The Role of Human Capital in Bankruptcy Prediction: A Study of the Differences of the Probability of Default for SMEs in Hungary

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Abstract
SMEs, along with most businesses, have suffered during the COVID-19 pandemic that has brought many to the brink of failure. It is to the benefit of banks, SMEs themselves, and other stakeholders to be able to predict which companies have a higher probability of default after challenges to businesses such as those faced during and following the pandemic. Many of the existing models that try to predict the probability of default fail to take into account the human capital aspect, focusing primarily on the financial aspects of the business and performance criteria. This study poses the research question: what is the role of human capital in bankruptcy prediction? To answer this research question, we have employed the concept of Integrative Reporting, as we aim to examine how the human capital aspect of SMEs affects the prediction of the probability of bankruptcy, through including human capital components in Ohlson's bankruptcy prediction model. It is found that human capital is indeed a key component in assessing the risk of bankruptcy, confirming the findings in the literature. Our study also highlights the need for Ohlson's model to be calibrated to local market specifications. The findings have distinct implications for practitioners and fill the current research gap of connecting non-financial capital to corporate value by proposing a new measurement tool through the inclusion of human capital in predicting corporate bankruptcy. Best practice and future research directions are highlighted such as how this study may be extended to consider specific elements such as level of education, employee skills, investment in training, and management competencies. For practitioners, this study provides a broader scope and allows greater accuracy in bankruptcy risk predictions, which will be of benefit to both major and minor stakeholders as challenges are faced by SMEs and other firms in the future.

Keywords
Bankruptcy prediction; SME; human capital; risk; Ohlson-model.

Introduction

Crises such as the pandemic pose a threat to the survival of companies around the world. Small and medium-sized enterprises (SMEs) in particular have been found to be more vulnerable to periods of economic turbulence (Jahur & Quadir, 2012), which may result in significant knock-on effects given the role of SMEs in economic growth (Altman & Sabato, 2007). Thus, it is in the interests of both academics and practitioners to assess indicators of financial distress and methods for calculating the probability of default in SMEs, especially given the current economic challenges (Sági et al., 2020).

The key prediction models that are used as indicators of financial distress are Altman's (1968) and Ohlson's (1980) bankruptcy prediction models and are often compared (e.g., Karamzadeh, 2013), although several empirical accounting researchers opt for the latter (Begley et al., 1996). Empirical studies employing bankruptcy prediction models often study them in relation to financial aspects such as financial ratios (Mehrani et al., 2005; Wang & Campbell, 2010). Some studies such as Wellalage and Locke (2012) examined the non-financial characteristics that may have an impact upon bankruptcy risk of SMEs.

Human capital has a key role to play in the success or failure of SMEs, such as in terms of the knowledge and qualifications of entrepreneurs. From a sample of 102 Austrian SME bankruptcies, Mayr et al. (2020) found that the age and gender of entrepreneurs, in particular, had an impact on the probability of failure. Wellalage and Locke (2012) found that management adequacy affected the survival rate of small firms. However, research applying this human aspect to bankruptcy prediction models seems scarce. To add to existing studies highlighting the need for further research into the role human capital plays in bankruptcy prediction (Ciampi et al., 2021) and provide insight and implications for practitioners in SMEs, our study aims to examine the role of HR (personnel)-related components in bankruptcy risk through employing these components to the Ohlson bankruptcy prediction model, thereby extending the original model.

We first present a theoretical background of the Ohlson model, and then consider empirical studies in this field, followed by methodology, results, and conclusions, which includes recommendations for practitioners and future research directions.

Theoretical background

In this section, we first present Ohlson's model as a means of calculating the probability of default and then introduce our theoretical model, which extends Ohlson's model to take human capital into account.

