/S**	-0.289	0.015	353.087	0.000
	QA/TA**	0.227	0.047	23.444	0.000
	QR**	-0.288	0.032	80.097	0.000
	SHP**	0.000	0.000	76.799	0.000
	size**	-0.694	0.028	619.631	0.000
	T/TA**	-2.930	0.512	32.800	0.000
	TL/NW	0.001	0.002	0.448	0.503
Categorical (dummy)	SB**	2.382	0.051	2,158.309	0.000
	IND**			34.301	0.000
	IND = n/a	-0.020	0.077	0.067	0.796

Categorical (dummy)	IND = 1**	-0.213	0.065	10.849	0.001
	IND = 2*	-0.161	0.069	5.457	0.019
	IND = 3**	-0.322	0.080	16.413	0.000
	OENEG**	-0.293	0.036	67.867	0.000
Interaction terms	SB x NI/S**	0.386	0.016	563.580	0.000
	SB x QR**	0.314	0.032	94.335	0.000

Note: *significant at 5% level, **significant at 1% level, B: coefficient estimate, SE: standard error.

4.2 Model testing results

Model testing was performed in terms of the AUC, while the survival probability, as a model outcome, was subject to testing. ROC curves were employed to evaluate the performance of the estimated hazard models, and the comparison between the AUC of the model was subjected to a non-parametric DeLong test.

The learning sample and out-of-sample results are presented in Table 5. The AUC value attained for the learning sample (70% of the data) was 0.878 in the case of Model 1 and 0.824 in the case of Model 2. The results for the test sample were comparable, with the AUC attaining a value of 0.881 for Model 1 and 0.83 for Model 2. The 95% confidence interval was based on the binomial distribution.

Tab. 5 – Model testing results. Source: own research

Sample	Model	AUC	SE	95% Conf. Int.
Learn	1	0.878	0.00301	0.875 to 0.881
	2	0.824	0.00383	0.821 to 0.827
Test	1	0.881	0.00442	0.877 to 0.885
	2	0.830	0.00566	0.826 to 0.835

Note: AUC: Area under the curve, SE: standard error.

The difference in AUC values between Models 1 and 2 was subjected to the DeLong test. The difference between Model 1 and Model 2, that is, the difference in model discriminatory power resulting from macroeconomic variable employment, is 5.4 pp for the learning sample and 5.1 pp for the test sample. Both these differences are statistically significant, meaning that adding macroeconomic variables led to a significant increase in the discriminatory power of the model.

Tab. 6 – DeLong test results. Source: own research

	Learn sample	Test sample
Difference between areas	0.054	0.051
Standard error	0.00413	0.00622
95% confidence interval	0.0459 - 0.0621	0.0388 - 0.0632
z statistic	13.084	8.203
Significance level	p-val. < 0.0001	p-val. < 0.0001

5. CONCLUSION

Managers are generally well aware that, to remain competitive, planning for the future is vitally needed. In addition, there is a consensus about the need to consider the development of external and internal business environments during the planning process. The question that remains unanswered is what factors of the external environment are the most crucial in business competitiveness or even its survival, and thus need to be taken into consideration. The present research shows that, in the case of SMEs, the employment rate, level of PC per employee, and interest rate play a significant role in determining the future financial position of SMEs and affect SMEs' competitiveness. The importance of this issue is magnified from the perspective that SMEs are more financially constrained than large businesses and are more vulnerable to environmental changes.

The results also show that the financial position of an SME is affected at the company level by the level of net profit margin and the structure of net working capital items, as well as from the non-financial perspective by industry specifics, the age of the business and business size.

From a methodological perspective, the presented topic of modelling the influence of the external environment on the probability of survival of SMEs is a more complex issue. Many scholars have argued that business survival must be treated as a multi-period process. Currently, there are a limited number of studies that deal with these issues by employing a hazard model approach for SMEs and utilising macroeconomic variables as the baseline hazard rate. Most of these studies focus only on US or UK data. To fill this gap, this study addresses SMEs from EU-28 countries.

The employed methodology of the Cox model is a rather flexible tool for the issue under analysis, as it is very flexible in terms of baseline hazard rate specification. At the same time, the parameters can be estimated even if the baseline hazard rate is left unspecified. This is a very useful feature for analysing the influence of the external environment on business survival probability.

Most studies on hazard models specify hazard rates in terms of time dummies or macroeconomic variables. In this study, the macroeconomic variables were utilised as explanatory variables, which could be viewed as a more flexible approach to the utilisation of the environmental approach. The employment rate, together with long-term interest rates and PC per employee, seems to play a significant role in SME survival probability. The employment rate is regarded as a proxy of demand, while the interest rate directly affects the availability of external sources of finance for SME development. The limited availability of external financing to SMEs is often perceived as a burden on their further growth, but the results of this study show that the interest rate has a direct effect on SME survival probability. The effect is especially significant in the case of changes to long-term interest rates, with a change in long-term interest rate by one percentage point multiplied by the relative risk of SME default by a factor of 2.9.

The created model, which employed only accounting variables, reached an AUC value of 0.831, which might be regarded as relatively high. However, by adding macroeconomic variables, the AUC increases to 0.881. This increase in AUC value or model discrimination power was statistically significant in terms of the DeLong test. The results show that further development of default prediction models needs to consider the external environment factors along with the company-specific variables. The general approach of using only company-specific financial ratios limits the further improvement of model accuracy.

As in any research, this research has its limitations, especially in focusing only on the main effects related to the analysed variables, which omits the interactions between variables. In particular, the industry effect may interact significantly with company-specific financial ratios. For future research, the factors of financial constraints, which better reflect the market conditions that SMEs must face to improve their competitiveness, should be analysed in more detail.

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