Corporate bankruptcy

The logistic regression method is suitable for modeling the relationship between some explanatory variables and the probability of a binary response (Hosmer & Lemeshow,

2005). The explanatory variables can be continuous and categorizers, whilst the outcome variable is a dichotomous dummy variable. Using the maximum likelihood method, it uses a logistic regression function for ordinal data (Sainani, 2021). The weighted score of independent variables expresses the probability of firms surviving and going bankrupt. The value obtained, which is between 0 and 1, indicates bankruptcy probability values only if a sample includes the same proportion of solvent and insolvent firms as the population does.
The Ohlson-O model (1) is based on logistic regression (Ohlson, 1980), and represents the probability of default (2) within the next two years for P>0.5 under 96% reliability:

$$O = -1.32 - 0.407 * log(TA/GNP) + 6.03 * TL/TA - 1.43 * WC/TA + 0.0757 * CL/CA - 1.72 * X - 2.37 * NI/TA - 1.83 * FFO/TL + 0.285 * Y - 0.521 * (NI_t - NI_{t-1})/(abs(NI_t) - abs(NI_{t-1})) \quad (1)$$

$$P = \frac{e^O}{1 + e^O} \quad (2)$$

TA = total assets
GNP = Gross National Product price index level
TL = total liabilities
WC = working capital
CL = current liabilities
CA = current assets
X = 1 if TL > TA, 0 otherwise
NI = net income
FFO = funds from operations
Y = 1 if a net loss for the last two years, 0 otherwise

The Ohlson-O score has lower popularity in the literature: the Ebsco database accounts for a number of 172 articles which is remarkably lower than the appearance of the Altman-Z score (N=2536). However, it can be converted to an exact default-probability instead of thresholds and the relative size of the company was involved to consider the too-big-to-fail effect as well as the cash flow. This approach was mostly used to calibrate and backtest other more specific models on big data analyses: US pricing anomalies were studied by Novy-Marx (2013), Stambaugh et al. (2012), or by Charitou et al. (2011).

Theoretical model

This study calibrates the Ohlson-O model on a randomly selected set of small- and medium enterprises in Hungary (the set covered all the mayor NACE-classes), using an N= 2969 sample between 2008 and 2019, where 82.3% of the panel avoided bankruptcy while the rest of them ceased to exist after the business year of 2016 (Ohlson-O_HU). We are using the same variable set like the Ohlson-O model, but we will extend (Ohlson-O_(HU,RoEmpl)) it later with the Return on Employees (RoEmpl_t) ratio (3) which is calculated as follows to capture the labor productivity:

$$RoEmpl_t = \frac{NI_t}{Employed_t} \quad (3)$$

This can provide an interesting comparison between the influence of the tangible asset productivity (Return on Asset) and the mainly intangible human capital of the company, which was captured by the RoEmpl_t ratio in year t.

Since the study focuses on the survivability of the small and medium enterprises due to the Covid-19 lockdowns, a broader sample was analyzed in the second step of this research, including an N=5097 sample. There were the calibrated Ohlson-O_HU and the extended Ohlson-O_(HU,RoEmpl) estimated again, to see their predictions for the sample according to the main NACE-classes.

Human capital and bankruptcy

The majority of bankruptcy prediction models over the past 50 years were designed using financial variables (Balcaen & Ooghe, 2006). This section examines the empirical studies that have looked into the potential effect of human capital on financial success or bankruptcy in SMEs.

Abdel Fattah et al. (2020) examined the impact of human capital and knowledge spillovers upon SMEs' financial soundness. They found that local educational level and knowledge spillovers improve SME financial soundness in four European countries. Schalck and Schalck (2021) examined the main factors of failure in French SMEs and found the factors to stem from both financial and non-financial sources. For our study, the finding that self-employment was the strongest in increasing the probability of failure is especially relevant. Wellalage and Locke (2012) also examined the factors that cause the failure of SMEs and suggest that larger firms may have a lower bankruptcy risk, not only as a result of higher access to finance than smaller firms but also due to a greater diversification of human capital. However, in contrast, Cultrera and Bauweraerts (2017) found larger and older firms had a greater risk of bankruptcy. However, a recent study by Chanatup et al. (2020) revealed that the disclosure of data about the company may have an effect on the perceived risk by shareholders.

Although not specifically targeted at SMEs, Thornhill and Amit (2003) examined 339 Canadian firms and found that failure among younger firms was due to issues relating to managerial knowledge and financial management abilities and in contrast, failure among older firms, due to an inability to adapt to environmental change. Whilst it cannot be assumed that all younger firms in the study were SMEs, it does highlight how empirical studies have found human capital has a role to play in the probability of bankruptcy failure.

Alongside the recent regulatory changes in accounting, the concept of Integrated Reporting is about linking financial and non-financial elements, i.e., human capital, into the process of corporate value creation (IIRC, 2013). Although the regulators intend to raise awareness about the qualitative aspects of corporate governance (Tjahjadi et al., 2020), the systematic understanding and measurement techniques of assessing these non-financial elements as determinants of the corporate value are still missing from the literature (Velte, 2021).

Prior literature reviews found that there is a positive relationship between corporate governance structures on the one hand and the adoption of sustainability or integrated reporting on the other (Guerrero-Villegas et al., 2018; Lai et al., 2016; Stacchezzini et al., 2016). However, other studies found that there was no significant improvement in the quality of these reports (Melloni et al., 2017) which proves that there is a lack of measurement tools for the contribution or added value of human capital to corporate value. Also, there is a lack of evidence as to whether the corporate value will decrease to the level of bankruptcy because of the financial and non-financial capitals. This research study contributes to the literature by filling, partly, the gap of connecting non-financial capital to corporate value by proposing a new measurement tool through the inclusion of human capital in predicting corporate bankruptcy.

Data and methods

This section summarizes the main properties of the dataset and presents the methodological background – namely the approaches to overcome the missing data problem and the summary of the logit regression. Since the Ohlson-O model highly depends on the availability of the different ratios, the effects of missing data will have a multiplicative impact on the result, drastically reducing the sample size. Therefore, it was crucial to overcoming this issue with the EM algorithm which will be summarized in this section.

Data

Data was acquired from the Amadeus database, to represent the main NACE-classes in 2019 among the Hungarian SMEs with consolidation codes U1-C2 and with A-B BvD Independence Indicators (Figure 1).

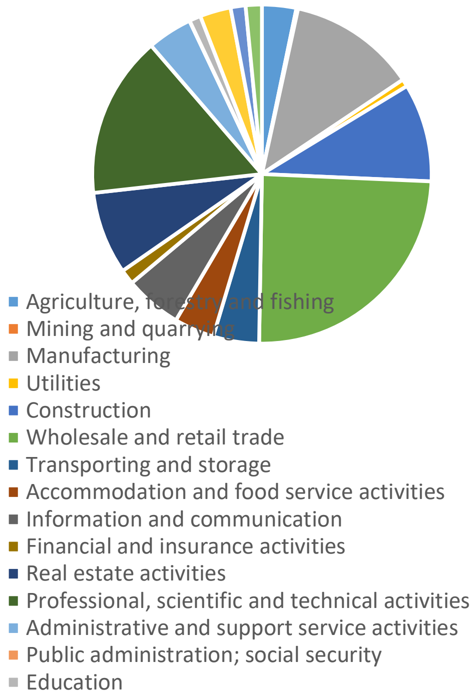

Figure 1. NACE-structure of the companies in the final model
(Amadeus database, Authors' own construction)

Logit regression

Panel data analysis describes the relationship among the dependent (y) and explanatory variables (x) in cross-sectional (N) and time (T) dimensions with an assumed non-observed variable (u_i).

The binary-answer models are focusing on the probability of one event, for example, the probability of default which is the focus of this paper. The dependent variable takes a binary value of 0 or 1 under the following (4) assumption of (Wooldridge, 2009):

$$P(y = 1|x) = G(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k) \quad (4)$$

Where the function G must fall between 0 and 1, providing an assumed probability between 0 and 1 as well. Therefore, it depends on the shape of the G function and which model will be applied to the data. For logit models, the G function takes the shape of the logistic function (5), therefore it can be characterized by (Wooldridge, 2009):

$$G(z) = \frac{e^z}{1+e^z} \quad (5)$$

It means that the value of the function will always be between 0 and 1, maintaining a 0 to 1 probability as well.

Missing data: EM method

Following Baraldi et al. (2015), there are four different approaches to assess the missing data problem: listwise deletion, last observation carried forward, mean-imputation substitutes, and lastly to reconstruct missing data through minimization of an error function, derived from mean, variance, or a likelihood ratio (Baraldi et al., 2015). Expectation maximization (EM) models apply maximum likelihoods to estimate variance, covariance matrixes of the data (Schneider, 2001). The expectation-maximization takes more computation time because EM algorithm may be as difficult to compute as the likelihood function itself (Ruud, 1991) and they require more specification of a data generation model (Houari et al., 2013), but they do not rely on the MCAR requirement is a feature that remains to be fully exploited. Unbiasedness under MAR and higher efficiency under MCAR make maximum likelihood the method of choice in a situation with incomplete multinormal data (Wothke, 1998). They are less biased than listwise and pairwise deletion and mean-imputation methods, but this advantage depends on the missing data rate, the covariance structure of the data, and size of the sample (Wothke, 1998).

Missing data problems can affect daily time series under multivariate applications like volatility spillover, extreme fluctuation, or contagion modeling, where assumptions about conditional variance, covariance, and correlation are critical.

Regularized expectation-maximization (EM) algorithm based on iterated linear regression analyses, but it replaces the conditional maximum likelihood estimation of regression parameters for Gaussian data (5), following Schneider (2001). For each $p_{(t,i)} \in P$ with missing values, the relationship between the prices with missing values (trading days) and the prices with available values is modeled by a linear regression model:

$$p_{NaN} = \mu_{NaN} + (p_a - \mu_a)B + \varepsilon \qquad (5)$$

Where a represents available data, and $B \in R^{(n_a \times n_{NaN})}$ is a matrix of regression coefficients with covariance matrix with missing and available data from n all sample markets. The $\varepsilon \in R^{(1 \times n_{NaN})}$ residual is assumed to be a zero-mean and $C \in R^{(n_{NaN} \times n_{NaN})}$ unknown covariance matrix-vector. In each iteration of the EM algorithm, estimates of the mean $\mu \in R^{(1 \times n)}$ and the $\Sigma \in R^{(n \times n)}$ covariance matrix are taken as given, and from these estimates, the conditional maximum likelihood estimates of the matrix of regression coefficients B and of the covariance matrix C of the residual are computed for each record with missing values.

Results

Calibration results

The calibration of the model on the randomized Hungarian panel sample provided similar coefficients to the original (Table 1). The high values of the relative size (TA/GNI), the short-term company's solvency (WC/TA), the Return on Assets (NI/TA), the leverage (FFO/TL), and the annual change of the Net Income (NItabs) contributed to low bankruptcy probabilities just as it happened in the original model. However, the debt ratio (TL/TA) was positive in the original model, but unsurprisingly it was negative in the Hungarian set since emerging economies can be more vulnerable to global funding disturbances.

Table 1. The results of the panel-logit model on the calibration sample

	$Ohlson - O_{HU}$			$Ohlson - O_{HU,RoEmpl}$		
variable	**coefficient**	**p-value**		**coefficient**	**p-value**	
const	-5.94227	2.78E-231	***	-1.68068	0.0028	***
TA/GNI	-0.57138	5.85E-96	***	-0.11507	0.0715	*
TL/TA	-0.00128	0.0287	**	0.117658	0.0002	***
WC/TA	-0.00166	0.0465	**	0.105267	0.0017	***
CL/CA	0.000209	0.2077		2.60E-05	0.9724	
NI/TA	-0.00057	0.5626		-0.24729	7.50E-06	***
FFO/TL	-0.00297	0.0439	**	-0.00542	0.0377	**
NItabs	-0.00231	0.094	*	-0.00025	0.931	
RoEmpl				-0.33722	1.09E-09	***
observation No	13345			25720		
correctly predicted	12591	94.30%		23223	90.30%	
	Predicted 0	Predicted 1		Predicted 0	Predicted 1	
Actual 0	12584	7		23206	15	
Actual 1	747	7		2482	17	

Meanwhile the Ohlson-O_(HU,RoEmpl) model had similar coefficient-signs to the Ohlson-O_HU model, where the Return on Employees (RoEmpl) became a significant variable with a decreasing power on the default probability. It is remarkable when we are focusing on the comparison of the Return on Assets and the Return on Employees ratios, the first one had higher importance in the avoidance of bankruptcy, and its inclusion reduced the value of the constant as well, pointing to the necessity of its utilization. This result underlines the importance of the intangible capital element for the Hungarian companies as well.

Model results of the 2019 Sample

To identify the difference in the probability of default among the different economic activities (defined by the main NACE-classes) one year before the COVID-19 shock hit the Hungarian SME sector, a big and comprehensive set of companies were analyzed.
While the inclusion of the highly intangible RoEmpl-ratio provided further benefits to the panel model, its application on the broader 2019 cross-sectional data presented

higher median values (and overall levels) for default probability (Figure 2). This result underlines the importance of these metrics since they distinguished better among the companies in the sample.

The inclusion of the highly intangible RoEmpl-ratio was also meant to tackle the valuation bias of human capital-intensive companies. As Damodaran (2009) pointed out, for companies that derive most of their value from intangible assets, and have high growth opportunities, the net income, and the book value are usually understated. This will lead to much higher PE, EV/EBITDA and book value multiples for stock-exchange traded companies; but will remain unrealized for most SMEs whose shares are not traded on stock exchange. This valuation bias originates from the accounting treatment of expenses related to the hiring, training, and compensation of employees, the brand name advertising, or the R&D personnel, which are recognized as operating expenses (so they decrease the company's net income). Instead, these personnel expenses could be considered as capital expenditures (to be added to the company's asset value), since they raise long-term benefits for the company; but this later solution is not admitted by the accounting standards. Therefore, the valuation bias remains. Consequently, we proposed to employ the Return on Employees ratio as a counterpart to the Return on Assets.

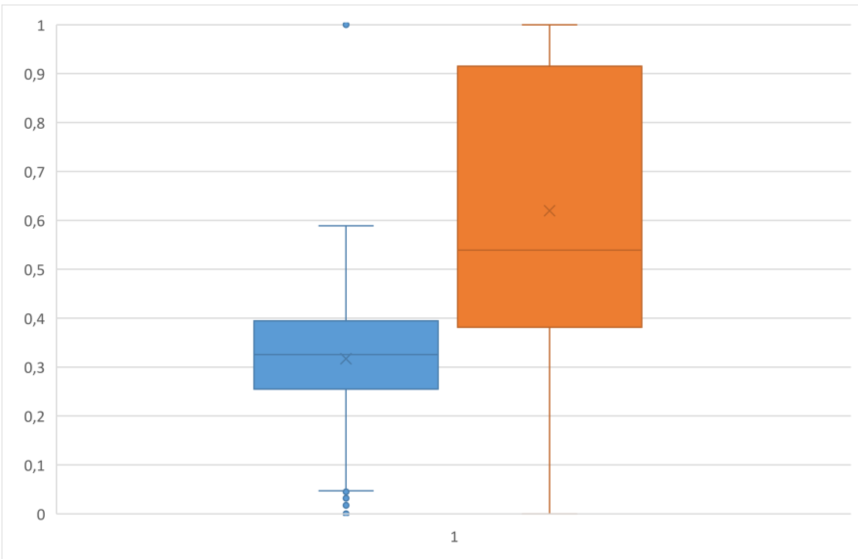

Figure 2. Differences between the Ohlson $-$ O_{HU} and the Ohlson $-$ $O_{HU,RoEmpl}$ models (entire 2019 sample)

When we are focusing on the differences according to the main NACE-classes (Figure 3), the upper difference remained significantly higher (see Appendix 1 for further details). They were similarly low at the agricultural, mining, manufacturing, utilities, construction, wholesale, real estate, and public administration companies, but they were remarkably high for those companies which were operating in the accommodation, information technology, financial, scientific, administrative, education, healthcare, entertainment, and other businesses. This result is acceptable since these business activities depend at most on the intrinsic knowledge and the added value of their employees which determines the probability of default of these companies.

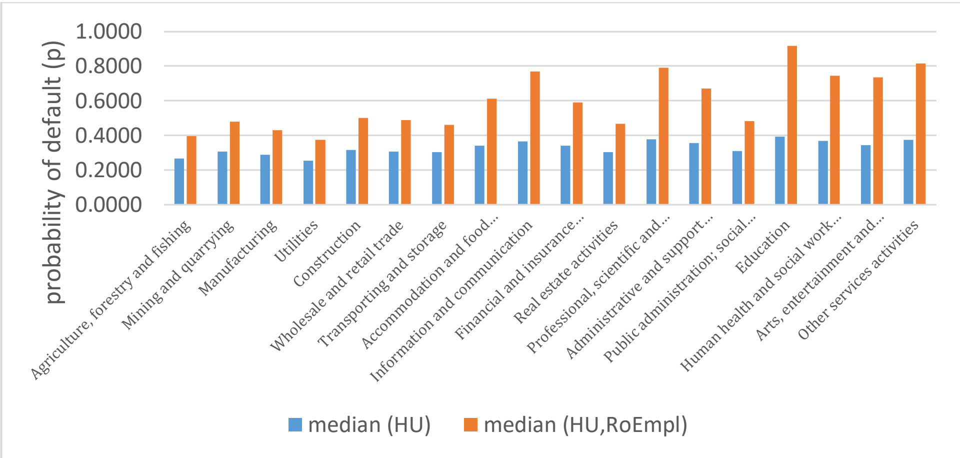

Figure 3. Differences between the Ohlson-O_HU and the Ohlson-O_(HU,RoEmpl) models (NACE-classes of the 2019 sample)

Conclusions

Our study aimed to examine the role of the HR (personnel)-related components in bankruptcy risk through employing these components to the Ohlson bankruptcy prediction model. Through the extension of this model, our findings have confirmed that human capital is a necessary consideration in the assessment of bankruptcy risks using prediction models. This finding is of distinct importance for future research directions as the inclusion of human capital will likely provide a broader scope and greater accuracy in bankruptcy risk predictions. Further research may be extended to consider specific elements such as level of education, employee skills, investment in training, and management competencies.

The results of this paper also highlight the necessity of the calibration of the general Ohlson-O model to meet the local market specifications and the importance of the inclusion of not just the productivity of the tangible assets but the highly intangible human capital as well due to its emerging importance in today's knowledge-based economy. This statement was verified by the results on the supposedly more human-capital intense businesses.

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Appendix 1: Detailed results, main NACE-classes

		$Ohlson - O_{HU}$			$Ohlson - O_{HU,RoEmpl}$			
	No. of companies	median	quantile 10%	quantile 90%	median	quantile 10%	quantile 90%	t-test
Agriculture, forestry and fishing	165	0.2650	0.1674	0.4074	0.3952	0.3203	0.9702	0.0000
Mining and quarrying	8	0.3066	0.1966	0.4132	0.4787	0.3347	0.9644	0.0131
Manufacturing	615	0.2868	0.1683	0.4175	0.4290	0.3216	0.9834	0.0000
Utilities	36	0.2544	0.1245	0.4310	0.3749	0.3042	0.9980	0.0000
Construction	474	0.3153	0.1966	0.4309	0.4997	0.3332	0.9978	0.0000
Wholesale and retail trade	1242	0.3068	0.1927	0.4312	0.4884	0.3382	0.9988	0.0000
Transporting and storage	221	0.3023	0.1803	0.4146	0.4593	0.3309	0.9811	0.0000
Accommodation and food service activities	193	0.3418	0.2212	0.4362	0.6115	0.3588	1.0000	0.0000
Information and communication	275	0.3659	0.2208	0.4417	0.7688	0.3526	1.0000	0.0000
Financial and insurance activities	72	0.3409	0.1743	0.4464	0.5913	0.2976	1.0000	0.0000
Real estate activities	399	0.3040	0.1832	0.4298	0.4660	0.3298	0.9986	0.0000
Professional, scientific and technical activities	781	0.3759	0.2512	0.4408	0.7913	0.3730	0.9996	0.0000
Administrative and support service activities	217	0.3544	0.2282	0.4371	0.6701	0.3555	0.9997	0.0000
Public administration; social security	1	0.3105	0.3105	0.3105	0.4816	0.4816	0.4816	NaN
Education	55	0.3919	0.2208	0.4437	0.9181	0.4585	1.0000	0.0000
Human health and social work activities	149	0.3672	0.2849	0.4317	0.7452	0.4163	0.9978	0.0000
Arts, entertainment and recreation	72	0.3432	0.2288	0.4425	0.7339	0.3791	1.0000	0.0000
Other services activities	78	0.3745	0.2612	0.4494	0.8146	0.3980	1.0000	0.0000